Silesian University of Technology
ul. Akademicka 2A
44-100 Gliwice

via:
The Council for Scientific Excellence
pl. Defilad 1
00-901 Warszawa
(Palace of Science and Culture, 24th floor, room 2401)

dr inż. Rafał Doniec

Application

dated August 10th, 2024

re.: commencement of the procedure for the conferment of the post-doctoral degree of doctor habilitated in the field of [1] biomedical engineering.

„Advanced methods of analysis and recognition of drivers' behavioral and cognitive activities using a simulator, sensors, and AI algorithms."

Pursuant to art. 221 para 10 of the Higher Education and Science Act dated 20 July 2018 (Polish Journal of Laws of 2018 item 1668, as amended) I hereby kindly request that the habilitation commission pass a resolution on the conferment of the post-doctoral degree of doctor habilitated in ~~**secret**~~/**open** voting[2].

I was advised of the following:
The President of the Scientific Council of Excellence with its registered office in Warsaw (pl. Defilad 1, 24th floor, 00-901 Warsaw) is the Administrator of personal data collected under the procedure for the conferment of the post-doctoral degree of doctor habilitated.
Contact us via e-mail: kancelaria@rdn.gov.pl, phone 22 656 60 98 or personally at our office. Personal data shall be processed pursuant to art. 6 para 1 letter c) Regulation (EU) 2016/679 dated 27 April 2016 in connection with art. 220-221 and art. 232-240 of the Higher Education and Science Act dated 20 July 2018, for the purposes of the procedure for the conferment of the post-doctoral degree of doctor habilitated and in order to exercise the rights and obligations as well as the right to appeal in this procedure.
For detailed information on processing personal data in the procedure see www.rdn.gov.pl/klauzula-informacyjna-rodo.html Szczegółowa informacja na temat przetwarzania danych osobowych w postępowaniu dostępna jest na stronie www.rdn.gov.pl/klauzula-informacyjna-rodo.html

Rafal Doniec
. . . . . .
(Applicants' signature)

[1] Classification of fields and disciplines according to the Regulation of the Minister of Science and Higher Education of September 20, 2018, regarding scientific fields and disciplines and disciplines in the field of art (Journal of Laws of 2018, item 1818)).
[2] *Delete as appropriate

Appendices:

Appendix 1. Personal Data of the Applicant.
Appendix 2. Copy of the document confirming the possession of a doctoral degree.
Appendix 3. Self-summary presenting a description of scientific achievements and achievements (referred to in Article 219 paragraph 1 point 2 of the Act of 20 July 2018 Law on Higher Education and Science (Journal of Laws of 2021, item 478, as amended) and containing information on: demonstrating significant scientific or artistic activity carried out in more than one university, didactic, organisational, and popularising achievements of science or art.
Appendix 4. List of scientific or artistic achievements constituting a significant contribution to the development of a specific discipline.
Appendix 5. The copies of the publications included in the series originate in English.

Appendix No. 1
to the Application dated August 10th, 2024, for Initiation of Habilitation Procedure

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Personal Data of the Applicant

Advanced Methods of Analysis and Recognition of Behavioral and Cognitive Activities Using Eye Movement-Recording Sensors and AI Algorithms

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1 Personal Data of the Applicant

1. Name: Rafał Doniec

Rafal Doniec

.....

(Applicant signature)

Appendix No. 2
to the Application dated August 10th, 2024, for Initiation of Habilitation Procedure

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Copy of the document confirming the possession of a doctoral degree

Advanced Methods of Analysis and Recognition of Behavioral and Cognitive Activities Using Eye Movement-Recording Sensors and AI Algorithms

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Contents

1 Copy of diploma translation **2**

Rafal Doniec
. . . . . .
(Applicant signature)

Sworn Translator of English
Certified translator entered on the list of sworn translators
[Address of office]

Certified translation of original Polish document.

[Document issued in the Polish language. A one-page diploma printed in black and red ink on light yellow, in-mass colour coated laid paper, A3 size, with calligraphical manual entries in black ink.]

[Dry seal: national emblem of the Republic of Poland]

The Republic of Poland

Silesian University of Technology

Faculty of Automatic Control, Electronics and Computer Science

Diploma

Holder of the diploma: **[NAME AND SURNAME]**

was awarded the academic degree of Doctor of Technical Sciences in the field of Biocybernetics and Biomedical Engineering
on the basis of the presented doctoral dissertation: "The use of artificial intelligence methods to control insulin levels in the human organism.", after passing the obligatory exams. The degree was conferred upon the holder by the resolution of the Council of the Faculty of Automatic Control, Electronics and Computer Science of 26 October 2010.

Doctoral Thesis Supervisor: **[NAME AND SURNAME]**
Associate Professor: **[NAME AND SURNAME]**, PhD Eng.
Reviewers of the Doctoral Thesis: **[NAME AND SURNAME]**
Assistant Professor: **[NAME AND SURNAME]**, PhD Eng.
Associate Professor: **[NAME AND SURNAME]**, PhD Eng.
Gliwice, on 28 May 2011
Dean:
[NAME AND SURNAME], Associate Professor at the Silesian University of Technology, PhD Eng.
[Signature illegible in blue ink]

Seal
(stamp)
(anonymized)

[Signature anonymized]

Sworn Translator of English
Certified translator entered on the list of sworn translators
[Address of office]

Chancellor:-/-
Associate Professor **[NAME AND SURNAME]**, PhD Eng.-/-
[Signature illegible in black ink.]-/-
-/-
No **[DOCUMENT NUMBER]**-/-
[Dry seal: national emblem of the Republic of Poland and inscription on the rim:] Silesian University of Technology *1* -/-
[Translator's notes written in italics in square brackets].-/-

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Herewith as a sworn translator of the English language, I, **[NAME AND SURNAME]**, confirm that this translation conforms to the document presented to me in the Polish language.
Date and place: **[CITY]**, **[DATE]**
Registered in the Repertory under the number **[NUMBER]**.

Seal
(stamp)
(anonymized)

[Signature anonymized]

Appendix No. 3
to the Application dated August 10th, 2024, for Initiation of Habilitation Procedure

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Self-summary

Advanced Methods of Analysis and Recognition of Behavioural and Cognitive Activities Using Eye Movement-Recording Sensors and AI Algorithms

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1 Personal data and employment history in scientific units

1.1 Name and surname

Rafał Doniec

1.2 Diplomas and degrees held

Doctor of Technical Sciences	Gliwice 2010, the Silesian University of Technology, Faculty of Automatic Control, Electronics, and Computer Science, discipline: biocybernetics and biomedical engineering, thesis title: "The use of artificial intelligence methods to regulate insulin levels in the human body", supervisor: professor Ewaryst Tkacz, PhD, DSc, Eng.
Postgraduate	Warsaw 2006, Warsaw School of Economics, management studies.
Postgraduate	Warsaw 2002, the Military University of Technology, Institute of Communications Systems, thesis title: "Design of hardware network security for a local computer network", supervisor: Lt. Dariusz Koenig, M.Sc., Eng.
Master of Science in Engineering	Gliwice 1999, Silesian University of Technology, Faculty of Automatic Control, Electronics and Computer Science, the field of study: electronics and telecommunications, specialization: biomedical electronics, thesis title: "Optimization of the method of measuring blood glucose concentration using Accutrend Glucose dry test strips", the final result of which was the proposal and production of a glucometer of own design in the "Remed" company in Gliwice. Scientific supervisor from the university: professor Ewaryst Tkacz, PhD, DSc, Eng; industrial supervisor from the "Remed" company in Gliwice: Zenon Okrajni, PhD, Eng.

1.3 Employment in scientific units

February 2024 -– July 2024	Universität zu Lübeck (Niemcy), Institute of Medical Informatics, position: Research assistant in the project "KI-Med-Ökosystem".
November 2018 -– present	Silesian University of Technology, Faculty of Biomedical Engineering, Department of Biosensors and Biomedical Signal Processing (until 09.2023): Department of Medical Informatics and Artificial Intelligence) (from 10.2023), position: assistant professor.
October 2017 - March 2019	Universität Siegen (Niemcy), Institute for Vision and Graphics, Medical Data Understanding in the Pattern Recognition Research Group, position: postdoc.
September 2013 -– February 2019	University of Economics in Katowice, Faculty of Computer Science and Communication, position: Assistant Professor.
October 2007 -– November 2014	Research and Development Centre of Polish Telecommunications S.A. (since 2012 Orange S.A.). Management of the Company in Warsaw position: expert in non-standard services.
October 1998 — January 1999	Research and Development Centre of the Long-Distance Network of the Office of Telecommunications in Siemianowice Śląskie, position: Operation Engineer.

2 Indication of scientific achievement by Article 219(1)(2b)[1]

2.1 The title of scientific achievement

Advanced methods of analysis and recognition of behavioral and cognitive activities using sensors that record eye movements and AI algorithms (single-topic series of publications).

2.2 List of publications constituting scientific achievements

Table 1 contains the overview of the articles with Impact Factor[2] (IF) or CiteScore[3] (CS) in the database Web of Science (WoS)/Scopus, constituting a scientific achievement according to the Article 219 of "The Higher Education Act".

Table 1: Publication data from IF or CS obtained from the evaluation statement https://omega.polsl.pl in the discipline of biomedical engineering as of 30.03.2024.

Item	Author, year of publication, DOI link to publication	IF	CS
[DR1]	Doniec et al., 2024, https://doi.org/10.1016/j.sasc.2024.200078	0,0	2,2
[DR2]	Doniec et al., 2023, https://doi.org/10.3390/s23125551	3,7	6,8
[DR3]	Doniec et al., 2022, https://doi.org/10.3390/electronics11182960	2,6	4,7
[DR4]	Hozhabr, et al., 2022, https://doi.org/10.3390/s22103634	3,7	6,8
[DR5]	Mocny-Pachońska, Doniec et al., 2021, https://doi.org/10.3390/ijerph18094448	4,8	4,5
[DR6]	Mocny-Pachońska, Doniec et al., 2021, https://doi.org/10.3390/app11188648	2,7	3,7
[DR7]	Doniec et al., 2021, https://doi.org/10.3390/healthcare9111513	2,5	2,0
[DR8]	Doniec et al., 2020, https://doi.org/10.3390/electronics9122002	2,6	2,7
[DR9]	Mocny-Pachońska, Doniec et al., 2020, https://doi.org/10.7717/peerj.8981	2,8	1,0
Summary IF and CS in Web of Science or Scopus		**25,4**	**33,1**

2.2.1 Publications with IF or CS

[DR1] **Doniec Rafał,** Piaseczna Natalia, Duraj Konrad, Sieciński Szymon, Irshad Muhammad Tausif, Ilona Karpiel, Mirella Urzeniczok, Huang Xinyu, Piet Artur, and Grzegorzek Marcin, The Detection of Alcohol Intoxication Using Electrooculography Signals from Smart Glasses and Machine Learning Techniques. Systems and Soft Computing, Volume 6, December 2024, 200078, https://doi.org/10.1016/j.sasc.2024.200078.

20 pts of the Ministry of Science and Higher Education (MNiSW), **SJR**[4] **IF = 0.288**, Scopus **CS = 2.2**, as of 12-06-2024.

Own contribution: Concept and methodology. Software implementation, formal analysis, validation and data visualization. Preparation of the first and final version of the article. Project management[5].

Contribution: 70%.

Detailed description of the contribution constituting a scientific achievement: as first author, I was the principal investigator of the project whose results are described in the article. I prepared the concept of the experiments and the software for their interpretation. I developed an evaluation method to evaluate the collected and selected data, subjected the selected signal channels to normalisation and filtering. I then calculated the desired features and applied machine learning using different classifiers. I prepared a working and approved final version of the article.

[DR2] **Doniec Rafał**, Konior Justyna, Sieciński Szymon, Piet Artur, Irshad Muhammad Tausif, Piaseczna Natalia, Hasan Md Abid, Li Frédéric, Nisar Muhammad Adeel, Grzegorzek Marcin. Sensor-based classification of primary and secondary car driver activities using convolutional neural networks. Sensors, MDPI, 2023, 23(12), 5551, https://doi.org/10.3390/s23125551.

100 pts MNiSW, **JCR IF = 3.7**, Scopus **CS = 6.8**, **TOP10**, as of 12-06-2023.

Own contribution: Conceptualization of a system to enable selection of relevant data among all signals

[1] Law on Higher Education and Science. Published in the Journal of Laws under the number Dz.U.2023.742. Binding act, version from: March 7, 2024 to: September 30, 2024, hereinafter referred to in the text as Article 219 of "The Higher Education Act".

[2] Impact Factor (IF) bibliometric indicator in the Institute for Scientific Information (ISI), now known as Web of Science (WoS), https://clarivate.com/the-institute-for-scientific-information/. Status compliant as of July 10, 2024, https://omega.polsl.pl/.

[3] CiteScore (SC) is a bibliometric indicator in the Scopus https://www.elsevier.com/products/scopus/metrics/citescore database. Status compliant as of July 10, 2024, https://omega.polsl.pl/.

[4] SCImago Journal Rank (SJR) is an alternative to IF (WoS) bibliometric indicator in the Scopus database.

[5] The term "Project Management" in cases where the actual project no. is not indicated, refers to the management of the research task under the project from which the article was funded, or the postdoctoral grant of the author of the paper.

recorded with JINS MEME ES_R glasses (manufacturer JINS Holdings, Inc., Tokyo, Japan), during driver testing. Development and implementation of a methodology for classifying accelerometer, electrooculogram and gyroscope signals using trained convolutional neural network models. Analysis, evaluation and processing of data. Article preparation. Management of the project starting from the acquisition of funds to enable data acquisition until the publication of the results obtained.

Contribution: 65%.

A detailed description of the scientific contribution: As the first author, I was the principal investigator of a project in which I defined from scratch and configured a data acquisition and flagging workstation for primary and secondary driver activities using JINS MEME ES_R glasses, on a driving simulator. I conducted an analysis of expert annotations in terms of consistency with their descriptions and a literature review of the application of 1D CNN[6] in identifying behavioral and cognitive activities of drivers. As part of the research work, I tested the feasibility of using the sliding window segmentation (SWS)[7] technique to segment the data based on the experiments described in previous publications. I tested various settings to select the length T and step size ΔS of the time window, and determined the most effective values empirically. I substantively and visually processed the results obtained and numerically verified the proposed approach. I prepared the initial and subsequent evaluations of the article, then completed and defined the final concluding version of the solution to the classification problem presented in the article.

[DR3] **Doniec Rafał**, Piaseczna Natalia, Li Frédéric, Duraj Konrad, Pour Hawzhin Hozhabr, Grzegorzek Marcin, Mocny-Pachońska Katarzyna, Tkacz Ewaryst, Classification of roads and types of public roads using EOG smart glasses and an algorithm based on machine learning while driving a car. Electronics, MDPI, 2022, 11(18), 2960, https://doi.org/10.3390/electronics11182960

100 pts MNiSW, **JCR IF = 2.6**, Scopus **CS = 4.7**, as of 18-09-2022.

Own contribution: Defining the current state of knowledge. Data acquisition and evaluation. Conceptualization of the classification algorithm. Development and implementation of methodology for segmentation of accelerometer, electrooculogram and gyroscope signals using trained models: classification trees, kernel, Gaussian, polynomial, k-nearest neighbor predictors, support vectors and mixed models. Project management.

Contribution: 65%.

A detailed description of the contribution constituting a scientific achievement: as the first author, I was the pcincipal investigator of the project, in which I defined from scratch and configured the station for the acquisition and flagging of activity during real journeys with a vehicle specially prepared for such experiments, which received permission to conduct research in cooperation with the driving school "Proteko". I performed analyses of the available solutions in terms of selecting the best model for classifying signals from the academic version of the JINS MEME ES_R device. I developed processing variants, taking into account/not taking into account the limitation of the ROC curve. I optimized the ROC-AUC curve evaluation method using machine learning techniques and all the calibration steps of the classifier algorithm (including the selection of input parameters, weights and selected standard evaluation metrics calculated from the classifier confusion matrix). I prepared all partial results using selected machine learning models. I prepared a draft and co-edited the final version of the paper with a final discussion describing the advantages and limitations of the designed classifier system. I developed and shared the database of data obtained during the experiments.

[DR4] Pour Hozhabr Hawzhin, Li Frédéric, Wegmeth Lukas, Trense Christian, **Doniec Rafał**, Grzegorzek Marcin, Wismüller Roland, A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars. Sensors, MDPI, 2022, 22(10), 3634, https://doi.org/10.3390/s22103634.

100 pts MNiSW, **JCR IF = 3.7**, Scopus **CS = 6.8**, **TOP10** as of 10-05-2022.

Own contribution: The current state of the art and the concept of the system. The research and development activities leading to publishing this article were supported by the German Federal Ministry of Education and Research (BMBF) as part of the LEICAR project (grant number: 01IS15048B) and the German Federal Ministry for Economic Affairs and Climate Action (BMWK) as part of the GEMIMEG-II project (grant number: 01MT20001L).

Contriubution: 8%.

Detailed description of the scientific contribution: as an author, based on previous participation and experience gained in the LEICAR project, I supported the development of the concept of a collision avoidance system on roads based on the analysis of data from JINS MEME ES_R glasses, I was a corresponding author and co-edited the last version of the article.

[DR5] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Wójcik Sylwia, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Tkacz Ewaryst. Evaluation of the most stressful dental treatment procedures of conservative

[6] For abbreviations, see the detailed description of the achievement.
[7] For abbreviations, see the detailed description of the achievement.

dentistry among Polish dental students, International Journal of Environmental Research and Public Health, 2021, 18(9), 4448; https://doi.org/10.3390/ijerph18094448.
140 pts MNiSW, **JCR IF = 4.799**, Scopus **CS = 4.5**, **TOP10** as of 22-04-2021.
Own contribution: Software development. Preparation and editing of the manuscript. Funding acquisition.
Contribution: 15%.
A detailed description of the contribution constituting a scientific achievement: as an author, I was the second beneficiary of the project, and I developed a comprehensive review of the literature. I was a corresponding author and co-edited the first and published version of the article related to the statistical interpretation of the results along with the selection of adequate supplementary literature for this part.

[DR6] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Pachoński Marek, Tkacz Ewaryst, The relationship between stress levels measured by a questionnaire and the data obtained by smart glasses and finger pulse oximeters among Polish dental students, Applied Sciences, 2021, 11(18), 8648; https://doi.org/10.3390/app11188648.
100 pts MNiSW, **JCR IF = 2.7**, Scopus **CS = 3.7**, **TOP10** a of 21-09-2021.
Own contribution: Development of the concept and implementation of the measurement system for signals recorded with JINS MEME ES_R glasses. Funding acquisition.
Contribution: 25%.
Detailed description of the scientific contribution: as an author, I was the second beneficiary of the project, I developed a literature review and methodologies for experiments using JINS MEME ES_R glasses. I was a corresponding author, I took part in the preparation of the first and published version of the article.

[DR7] **Doniec Rafał**, Wójcik Sylwia, Valverde Raul, Piaseczna Natalia, Szymon Sieciński, Duraj Konrad, Tkacz Ewaryst. Extreme situation experienced by dental students of the Medical University of Silesia due to the SARS-CoV-2 epidemic during the first lockdown, Healthcare 2021, 9(11), 1513; https://doi.org/10.3390/healthcare9111513.
40 pts MNiSW, **JCR IF = 2.5**, Scopus **CS = 2**, as of 5-11-2021.
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of an assessment algorithm and stress scale, including a scale for assessing pattern imitation. Preparation of the first and editing of the final version of the article. Project management. Funding acquisition.
Contribution: 55%.
A detailed description of the contribution constituting a scientific achievement: as the first author, I was the principal investigator of the project, I reviewed the literature, and proposed an algorithm for assessing stress during dental students' classes in the COVID-19 pandemic based on the PSS-10 test and the dedicated questionnaire. I performed statistical interpretation and visualization of the results. I participated in the preparation of the first and published version of the article.

[DR8] **Doniec Rafał**, Sieciński Szymon, Duraj Konrad, Piaseczna Natalia, Mocny-Pachońska Katarzyna, Tkacz Ewaryst, Recognition of drivers' activity based on 1D convolutional neural network. Electronics, MDPI, 2020, 9(12), 2002, https://doi.org/10.3390/electronics9122002.
100 pts MNiSW, **JCR IF = 2.6**, Scopus **CS = 2.7**, as of 25-11-2020.
Own contribution: System concept development and implementation. Data acquisition. Verification of results. Preparation of the manuscript. Project management.
Contribution: 65%.
Detailed description of the contribution constituting a scientific achievement: as the first author, I was the primary investigator of the project which results are described in the article. I participated in the development of the multi-modal data acquisition system. I participated in the conceptual work of building the station in the vehicle where the experiments were carried out. Finally, I developed a data visualization tool, which is described in the article. This tool, along with the database, is publicly available as part of IEEE DataPort. I participated in the work of verifying the next steps of the analysis, the implementation of a one-dimensional convolutional neural network. I prepared the first version of the article, edited the entire text, which led to its publication.

[DR9] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Trzcionka Agata, Pachoński Marek, Piaseczna Natalia, Sieciński Szymon, Osadcha Oleksandra, Łanowy Patrycja, Tanasiewicz Marta. Evaluating the stress-response of dental students to the dental school environment, PeeJ 2020, 8, e8981; https://doi.org/10.7717/peerj.8981.
100 pts MNiSW, **JCR IF = 2.8**, Scopus **CS = 1.036**, as of 6-05-2020.
Own contribution: Analysis of the current state of the art. Implementation of a measurement system for signals recorded with JINS MEME ES_R glasses. Conceptualization and development of a test evaluation algorithm dedicated to dental students, together with the development of a scale for evaluating pattern imitation. Preparation of the first and approval of the final version of the article. Coordination of the

publication process.
Contribution: 15%.
Detailed description of the scientific contribution: as the author, I was the second beneficiary of the project, I developed the literature review, proposed and designed experiments based on the recording of the EOG signal, analyzed the data, authored or co-edited the first drafts of the article and approved the final version.

2.2.2 Other publications scored and indexed by the Ministry of Science and Higher Education, Scopus, and WoS

Other articles indexed in the Web of Science (WoS) or Scopus databases comprising a scientific achievement in accordance with Article 219 of "The Higher Education Act" are summarized in Table 2.

Table 2: Publication data from the WoS or Scopus databases obtained from the evaluation statement https://omega.polsl.pl in the discipline of biomedical engineering as of 30-03-2024

Item	Author, year of publication, DOI link to publication	WoS	Scopus
[DR10]	Grabny et al., 2023, https://doi.org/10.1007/978-3-030-99112-8_25		✓
[DR11]	Gabor et al., 2021, https://doi.org/10.1007/978-3-030-83704-4_1	✓	✓
[DR12]	Doniec et al., 2021, https://doi.org/10.1007/978-3-030-49666-1_28		✓
[DR13]	Doniec, et al., 2022, https://doi.org/10.1007/978-3-031-38430-1_18		✓
[DR14]	Piaseczna et al., 2023, https://doi.org/10.1109/EMBC40787.2023.10340736		✓
[DR15]	Mocny-Pachońska, 2019, https://doi.org/10.1007/978-3-030-30275-7_43	✓	✓
[DR16]	Doniec et al., 2022, https://dx.doi.org/10.21227/4yte-5s06		
[DR17]	Doniec et al., 2020, https://dx.doi.org/10.21227/q163-w472		

[DR10] Grabny Łukasz, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, The application for reading comprehension and reading speed test. Innovations in Biomedical Engineering. Lecture Notes in Networks and Systems, vol. 409: 245–254, Springer Cham. 2023, https://doi.org/10.1007/978-3-030-99112-8_25.
20 pts MNiSW, **CS = 0.7**; conference materials indexed in WoS, as of 03-03-2024
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of the algorithm. Preparation of the first and coordination of the final version of the article.
Contribution: 45%.
Detailed description of the contribution constituting a scientific achievement: as an author, I developed a literature review, set up the measurement system, and proposed an algorithm for assessing reading speed along with evaluating reading comprehension based on the technique of approximate inference using fuzzy sets, enabling the definition of parameters of segmented structures for the EOG signal.

[DR11] Gabor Dominika, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Tkacz Ewaryst, Automatic assessment of Benton Visual Retention test results: a pilot study. Biocybernetics and Biomedical Engineering - Current Trends and Challenges Proceedings of the 22nd Polish Conference on Biocybernetics and Biomedical Engineering, Warsaw, Poland, May 19-21, 2021, vol. 293: 1–8, Springer Cham. 2023, https://doi.org/10.1007/978-3-030-83704-4_1.
20 pts MNiSW, **CS = 0.7**; conference materials indexed in WoS, as of 3-03-2024.
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of the algorithm. Preparation of the first and coordination of the final version of the article.
Contribution: 45%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed a literature review, set up a data acquisition system, and proposed an evaluation algorithm for Benton's visual memory test, along with the development of a pattern imitation evaluation scale based on a graphical similarity grouping method in ten prepared patterns.

[DR12] **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Mocny-Pachońska Katarzyna, Lang Marta, Szymczyk Jacek, The classifier algorithm for recognition of basic driving scenarios. Information Technology in Biomedicine, Advances in Intelligent Systems and Computing, vol. 1186, 2021, Springer, 337 p., ISBN 978-3-030-49665-4, https://doi.org/10.1007/978-3-030-49666-1_28.
20 pts MNiSW, chapter of the monograph, Scopus **CS = 0.9**, as of 12-06-2023.
Own contribution: Current state of the art. System concept. Development of the segmentation algorithm. Development of the preprocessing algorithm. Proposing modifications to the input data. Implementation. Preparation of the article. Project management.

Contribution: 80%.
Detailed description of the contribution constituting a scientific achievement: Based on a detailed analysis of available solutions, I tested the feasibility of various models for building BSF feature dictionaries, in terms of supporting feature extraction for real-world motor vehicle transit scenarios. I developed a proprietary model for building and flagging signals from the academic version of the JINS MEME ES_R device. Using the BSF dictionary method, I developed a mobile signal segmentation architecture with a variable window size, which, based on the entropy principle, determines the optimal window size for a specific signal feature corresponding to a selected activity. I proposed the use of clustering of probability values and changing the size of BSF dictionaries, which further improved the segmentation results. I conducted an analysis of the effect of the selected learning parameters and the restriction of the region of interest on the segmentation result. I compiled the obtained results, performed their visualization and prepared a working version of the article. I determined the final version for discussion describing the advantages and limitations of the designed system.

[DR13] **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Chwał Joanna, Gawlikowski Maciej, Tkacz Ewaryst, Classification of Recorded Electrooculographic Signals on Drive Activity for Assessing Four Kind of Driver Inattention by Bagged Trees Algorithm: A Pilot Study. The latest developments and challenges in biomedical engineering. Proceedings of the 23rd Polish Conference on Biocybernetics and Biomedical Engineering, Lodz, Poland, September 27-29, 2023 / Strumiłło Piotr [i in.] (red.), Lecture Notes in Networks and Systems, 2024, vol. 746, Cham, Springer, s.225-236, ISBN 978-3-031-38429-5, https://doi.org/10.1007/978-3-031-38430-1_18.
20 pts MNiSW, chapter in the monograph, Scopus **CS = 0.7**; as of 12-06-2023.
Own contribution: Current state of the art. Conceptualization of the system. Development of measurement methodology. Development of the pre-processing algorithm. Proposing modifications to the input data. Implementation of the algorithm. Preparation of the article. Project management.
Contribution: 80%.
A detailed description of the contribution constituting a scientific achievement: as the author, based on the bioethics committee's approval, I prepared the experiments so as to enable the extraction of the characteristics of the selected scenarios simulating the passage of a motor vehicle. I developed a proprietary model for building flagging and then filtering data for recorded signals from the JINS MEME ES_R device. Based on statistical methods, I extracted the characteristics of the monitored signals. I performed experiments using the MATLAB environment and, based on decision tree rules, implemented the final classification system. I compiled the obtained results, made their visualization and prepared a working version of the article. I set the final version for discussion describing the advantages and limitations of the designed system.

[DR14] Piaseczna Natalia, Duraj Konrad, **Doniec Rafał**, Tkacz Ewaryst, Evaluation of Intoxication Level with EOG Analysis and Machine Learning: A Study of a Driving Simulator. Institute of Electrical and Electronics Engineers: 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Sydney, Australia 24-27 July 2023, 2023, Piscataway, Institute of Electrical and Electronics Engineers, 1500 s.1-4, ISBN 979-8-3503-2448-8, https://doi.org/10.1109/EMBC40787.2023.10340736.
20 pts MNiSW, Scopus **CS = 2.1**; chapter in a scientific monograph indexed in WoS.
Own contribution: Concept and preparation of the article.
Contribution: 5%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed the course of experiments using alco-goggles and a driving simulator. As a corresponding author, I contacted the publisher, edited the initial version, and accepted the final version of the article.

[DR15] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Trzcionka Agata, Lang Marta, Pachoński Marek, Piaseczna Natalia, Sieciński Szymon, Twardawa Henryk, Tanasiewicz Marta. The Stress Level Assessment Based on Socio-demographic and Gender Factors Among Polish and Taiwanese Female and Male Junior Dental Students. Information and Software Technologies. ICIST 2019. Communications in Computer and Information Science, vol 1078. Springer, Cham. https://doi.org/10.1007/978-3-030-30275-7_43.
20 pts MNiSW, Scopus **CS = 0.7**; conference materials indexed in WoS.
Own contribution: Current state of the art. Development of the algorithm. Verification of the results. Preparation of the article.
Contribution: 10%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed a literature review and an algorithm to classify stress levels in a multimodal data set using statistical methods. The algorithm allows comparison of stress levels based on EOG, ACC, GYRO and pulse signals in Polish and English-speaking student groups, which has a direct impact on the insertion and guidance

of the dental tool during the practice procedure of filling dental cavities. The final result of the study was the development of the dedicated stress scale.

[DR16] **Doniec Rafał**, Piaseczna Natalia Li Frédéric "A dataset for classification of road and types using eog smart glasses", own data repository IEEE DataPort, 2022, License: CC BY 4.0, doi: 10.21227/4yte-5s06.
Own contribution: Acquisition of multimodal data related to the simulation of car journeys, description, and development of data analysis methodology. Prepare the repository.
Contribution: 85%.

[DR17] **Doniec Rafał**, Duraj Konrad, Mocny-Pachońska Katarzyna, Piaseczna Natalia, Sieciński Szymon, Tkacz Ewaryst, "Drivers' activity tracking with jins meme smart glasses", own data repository IEEE DataPort, V2, 2020, License: CC BY 4.0, doi: 10.21227/q163-w472.
Own contribution: Acquisition of multimodal data related to actual car trips, Data description, and processing. Development of a methodology for data analysis. Prepare the repository.
Contribution: 85%.

2.2.3 Summary of the series of articles

To collectively quantify the applicant's personal contribution to the publications constituting the scientific achievement following Art. 219 of the "Act on Higher Education and Science", Tables 3 and 4 present data consistent with the evaluation statement available on the website of the Silesian University of Technology https://omega.polsl.pl.

The detailed breakdown of the personal contribution and co-authors' contributions has also been presented in a tabular format in Appendix 6 *"Statements of co-authors regarding individual substantive contributions to the publications included in the discussed series"*.

Table 3: Collective determination of the author's share in publications

Item	The first or corresponding author	Second author
Articles [DR1] to [DR9]	8	1
Articles [DR10] to [DR17]	6	2

Table 4: Data based on the evaluation statement https://omega.polsl.pl in the discipline of biomedical engineering as of 30-03-2024.

Author's publications	Date of the declaration under the IB	IF WoS	Pts MNiSW	Share point value	Individual contribution of the author
Collectively, based on data from the 2018-2021 and 2022-2026 IBIO evaluations	16-02-2024	42,27	1530	540	7,13
Only articles from the selected series		25,399	920	321,55	3,89

3 Description of the scientific achievement

3.1 Scientific purpose, motivations and possibilities of using them

The author submits, as part of the habilitation procedure, a series of nine thematically related scientific articles, primarily from journals with an Impact Factor (IF), indexed in the Web of Science[8] (WoS) — these are items [DR1] to [DR9]. Items [DR10] to [DR15] comprise six book chapters, supplementing the series, also indexed or scored in WoS, by the Ministry of Science and Higher Education (MNiSW), or within the Scopus database. Additionally, the author submits two data repositories [DR16] and [DR17], indexed with DOI (Digital Object Identifier). These repositories were published to facilitate the verification of the author's findings within the IEEE DataPort community. The final element of the achievement is one technical solution submitted to the Patent Office of the Republic of Poland[9], which has not yet been published in the Office's databases. All items in the presented series have the following bibliometric parameters: a total WoS IF of 25.399 and a total MNiSW score of 920 (details in Table 5).

Table 5: Methodology for calculating bibliometric parameters of achievement, by Article 219(1) (2a), (b), (c) of the Law on Civil Procedure published in the Journal of Laws 2023.742 of 10 March 2023.

Type of publication	Summary [IF; CS.; pts. MNiSW]	Author's contribution
IF articles: 9 articles from the cycle [DR1–DR9]	IF = 25,399; CS = 33,138; MNiSW = 800	8% to 70%
Other 6 publications [DR10–DR15]	IF = 0,0; CS = 5,8; MNiSW = 120	5% to 80%
2 data repositories [DR16, DR17]	–	85%
1 technical solution	–	–
Summary	IF = 25,399; CS = 38,936; MNiSW = 920	5% to 85%

Scientific Problem:

Current methods of segmentation and classification of recorded multimodal signals are not sufficiently effective for accurately identifying driver actions, recognizing road events according to regulations, and analyzing emotional states in various scenarios encountered in cognitive and educational processes for selected professional groups.

Thesis:

The development and implementation of proprietary computer-aided systems based on advanced methods of segmentation and classification of recorded multimodal signals will significantly improve accuracy in identifying drivers' actions, recognizing road events, and analyzing emotional and cognitive states in specific research contexts related to education for two distinct professional groups, namely future drivers and dental practitioners.

The scientific achievement aimed to verify the methods of segmentation and classification of recorded multimodal signals, and then to develop proprietary systems for computer-aided operation:

- identification of primary and secondary activities of motor vehicle drivers[10] [DR1, DR2, DR8, DR13];
- recognizing road incidents defined by the laws and regulations of the Polish Ministry of Infrastructure, [DR3, DR4];
- analysis of emotional states among students participating in laboratories of conservative dentistry with endodontics SUM, [DR5, DR6, DR9];
- recognition of emotional states and activity in other selected research scenarios [DR14].

Due to the exceptional situation caused by the COVID-19 pandemic, some of the experiments had to be adapted to epidemiological requirements. This unusual situation affected the mental state of society, which forced the author to reassess his previous goals. Algorithms for the arbitrary diagnosis of stress and depression that occur during the COVID-19 pandemic are additional achievements defined by the author as computer support.

[8] The Impact Factor (IF) is a measure of the impact of scientific journals, calculated by the Institute for Scientific Information (ISI), now known as Web of Science. The Web of Science database contains citation information from various scientific journals. The IF is calculated based on the number of citations received by articles published in a particular journal over a specified period, usually annually. The IF is often used as an indicator of a journal's prestige and impact within a given scientific field. https://clarivate.com/the-institute-for-scientific-information/, accessed on 10th July 2024.

[9] The Patent Office of the Republic of Poland's database is a collection of data containing information on submitted and granted patents as well as utility models in Poland, https://uprp.gov.pl/pl/wyszukiwarki, 10th July 2024.

[10] As part of the category "B" driving license, in accordance with the requirements of the Polish Ministry of Infrastructure.

- identification and classification of emotional states and assessment of the level of stress of dental students in the context of the outbreak of the COVID-19 pandemic, [DR7];
- analysis of states and assessment of the level of cognitive advancement in the context of the outbreak of the COVID-19 pandemic, [DR10, DR11, DR15]. The achievement is the result of three projects initiated and carried out by the author:
- "LEICAR" (grant number 01IS15048B) at the University of Siegen 2017-2019 - investigator,
- "The use of modern information and mathematical technologies to analyze emotions during various life activities" (Resolution No. KNW/0022/KB1/79/18 of 16.10.2018, Medical University of Silesia) - beneficiary,
- habilitation project No. 07/040/RGH22/1015, supported by a grant awarded by the Rector of the Silesian University of Technology - beneficiary.

Table 6: Linking of individual achievements, resources, and items from the cycle by Article 219(1)(2b) of the Law on Civil Procedure published in the Journal of Laws 2023.742 of 10 March 2023

Resources	"LEICAR" Project (grant number 01IS150488)	Resolution No. KNW/022/KB1/79/18, Medical University of Silesia	Habilitation project No. 07/040/RGH22/1015
Computer-aided recognition of primary and secondary driving activity for category B entitlements according to the requirements of the Polish Ministry of Infrastructure	[DR8], [DR13]	[DR1], [DR2], [DR8], [DR13]	[DR1], [DR2]
Computer-aided recognition of traffic incidents as defined by rules and regulations of the Polish Ministry of Infrastructure	[DR4]	[DR3], [DR4]	[DR3]
Computer-aided recognition of emotional states in a group of students participating in conservative dentistry with endodontisc laboratories at the Medical University of Silesia	[DR9]	[DR5], [DR6], [DR9]	[DR5], [DR6]
Computer-aided recognition of emotional states and activities in other selected research scenarios	[DR14]	[DR14]	
Computer-aided recognition and classification of emotional states and the assessment of stress level of dental students in the context of the SARS-CoV-2 virus pandemic outbreak		[DR7]	[DR7]
Computer-aided recognition of the state recognition and cognitive assessment in the context of the SARS-CoV-2 virus pandemic outbreak		[DR15]	[DR10], [DR11]

Solving the scientific problem:

Research on the recognition of human cognitive activity and behaviour has developed along with the progress of knowledge and the availability of IT tools. Initially, the author used the adaptation and combination of existing algorithms to solve new problems and also sought to introduce innovative methods of signal analysis and classification. Due to ethical and legal restrictions on access to medical data, cooperation with a medical unit has become indispensable, which is confirmed by a positive opinion of the Bioethics Committee of the Medical University of Silesia. The author continued his research, focussing on computer-assisted medical diagnostics of

healthy people and designing methods for the segmentation and classification of medical data. 67 volunteers holding or applying for a driving licence under category "B" participated in experiments related to recognising driver activity. Experiments on recognising emotional states, including stress, included the participation of 50 randomly selected students from the Medical University of Silesia and 360 dental students. The author's research work includes the implementation of algorithms developed in the field of telemedicine and eHealth, which have been widely used during the COVID-19 pandemic. The author of the habilitation project used various classification methods and statistical tests in the analysis of behaviors and emotional states, which resulted in a series of scientific publications and the submission of one technical solution to the Patent Office in the field of computer-aided recognition and classification with the use of:

- statistical tests, such as χ^2, Mann–Whitney, Kruskal–Wallis [DR5, DR7], Dunn–Bonferroni, Friedman's [DR6], Shapiro–Wolf test [DR9],
- machine learning methods, m.in., random forest, bagging, SVM, K-nearest neighbor, kernel predictors [DR3],
- neural 1D CNNs and DNNs in supervised machine learning tasks [DR2, DR4, DR8],
- manual and mixed methods [DR10, DR11, DR12, DR13, DR14, DR15].

3.2 Computer-aided diagnostics of cognitive behaviour and human activity

Technological advances, especially in data analysis, machine learning, and artificial intelligence, are revolutionizing the diagnosis of individual behavior and activity, allowing for a more accurate assessment of health status and the identification of anomalies. Research in the field of biomedical engineering is attracting increasing interest, as confirmed by scientific publications, such as the report published by [1], which highlights the use of advanced techniques of the fourth industrial revolution in medical applications in the field of data analysis in combination with data from sensors, health monitors, and other sources, dedicated to rapid and objective assessment of health status, and identification of abnormalities in these diagnosed behaviours. In addition, research by Yang et al. has shown that modern machine learning algorithms can predict certain patterns of behaviour, which could have applications in the prevention and treatment of diseases [2].

The basic research equipment in the habilitation project, providing data, is the JINS MEME ES_R academic package designed for academic research. The JINS MEME ES_R Customised Academic Kit captures raw data from EOG sensors and 6-axis gauges, dedicated to the gyroscope and accelerometer, and offers insights into cognitive states and related eye movements. The standard sampling rate for JINS MEME ES_R, as part of the academic package, is 100 Hz. Data transmission for Bluetooth: 50 Hz or 100 Hz. Types of data acquired in standard mode: EOG data (50/100 Hz), accelerometer data (ACC). Full mode of EOG data acquisition and ACC and gyroscope (GYRO) data.

With the JINS MEME ES_R Academic Pack, algorithms supporting road safety [3], human physical activity [4], cognitive activities [5], emotional states [6] and many other applications can be successfully developed.

The achievement referred to "The Higher Education Act", paragraph 1 point 2, chapter 3 – "Habilitated doctor's degree" is represented by a series of publications that are part of two areas of computer-aided interpretation and monitoring of multimodal signals, aimed at identifying patterns supporting cognitive-behavioral diagnostics in the study of groups of students and employees of universities and driving schools. And also increasing the efficiency of these processes in the case of analyzing disturbed driver behavior to improve road safety.
The stress study compares stress levels in Polish and foreign dental students, as well as professionally active dentists, using physiological data obtained thanks to wearable technologies.
In the research on driver behavior, innovative recognition algorithms and behavior classifiers were identified, based on the analysis of physiological signals and using advanced neural network models.

Moving on to the stress analysis, the study of the author is a comparative study of stress levels among Polish and Taiwanese dental students [DR15]. Using previous experience and the JINS MEME device, ES_R, and "smart wristwatches". The stress analysis study recorded physiological data accompanying the performance of dental tasks to understand statistical differences in stress levels in different cultural and linguistic environments and the final implementation of an arbitrary stress measurement system that was not based solely on opinions and scales in the studies themselves. In addition, they investigated the complex interaction between perceived stress levels and physiological signals, including heart rate, head movements, and electrooculographic signals. Wearable devices are becoming key tools in stress assessment, showing significant changes before and during tasks. Similarly, the exploration of stress among dental students and professionally active dentists is discovered through the prism of wearable devices, with electrooculographic data, heart rate, accelerometer, and gyroscope,

revealing the conclusions presented in the following paragraphs of the self-report for various student and professional groups. Together, the findings highlight the potential of wearable devices to monitor stress in real-world settings, capable of transforming practical exercises and methods to assess and prevent stress [DR5, DR6, DR9, DR14].

During the research on driver behavior and its impact on road safety, the author presented many aspects of the investigation. For starters, a novel reconnaissance algorithm was introduced that uses physiological signals from JINS MEME ES_R glasses to effectively classify common road types. Data from real driving situations from 30 participants were used, and precisely extracted statistical features made it possible to train a classifier of a decision-making, random forest. This manually calibrated approach achieved an overall accuracy of 87.64%, a precision of 86.30%, a recall of 88.12%, and an F1 score of 87.08% on the test set, adequately identifying urban streets, highways, residential areas, and undeveloped areas [DR3]. In the meantime, addressing the topic of accident patterns in driving analysis, an innovative framework for the automatic detection of car accidents is presented. Using sensors inside the vehicle, several feature extraction methods were thoroughly evaluated, showing promising results, especially for CNN features together with the SVM classifier. Moving on to the area of driver behaviour, this study introduces a classifier of basic driving activities, using one-dimensional convolutional neural networks in combination with electrooculographic signals [DR1, DR2, DR4, DR8, DR13]. The proposed architecture of the CNN model along with the implemented scheme is shown in Figure 1. The results present impressive accuracy considering the complexity of the driving process or the elusiveness of emotional states and highlight the potential of advanced cognitive recognition.

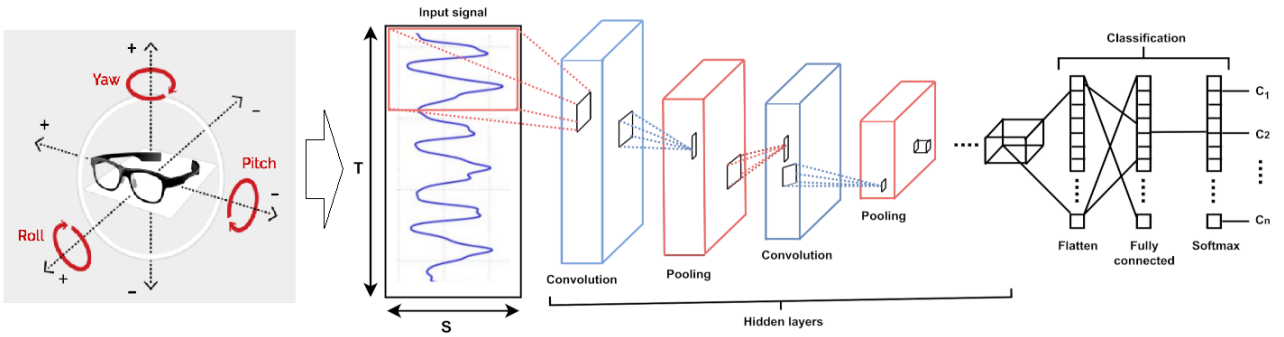


Figure 1: Convolutional neural network architecture for time series data classification. T represents the time window, S represents the number of sensor channels, c represents the class, and n represents the number of classes.

The biomedical signal processing process, together with the proposed implementation of 1D CNN, is an important area of research. The author evaluates the performance of the most advanced model in defined classification tasks, where labels or classes are categorized discretely. The categorical loss of entropy, used in this assessment, measures the difference between the actual labels and the predicted labels by calculating the cross-entropy.

Cross-entropy is a measure of the difference between two probability distributions, where in the case of classification, the actual labels are one distribution and the predicted labels are the other. The lower the cross-entropy value, the better the model does at predicting labels. The formula for the categorical loss of cross-entropy usually takes the following form:

$$J(\Theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} log(\hat{y}_{ij}), \tag{1}$$

where:
N is the number of samples in the dataset,
M is the number of classes,
y_{ij} is the actual value of the sample i and the class j,
$\hat{y}$ is the actual value of the sample i and class j,
Θ denotes the parameters of the model.

Despite these significant advances, there is a need for further research on improving algorithms and data analysis methods to achieve even greater accuracy and versatility in the diagnosis of human behavior and activity, increasing the number of experiments and scenarios considered, and building a kind of digital footprint of human behavior and cognitive activity.

3.2.1 Achievements related to the recognition of human behavioural and cognitive behaviour patterns

Pattern recognition using machine learning is a process in which machines are trained to recognise characteristic patterns or dependencies in data. Various methods and machine learning algorithms are employed to enable computers to automatically detect and classify patterns in data.

A key element of the project is the utilisation of the academic package JINS MEME ES_R, which provides raw data from EOG sensors and 3-axis indicators. Due to its sampling frequency and the capability to capture data from various sensors, it is possible to analyse cognitive states, eye movements, and other physiological parameters. This enables the development of algorithms to support road safety, monitor physical activity, analyse emotional states, and other applications.

The scientific publications resulting from this achievement of the habilitation focus on the interpretation of data obtained with JINS MEME ES_R and other wearable devices to isolate patterns of human behaviour and activity. This research aims to support cognitive-behavioral diagnostics among groups of students and to increase road safety by analyzing driver behavior.

In the area of stress analysis, the research focuses on comparing stress levels in different groups of dental students and on developing an arbitrary system for measuring stress, using wearable devices and physiological data. This research aims to understand the differences in stress levels in different language environments and to develop arbitrary and practical methods for assessing stress in real-world settings.

The author contributed to the development of the field of biomedical engineering by creating an arbitrary stress scale based on biomedical signals, such as EOG and pulse, for monitoring physiological and mental states in response to challenges or situations requiring adaptation or adaptation.
Another contribution was the use of multimodal signals and artificial intelligence algorithms to recognize patterns related to human cognitive activities and their use in the prediction and diagnosis of events. The author also focused on the development of innovative recognition algorithms, analyzing anomalies related to driving safety.
Building a database of the digital footprint of human behavior was a major achievement that enabled precise monitoring of aspects of human mental health. Such as coping with stress or cognitive functioning. These resources have been made available through the IEEE DataPort initiative not only to the biomedical engineering community, to support the development and verification of the author's algorithms in the future.

The next segment of the self-paper will discuss publications and scientific areas supporting machine recognition of behavioural-cognitive behavior, as well as present tools and developed models that illustrate the progress of knowledge in the face of growing challenges in the course of subsequent research projects.

3.2.2 Cluster, statistical and ensemble methods in determining stress states and limited human perception

In the case of the article [DR5], statistical analysis was performed using Statistica software version 9.0 (StatSoft, Inc., Tulsa, OK, USA). Due to significant differences between students representing subsequent years of study and gender, the nonparametric χ^2 test of independence was used. The Mann-Whitney test was used to assess the significance of differences in scales between sexes for subsequent years of study. Sex differences between successive years of education were assessed using the Kruskal-Wallis test. The statistical analysis was supported by post hoc tests in two variants: the Dunn test (Dunn-Bonferroni test) and the Conover test. The level of statistical significance (p) was set at 0.05. The last step was the implementation of separate stress thresholds in the form of an electronic questionnaire.

In another study, the problem of scaling stress as an indicator of physical activity of the eyeball to the mental or emotional response to change is an important issue in modern society [DR6]. In addition to questionnaires, stress levels can be assessed by monitoring physiological signals such as photoplethysmogram (PPG), electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), facial expressions, and head and body movements. The study sought to identify the relationship between perceived stress levels and physiological signals such as heart rate (HR), head movements and electrooculographic (EOG) signals. The level of perceived stress was determined using self-reported questionnaires in which participants rated their levels of stress before, during, and after completing a task. Heart rate was measured with a finger pulse oximeter, while head movements (linear acceleration and angular velocity) and electro-oculographic signals were recorded with JINS MEME ES_R glasses (manufacturer: JINS Holdings, Inc., Tokyo, Japan). Significant differences were observed between perceived stress levels, heart rate, linear acceleration power, angular velocity, and EOG signals before and during the task. However, except for HR, these signals were poorly correlated with the perceived level of stress obtained during the task. The perceived stress level between the three bound samples (before,

during, and after the task) was expressed on an ordinal scale (0-6), so the Friedman test described in [7, 8, 9] was used to assess the differences between the analyzed phases of the experiment.

In the three phases analyzed, the heart rate is measured and expressed on a compartmental scale. In this study, the normality of the decomposition of the entire sample was assessed using the Shapiro-Wolf test, as defined in the paper [10]. Then, a sphericity test, described by Mauchly in [11], was performed to check the symmetry of the composition of the data, and finally, the Friedman test was used. The statistical significance of the differences between the analyzed phases was estimated using Conover's and Dunn Bonferroni's post hoc tests, which are commonly used after the Friedman test. To analyze EOG signals, linear acceleration, and angular velocity, the χ^2 test was used. The association between measured values of heart rate, EOG signal, head movement signals, and reported level of perceived stress was assessed by Spearman rank correlation, taking into account the use of an ordinal scale [12]. The level of statistical significance of α was set at 0.05. As in the case of [DR5], the last step was the implementation of isolated stress thresholds in the form of an electronic survey, a signal acquisition station, and a result interpreter.

The COVID-19 pandemic, announced in 2020, disrupted the author's habilitation project while opening new research areas due to its uniqueness. In a study conducted among dentistry students at the Medical University of Silesia in Katowice, the level of stress was assessed in connection with the outbreak of the COVID-19 pandemic [DR7]. The results showed that 67.7% of college students reported high levels of stress, and older female students experienced it more than younger ones. The mean age of the participants was 23 years. The survey was available online and the response rate was 0.8. The study included 164 out of 225 dental students. The research was carried out among students between 10 and 24 April 2020, during the announced COVID-19 pandemic in Poland and worldwide. A link to the author's questionnaire was posted on the university's website and sent by e-mail to students. For reference, the PSS-10 Cohen scale, which is commonly used to measure stress levels, was used [13]. This method has been proposed as a self-assessment method and screening tool to identify people in need of psychological or medical support [14]. The article recommends more intensive psychological care in universities as a first aid strategy in the event of natural disasters or epidemics.

Drawing on the experience gained in projects associated with the medical university, studies on the behaviour of drivers under the influence of alcohol were conducted, which can adversely affect their cognitive abilities, reaction time, coordination and decision-making abilities, increasing the risk of road accidents. Therefore, it is crucial to develop reliable methods for detecting and assessing the level of alcohol intoxication [DR14]. An approach is electro-oculography (EOG), a technique to measure and monitor the range of eye movements, which has been correlated with the level of alcohol intoxication and may be useful in its estimation. In recent years, machine learning algorithms have been employed to analyse EOG signals to assess physiological states and behaviours. Data obtained from JINS MEME ES_R glasses included three channels of accelerometer data sampled at 100 Hz and four channels of EOG data sampled at 200 Hz. In this study, only EOG signals were utilised. Prior to feature extraction, each signal was normalised and subjected to third-order median filtering. The signals were then divided into windows of 200 samples (1 s) with a step of 50 samples. Within each window, a series of characteristics were calculated, such as amplitude, skewness, kurtosis, variance, μ (mean) and σ (standard deviation) of the normal distribution fitted to the data [15]. A feature matrix of dimensions 22679x24 was obtained, which was subsequently divided into training sets (70%), validation sets (20%), and tests (10%), to create the classifier. To select an appropriate classifier, a built-in tool was employed within the MATLAB environment, which, after initial tests, indicated that the best results were achieved using decision trees. Subsequently, a Bayesian optimisation process based on programming language libraries was performed to select optimal hyperparameters, resulting in the choice of a decision tree classifier with adaptive boosting, 443 training sets and 2073 branches.

The study aimed to test the feasibility of using EOG analysis and machine learning to estimate the level of alcohol intoxication in a simulated driving scenario. EOG signals were measured using JINS MEME ES_R glasses, and intoxication levels were simulated using glasses that mimicked the state after alcohol consumption. Traditional signal processing techniques and feature engineering were used. Boosted decision trees were used for classification, achieving a prediction accuracy of more than 94% for the four classes. The results suggest that EOG analysis and machine learning can be effective tools for accurately estimating the level of alcohol intoxication in a simulated driving scenario. The study was carried out on nine healthy participants, including seven men and two women between the ages of 20 and 25, who agreed to participate.

The final and key finding of the research on stress and perceptual disorders was to test in practice whether professional groups, such as dentists, have experienced significant levels of stress since their student days in dental schools [DR9]. The stress of studying dentistry can have a negative impact on the personal and professional lives of dentists, especially in terms of the quality of their clinical work [16, 17, 18, 19, 20]. Stress from external factors, both physical and mental, can affect an individual's physical and mental well-being, as well as reduce work productivity, and affect the accuracy of diagnostic and therapeutic decisions [16, 18].

Based on the experiences described above, it was decided to create an objective scale to assess stress levels in students at different stages of education and practicing dentists. Thirty dental students participated in the study, ten from each year of study: first, middle, and last. They were randomly divided into two groups, one

of which was subjected to stressors, while the other group was not. JINS MEME ES_R glasses and Garmin Vivoactive 3 smartwatches were used to collect the data, which recorded electro-eye-tracking (EOG), heart rate (HR), accelerometer (ACC), and gyroscope (GYRO) data. The subjects performed dental exercises on a phantom tooth. The heart rate of more experienced upper-year students was lower than that of first-year students. The EOG, ACC, and GYRO signals showed many differences in the measurement of amplitude and frequency of episodes. Pilot results show that electronic tools such as minimally invasive glasses with software and sensors can be useful in monitoring stress levels in dental students in a preclinical setting.

3.2.3 Real-world human activity models based on supervised machine learning

An intriguing challenge was the creation of a model capable of identifying driver activities during travel. Driving has become an integral part of our daily lives, even in the current era of early autonomous vehicles. Research on road safety is becoming increasingly important. In publication [DR3], an algorithm is proposed for recognition based on physiological signals collected via JINS MEME ES_R glasses (electrooculography, acceleration, and angular velocity), aimed at classifying four types of roads: urban street, highway, residential area, and undeveloped area. Data from 30 drivers were collected under real driving conditions. Handcrafted statistical features were extracted from the physiological signals, which were then used to train and evaluate a random forest classifier. During the testing of various sets of hyperparameters, the set with the lowest classification error was selected. The tested hyperparameters included:

- Preset: specifies the type of classifier to use, available types are boosted trees, bagging trees, discrimination in subspace, KNN in subspace, and RUSBoost trees.
- Ensemble method: a method of combining weak learners into a high-quality model, a different selection of ensemble methods was available for each preset.
- Number of learners: a parameter that specifies the number of weak learners to use in the ensemble.
- Learning rate: adjusts the speed of the training process, a smaller learning rate helps to avoid overfitting the model.
- Maximum number of splits: a parameter that controls the depth of the learning trees (i.e. "branching points").

The most effective model was the RUSBoosted Trees model [21], in which each poorly learning algorithm (e.g., a decision tree) is trained on a random subset of the entire training set, which is then sampled against the dominant class. Weights are initialized according to a uniform distribution for the first iteration, and then iteratively updated based on the loss from the previous iteration. In the end, the optimal hyperparameters of the model were as follows:

- Preset: RUSBoosted Trees.
- Ensemble: AdaBoost.
- Learning Type: Decision Tree.
- Maximum number of divisions: 2078.
- Number of training cycles: 451.
- Learning rate: 0,81048.

The overall accuracy, precision, recall and F1 score obtained were 87. 64%, 86. 30%, 88. 12%, and 87. 08%, respectively, in the test set. Ultimately, the receiver operator characteristic (ROC) curve was employed as a tool to assess the classifier's effectiveness. This tool allows for the joint evaluation of sensitivity and specificity; in other words, it represents the relationship between the true positive rate and the false positive rate [22, 23]. In a multi-class model, one can plot N AUC (area under the curve) and ROC curves for N classes by applying the one-vs-all methodology. For the threshold of class 1, which minimizes or maximizes the overlap of distributions, the AUC was approximately 0.9, indicating a 90% chance of correctly distinguishing the positive class from the negative [24]. When comparing the results obtained with similar studies on the assessment of driver drowsiness or anger using ROC-AUC, the AUC values for the models were 0.904, 0.863, and 0.805, respectively, for the classification balancing AUC and the ROC curve for drowsiness [25], and 0.7914–0.8635 for the assessment of driver anger [26].

3.3 Deep neural network models of human cognitive activity

Driving is one of the cognitive activities characterised by its complexity and involves movements of the entire body. Numerous studies have aimed to improve road safety, including the analysis of driver behaviour, such as assessing limitations or predispositions to driving. These studies involve the recording and analysis of multiple signals, such as electroencephalography (EEG), electrooculography (EOG), and facial images of the driver. Eye movement analysis can provide valuable information on the causes and progression of activity. However, most eye movements are unconscious and remain beyond the control of deliberate action. In the studies, an attempt was made to develop a classifier for scenarios related to driving based on data collected under real-world traffic conditions using JINS MEME ES_R glasses [DR8]. The evaluation of driver actions utilised both electrooculography (EOG) and a deep learning-based approach. The data were obtained using JINS MEME ES_R glasses, equipped with 3-point EOG electrodes, a 3-axis accelerometer, and a 3-axis gyroscope. Sensor data were collected from 20 drivers (ten experienced and ten novice) during a journey along the same 28.7 km route under real traffic conditions in southern Poland. While driving, the drivers performed several tasks, wearing the glasses, related to the signals recorded during the journey. A one-dimensional convolutional neural network (1D CNN) was employed to recognise four activities (parking, roundabout navigation, urban driving, and intersection crossing). The extracted EOG signal was subsequently processed to detect eye movements associated with the performance of the aforementioned activities by the driver. The best model based on 1D CNN achieved an accuracy of 95.6% on the validation set and 99.8% on the training set. These results confirm that the 1D CNN-based model is effective in classifying the activities performed by drivers.

3.3.1 Monitoring and modeling the actual driving of the car driver using 1D CNN

To maintain the safety of other road users, certain situations and scenarios cannot be practiced during actual driving; therefore, the modelling of these so-called secondary tasks (not directly related to vehicle operation) is typically conducted using driving simulators. To drive safely, the driver must be aware of their surroundings, pay attention to traffic, and be prepared to adapt to changing circumstances. Most studies on driving safety focus on detecting irregularities in driver behaviour and monitoring cognitive abilities [27, 18]. In this study, a classifier for basic driving activities was proposed, based on a similar approach that can be applied to recognising fundamental activities in daily life, using electrooculographic (EOG) signals and a one-dimensional convolutional neural network (1D CNN) [DR2]. The classifier achieved an accuracy of 80% for 16 primary and secondary activities. The effectiveness associated with driving-related activities, such as turning, parking, navigating roundabouts, and others, was 97.9%, 96.8%, 97.4%, and 99.5%, respectively. The F1 score for secondary driving tasks (0.99) was higher than for primary driving activities (0.93–0.94). Furthermore, the same algorithm enabled the distinction of four daily life activities (eating, drinking, bending over, reaching for something), which become secondary tasks during driving. To drive safely, the driver must be sufficiently aware of their surroundings, focus on the road and traffic, and be alert enough to react to unexpected circumstances.

3.3.2 Monitoring and modeling the simulated driving of the car driver using 1D CNN

In order to maintain the safety of other road users, some situations and scenarios cannot be practiced during real driving, therefore modeling these so-called secondary activities (not directly related to driving) are usually performed using driving simulators. To operate a vehicle safely, a driver must be aware of his surroundings, pay attention to traffic, and be willing to adapt to changing circumstances. Most research on driving safety focuses on detecting irregularities in driver behavior and monitoring his cognitive abilities [27, 18]. This study proposed a classifier of basic driving activities based on a similar approach that can be used to recognize basic activities in everyday life, using electro-oculography (EOG) signals and a one-dimensional convolutional neural network (1D CNN) [DR2]. The classifier achieved an accuracy of 80% for 16 primary and secondary activities. The efficiency related to driving activities such as turning, parking, navigating roundabouts and others was 97.9%, 96.8%, 97.4% and 99.5%, respectively. The F1 score for secondary driving activities (0.99) was higher than for primary driving activities (0.93–0.94). Moreover, the same algorithm allowed us to distinguish four activities related to everyday life (eating, drinking, leaning, reaching for something) that become secondary while driving. To drive safely, a driver must be sufficiently aware of his surroundings, concentrate on the road and traffic, and be alert enough to respond to unexpected circumstances.

Tasks directly related to driving are considered primary driver activities, while others are treated as secondary. Detecting irregularities in driver behaviour to prevent accidents, through the use of personalised driving style indicators through facial recognition or personalised sensor technologies, enables the monitoring of correct cognitive and safe driving behaviours. To further explore the research challenges, the next objective was to identify road conditions using EOG signals monitored during the journey and to determine whether drivers improve their skills, such as vehicle parking. Using a three-point electrooculography (EOG) and an inertial measurement unit (IMU) with a gyroscope and accelerometer, ten channels were acquired: linear and angular acceleration on the X, Y, and Z axes, as well as four EOG channels: the electric potentials on the right (EOG

_R) and left (EOG _L) electrodes, and the vertical (EOG _V) and horizontal (EOG _H) differences between them. Road conditions were recognised based on electro-oculograms obtained from drivers wearing the JINS MEME ES_R glasses.

The highest precision, sensitivity, and F1 score were observed for the activity of drinking beverages (1.00 for each measure), while the lowest results were observed for parallel parking on the left side (precision 0.44, sensitivity 0.4 and F1 score 0.42). Most misclassifications occurred in the group of mutually similar activities, such as parking on the left and parking on the right side. The binary classification between secondary and primary activities achieved an accuracy level of 99.5%. This study used the recognition of primary and secondary driver activities based on EOG signal processing using a convolutional neural network, resulting in excellent recognition performance, although certain limitations exist. The first of these was the acquisition of EOG signals in a simulated driving experiment. Although the experimental results demonstrated that the turning or parking state was effectively induced and the effectiveness of the experimental scheme was verified, it cannot be compared to the complexities of real-world driving conditions. The second limitation was the restriction on the number of experimental data segments. This setup can be applied in future studies that do not expose volunteers to the dangers of real traffic conditions. The classification models were trained on short signal samples. The third limitation was the use of only one time window width (5.6 s) to calculate the EOG features, without fully exploring the impact of other time window divisions on classification outcomes. A machine learning model based on a convolutional neural network (CNN) was used to classify nine primary and four secondary driver activities based on physiological sensor data from the JINS MEME ES_R. A comparative analysis of sensor data for nine primary and four secondary (driver-disruptive) activities was conducted. The proposed system achieved an impressive overall accuracy of 97% (± 2) and an average F1-score of 95% (± 2) in recognising these activities. Furthermore, the model has the potential to prevent road accidents by informing about improper driver behaviour, without the need to implement expensive safety equipment, but simply by installing an application on mobile devices. To validate the approach, future studies will include the acquisition of additional data from real traffic conditions. This method of use could be beneficial for drivers, especially older adults or individuals with disabilities.

3.3.3 Detection of simulated accidents and events using deep learning

The analysis of road traffic accidents and the identification of their patterns constitute a significant area of research within the domain of driving analysis. Applications related to environmental safety and fleet management are increasingly benefiting from research into accident detection in order to minimise risks for drivers and vehicles. Previous literature has proposed various solutions for automatic accident detection, based on traffic data or the application of external sensors attached to the human body. However, access to data from real-world traffic scenarios can be limited, and external sensors may be difficult to configure, unstable depending on the conditions of use, and even prohibited. Additionally, the limited availability of data concerning the detection and progression of road accidents has significantly influenced the types of approaches used to date, leaving the area of machine learning in road anomaly detection relatively unexplored. Consequently, a machine learning algorithm is proposed for the automatic detection of road traffic accidents, based on multi-sensor devices mounted in vehicles [DR4]. This work represents a unique and innovative study on the practical detection of road accidents, employing feature extraction methods using basic vehicle sensors. In total, five different approaches to feature extraction were tested, including techniques based on multimodal signal feature engineering and supervised learning, using deep learning on accident data from the naturalistic driving study within the Strategic Highway Research Programme 2 (SHRP2). The main findings of this study are as follows: (1) CNN features with an SVM classifier achieve very promising results, outperforming all other tested approaches. (2) Approaches based on feature engineering and supervised learning exhibited different features with the best performance. Hence, the fusion experiment indicates that these two feature sets can be effectively combined. (3) Unsupervised feature extraction achieved outstanding performance results. An algorithm was proposed for accident detection using the most basic in-vehicle sensors within the naturalistic accident dataset from the Strategic Highway Research Program 2 (SHRP2), employing machine learning. The latest feature extraction methods, including traditional manual feature extraction and supervised learning, were combined with two classifiers. CNN features with an SVM classifier outperformed all other tested approaches, achieving an accuracy of 85.72%, a weighted F1-score of 84.9%, and a mean F1-score of 79.10%. This result is very promising, considering that the data used in this study are based on naturalistic accidents, and very few samples represent severe accidents, recognisable only by four basic in-vehicle sensors. Moreover, interpretability studies have shown that HC and DNN approaches extracted their optimal features from different sensor channels and could therefore be effectively combined due to their complementary nature.

3.4 Supporting the recognition of behavioral-cognitive behavior using mixed and manually configured methods

The involvement of the author of the proposal in the development of computer systems for the recognition of behavioral-cognitive patterns (KRWBK) largely concerns the issues of analyzing the behavior and activity of drivers and the attempt to develop an original stress measurement scale, based on the identification and association of eye movements recorded with the JINS MEME ES_R device.

As mentioned in the introduction, the implementation of the habilitation project was disrupted by the introduction of epidemiological regulations throughout the country. In the period from 2019 to 2021, the continuation of research as originally intended would require a violation of the restrictions. Nevertheless, this particular period made it possible to carry out other studies that also concerned the support of the recognition of behavioral-cognitive behavior. In his opinion, the algorithms dedicated to these issues, proposed by the author, are a valuable addition. A description of these methods has been published in articles, and monographs indexed in the WoS and SCOPUS databases [DR10, DR11, DR12, DR15].

3.4.1 Machine learning algorithms and fuzzy set elements dedicated to the assessment of reading comprehension skills

Electrooculographic (EOG) signals have been used in the analysis of reading comprehension [DR10]. In this study, EOG signals were recorded using JINS MEME ES_R glasses, equipped with a 3-axis accelerometer, a 3-axis gyroscope, and three dry EOG electrodes made of stainless steel [28]. These glasses were equipped with a Bluetooth module, enabling wireless communication with a computer or mobile device. To establish a connection between the computer and the glasses via Bluetooth, it was necessary to connect a Bluetooth module via USB and use the ES_R Development Kit application. The sample rate of the EOG signal was 100 Hz.

The study developed an app to measure reading speed and assess reading comprehension using glasses that can visualize the reading process by tracking eye movements using EOG. The detection algorithm was based on signal pre-processing and fuzzy clustering, especially fuzzy c-means. MATLAB software was used to design the signal processing algorithms, and the graphical interface was implemented in .NET Windows Presentation Foundation (WPF) due to the need for integration with smart glasses.

The detection method proved to be highly effective and precisely determined the temporal position of the saccadic movements of the eye, even at a low signal-to-noise ratio. This method has the potential to be useful in EOG signal processing systems for visual acuity assessment. However, the quality of the recorded EOG signal was dependent on blinking and sensitive to the lack of skin contact with the electrodes, which determined the visualization of the reading. The study found that the text-reading animation was reliable in 7 out of 9 cases (77%). Due to the limited number of study participants, it should be considered a pilot study. Nevertheless, the developed application works properly as long as the EOG signal does not contain artifacts from interfering factors.

Eye movement analysis has important applications both in clinical practice and in scientific research. An animation app for text tracking and comprehension assessment can be useful in researching the level of awareness during the process of learning new content. The classifier used achieved an accuracy of about 92%, which allows the application to be used in more complex clinical cases related to rehabilitation after vision loss or visual impairment.

3.4.2 Methods of segmenting image changes using machine learning dedicated to BVRT diagnostics

Research on the functioning of visual memory plays an important role in the processes of learning to read, write, type, or draw. Visual memory dysfunctions can be identified using tests such as the Benton Visual Retention Test (BVRT), which involves presenting ten patterns for ten seconds each and asking the subject to reproduce them. The study aimed to automate the Benton test by developing a computer application [DR11].

Automation of the evaluation of hand-drawn geometric shapes (triangles, circles, rectangles) was achieved through machine learning and computer vision techniques, including ResNet50, which was trained to recognize triangles, circles, rectangles, and other shapes, fill the shape, and determine the type of triangle. The proposed algorithm has proven its effectiveness, especially for people with limited ability to draw shapes, and has been incorporated into a computer application that can be used to study visual perception and visual memory.

The study was conducted on a group of 9 residents of a nursing home in Borowa Wieś, a district of Mikołów (Poland), who had the ability to read, write and draw. These people were divided into three categories based on their degree of disability: mild (A), moderate (B) and severe (C). The degree of disability of each person was determined by the primary care facilities after they were admitted to the nursing home.

The shape recognition process involved pre-processing and the use of a Deep Neural Network (DNN) trained on 40 examples of triangles, rectangles, circles and other shapes painted red. Each geometric shape was represented by 10 examples. The DNN was implemented in C# and used TensorFlow to perform transfer learning,

leveraging the ResNet50 network [29]. The result of the classification was presented in the form of a description of the shape ("p" for rectangle, "t" for triangle, "o" for the circle i "i" for a different shape).

The BVRT test results were evaluated based on a description published by [30]. For each category, the number of correctly recognized rotations, distortions, resizing, omissions, triangles, circles, and rectangles was 10 out of 10 geometric shapes evaluated. The number of correctly recognized erroneous rotations was 6, which resulted from incorrect coding of the hand-drawn triangles. In four cases, the classification of triangles was incorrect due to incorrect recognition of the correct rotation.

3.4.3 Manually calibrated methods for segmenting EOG signal changes to recognize driver activity during real-world trips

The analysis of human physical activities constitutes a significant field, which, as can be stated, already has established categories of activities [31, 32, 33]. Those related to basic life needs—such as breathing, eating, sleeping, and walking—are particularly well described [34, 31, 35], and so forth. Beyond vital signs, each individual can be characterised by their cognitive abilities. Cognition, the mental processes involving comprehension, awareness, perception, knowledge, intuition, and judgement, is a critical aspect for drivers [33]. Based on this convention, it was decided to investigate activities associated with the task of driving a car [DR12].

The classification of activities and scenarios was based on determining the Best Fit Sequence (BFS) from features derived from data obtained using JINS MEME ES_R glasses. This method builds on a codebook approach described in works [36, 37, 33]. The discussed automatic classification method consists of several steps, in which the model's input data are segmented and then grouped according to the most statistically significant elements of driver activity. Before the proper stages of signal analysis, there is a phase of signal disturbance and amplitude sequence detection, where a moving detector achieves the maximum number of repetitions. The classification of activities and scenarios is based on determining the Best Fit Sequences (BFS) from sequences of labelled activities visible in the data. The Best Fit Sequence (BFS) represents the most frequent sequence of signals associated with the labelled activities. These labelled activities are then divided into specific time intervals and result from a series of sub-sequences shifted in time. The Best Fit Sequence Dictionary (BFSD) is constructed from a set of BFS as part of the training phase. The first step in creating the BFSD is to find the most appropriate BFS, where the length of each BFS corresponds to the length of the data sub-sequence sets from the classifier's training set, which fits a particular time window width 'w'. Two different time window shift methods were used: shift and overlap. The next step in classification was to group all extracted subsequences into N different clusters. After clustering, each cluster centre became a BFS, and each subsequence was then assigned to the most similar BFS in the given sequence. Then a histogram was extracted that represents the frequency of each BFS was extracted. After creating the BFSD, half of the labelled data set was used to train the driver activity classifier, based on sequential multidimensional sensor data corresponding to measurements of three quantities (a three-axis accelerometer, a three-axis gyroscope and four-channel EOG). However, the results were not promising—the maximum correctly classified activities amounted to 62% before averaging the results of two-fold cross-validation. Therefore, in the subsequent experiment, only four classes of driving-related activities were used, to which the collected data were assigned, allowing for significantly better results, with the best average probability score from two trials reaching 85%.

The experimental results indicate that the BFSD approach can be effectively utilised to diagnose activities related to driving. Additionally, the BFS-based entropy test proved to be a useful analytical tool for obtaining information on the characteristics of the time window for a given class of activity. These findings may be helpful in building a knowledge base on cognitive activities related to driving, where there is a lack of sufficient studies and research on the characteristics of individual cognitive activity classes in this field.

3.4.4 Manually calibrated methods for segmenting EOG signal changes dedicated to stress recognition among a group of dental students

Assessment of the stress level among first-year dental students based on socio-demographic factors and gender, comparison of Polish and Taiwanese students [DR15]. The aim of the study was to examine the perceived levels and sources of stress in Polish first-year dental students, both women and men, studying in Poland, and then to compare these results with first-year Taiwanese dental students studying in English, which is not their native language. The study used the JINS MEME ES_R device, equipped with three-point electrooculography (EOG) and a six-axis inertial measurement unit (IMU) (three-axis accelerometer and three-axis gyroscope). A Garmin Vivoactive 3 GPS smartwatch was used to measure heart rate [17, 18, 19].This device is equipped with a heart rate sensor located on the back, which allows you to measure your current heart rate in beats per minute (bpm), which is presented on the watch in the form of a graph.

As mentioned earlier, professional stress begins as early as dental studies [DR9]. This stress can negatively affect their personal and professional lives – especially when it comes to the quality of their clinical work. Results reported by Boran et al. in [38] show that qualified dentists had lower stress levels compared to college students

and general dentists, which is consistent with other studies [39, 40, 41]. When stress persists, students may find it difficult to continue working, and they may also face problems interacting with patients [42, 43]. It can also be expected that students from other countries, who have to cope in a foreign environment and are additionally exposed to stress related to socio-cultural confrontation, may be less resistant to stress in contact with a patient, for example due to the language barrier. During the experiments, the occurrence of eye blinking (its speed and strength), vertical and horizontal eye movements, and head movement (rotation in the plane around the X, Y and Z axes) were assessed [31].

The study was carried out on 20 third-year students from the Faculty of Dentistry of the Medical University of Silesia in Katowice, who were divided into four groups: Polish Dental Students (PFJS), Polish Dental Students (PMJS), Taiwanese Dental Students (TFJS) and Taiwanese Dental Students (TMJS).). Taiwanese students were included to examine the impact of English communication as an additional stressor. All participants in the experiment received detailed information about the task to be performed, which included completing a dental knowledge test consisting of 5 questions with five descriptors, analysis of the 3D model, and an explanation of the time limit for preparation.

Polish students in the PFJS and PMJS groups received instructions in their native language and the test itself was also in Polish. However, the test prepared for Taiwanese students (groups: TFJS and TMJS) was in English. During the test and cavity preparation procedure, all participants in the experiment were equipped with a set of monitoring devices (glasses and a watch) to control vital parameters defining the intensity of stress. The average time to complete the test in the PFJS group was 2 minutes and 11 seconds, and the results achieved included two good grades, one satisfactory grade, and two fail grades. In the PMJS group, the results were two failed attempts, one satisfactory grade and two good grades, with an average test time of 2 minutes and 13 seconds. For the TFJS group, the average completion time was 2 minutes, with students obtaining two good grades, two satisfactory grades, and one student failing. In the TMJS group, four good grades and one satisfactory grade were obtained, with an average test time of 2 minutes and 25 seconds.

Heart rate analysis showed no statistically significant differences between groups. However, higher heart rates were observed in women compared to men when they performed the same tasks. The heart rate was measured both before starting the procedure (tooth modeling or writing a test) and after its completion. Electrooculography data describing eye movements in the horizontal (right-left) and vertical (up-down) axes showed higher signal amplitudes in both Polish and Taiwanese women compared to men.

Statistical analysis has shown that the arithmetic mean is the most common value in a normal distribution, although it may not be observed in the data set. However, the median is the preferred measure of central tendency in stressful situations. This suggests that an average value may not be the best way to accurately reflect differences in signal amplitude. When analysing differences between genders and different test settings, the confidence interval for the difference between two measures determines the range of values over which a difference between the means of two populations can occur.

3.5 Monitoring and recognizing human behavior patterns as part of personalized telemedicine

An important supplement to the designed systems [Computer Recognition of Behavioural and Cognitive Patterns - KRWBK] is an article summarizing the seven-year period of existence of the conference "Telemedicine and eHealth" (2014-2021). Although it does not refer directly to computer-aided medical diagnostics, in the author's opinion it raises a very important aspect related to the subject of personalized medicine. The research, the effects of which were presented at subsequent annual conferences, made it possible to track and demonstrate the impact of conference presentations on their scientific maturity, expressed in publications directly related to them. The narrative of the review referred to selected achievements of telemedicine and eHealth in Poland and showed the whole phenomenon in the context of the development of telecommunications.

Attention was also paid to the technological and historical environmental aspects of telemedicine challenges. This review also addressed current challenges, policies and solutions in countries where innovations in the field of telemedicine development are widely introduced. The pandemic period has undoubtedly increased and accelerated the interest in and use of telemedicine as a safe and effective pathway for the delivery of health services, and [KRWBK] may prove to be an important tool for the initial diagnosis of diseases [44].

3.6 Signal repositories and technical solution to the problem

Another dataset includes recordings of signals obtained from vehicle (car) drivers, including ten experienced drivers and ten learners who drove the same 28.7 km route in the Silesian Voivodeship, in the south of Polish. Experienced drivers performed these tasks in their own cars, while the learning drivers performed the tasks under the supervision of a driving instructor in specially marked vehicles (with an "L" plate). The tasks included driving on the motorway, urban traffic in Bytom, Radzionków, Piekary Śląskie, Tarnowskie Góry, driving in

residential areas, driving on a roundabout, parking and driving through an intersection. The repository is titled 'Drivers' activity tracking with Jins meme smart glasses ", [DR17].

The final dataset is "Acoustic signals from the knee", which contains acoustic signals from the knee surface from 14 participants and is available at [DR18].

In the context of solving a technical problem covered by copyright and patent rights, the author informs that in the period from November 2014 to December 2016 he held the position of Project Manager under the project POIG.01.04.OO-24-275/13. The main objective of this project was to develop an innovative retail stand and cash register. The total cost of the project was PLN 1,772,363.60. The substantive and financial scope of the project was completed by the end of June 2015, and the implementation of the practical part by the end of December 2017. The development work included patent applications and industrial designs, namely: patent: FLASH FILE SYSTEM, patent: CASH MODULE, exclusive right number: Pat.228389. The industrial designs were marked from 002877787-0001 to 0004 (Appendix No. 7, p. 2).

3.7 Summary

This paper presents the scientific achievements of the author of the application in the field of research and design of advanced methods of EOG and multimodal signal analysis for applications in computer-aided recognition systems of cognitive-behavioral activities [CRSCBA]. The content of publications constituting a single-topic cycle of research and the author's achievements has been compiled and described, among which the following should be mentioned:

- development of an innovative method of signal segmentation used to build models for dictionaries of BSF characteristics related to the recognition of physical activities of drivers, [RD12];
- development of an innovative and at the same time the first method based on deep neural networks for segmentation of driver activity during primary and secondary activities related to driving, implemented and verified using a proprietary network architecture 1D CNN, [DR2, DR8];
- implementation of computer-aided recognition of the activity of primary and secondary persons driving motor vehicles under category "B" authorizations in accordance with the requirements of the Polish Ministry of Infrastructure, [DR1, DR2, DR8, DR13];
- development of an innovative and at the same time the first based on computer-aided recognition of road incidents defined by the laws and regulations of the Polish Ministry of Infrastructure, [DR3, DR4];
- development of an innovative and at the same time the first arbitrarily determined method of supporting the recognition of emotional states in a group of students participating in the laboratories of conservative dentistry with endodontics SUM [DR5, DR6, DR9];
- proposing an original measurement method and partial implementation of the concept of recognizing alcohol intoxication in other selected scenarios related to driving a car, [DR14];
- conceptual and executive development of proprietary stations for multimodal data acquisition dedicated to the recognition of cognitive-behavioral patterns, [DR1, DR2, DR3, DR6, DR7, DR8, DR9, DR12, DR13];
- conceptual development of the use of EOG signals to recognize reading comprehension skills, [DR10];
- conceptual and implementation development of measurement and implementation protocols for the above-mentioned archiving and data acquisition stations [DR1, DR2, DR3, DR6, DR7, DR8, DR9, DR12, DR13, DR14, DR15].

As part of the experiments, by Resolution No. KNW/0022/KB1/79/18 of 16 October 2018 of the Bioethics Committee of the Medical University of Silesia in Katowice, a total of 374 volunteers were tested. In the context of experiments on identifying driver activity, 67 volunteers aged 19 to 70, holding or aspiring to obtain a driving licence under category "B", by the announcement of the Journal of Laws of 2017, item 978, took part. On the other hand, as part of experiments related to the identification of emotional states, including stress, 50 randomly selected students of the Medical University of Silesia took part. In addition, a total of 360 students of dentistry at the Faculty of Medical Sciences of the Medical University of Silesia (Zabrze, Poland), representing the third, fourth and fifth year on the basis of the study program, were invited to take part in the survey. The study took place between January 7 and January 31, 2020, and a total of 257 participants completed the study.

Table 7 below compares the mapping methods from the nine submitted papers, broken down by the quality of the pattern's precision. The "High" and "Data-Dependent" values are general designations and can be adjusted

based on the specific results and context of the study. The precision of the pattern mapping can be measured using various metrics to evaluate the quality of the model, such as accuracy, ROC curve, or F1 factor, depending on the specifics of the problem and the data.

Table 8 summarizes the author's activities and achievements in accordance with Article 219 section 1, points 2a, b, c of "The Higher Education Act", including those from outside the series, discussed in detail in the remaining chapters of the self-report.

Table 7: Summary of statistical tools and effectiveness of classification methods.

Publication	Tools used	Precision of pattern reproduction (accuracy)
[DR1]	Combined classifier (bagged trees), supervised learning, and High, depends on the quantity and quality of the data	High (79%)
[DR2]	One-dimensional convolutional neural network, supervised learning	High (97%)
[DR3]	Mixed classifier (boosted trees), supervised learning	High (88%)
[DR4]	Mixed Classifier (Convolutional Neural Network, SVM)	High (86%)
[DR5]	Analysis using statistical tests of data	-
[DR6]	Analysis using statistical tests of data	-
[DR7]	Analysis using statistical tests of data	-
[DR8]	One-dimensional convolutional neural network	High (96%)
[DR9]	Analysis using statistical tests of data	-

Table 8: Summary of the activities and achievements of the author of Article 219 section 1, points 2a, b, c of "The Higher Education Act", including those from outside the series, discussed in detail in the remaining chapters of the self-report.

I Information on scientific achievements reffered to in art. 219 sec. 1 p. 2 of the Act (cycle)			
Applicant's Activities	Pre-doctoral	Post-doctoral	Overall
Publications from the WoS database submitted as part of the habilitation cycle (first or corresponding author)	-	8 (7)	8 (7)
Chapters in monographs submitted as part of the habilitation cycle	-	7	7
Data repositories	-	2	2
List of project, design, and technological achievements	-	1	1
Citations (WoS|SC|GS)	2|-|-	78|110|230	80|110|230
Citations without self-citations (WoS|SC|GS)	2|-|-	58|-|-	60|-|-
II Information about scientific activity (out of cycle)			
Publications indexed in the database WoS	1	9	10
Data repositories	-	1	1
Monographs and others	-	25	25
List of design, construction and technological achievements	1	5	6
Cooperation in national or international scientific conferences (foreign)	7 (4)	32 (7)	39 (11)
Information about participation in the conference organizing committees	-	11	11
Membership in international or national organizations (foreign)	2 (0)	2 (1)	4 (1)
Information about internships completed in foreign scientific institutions	-	2	2
Information about peer-reviewed scientific works (journals|conferences)	-	14|9	14|9
Scientific activity in research institutions (foreign)	1 (0)	15 (12)	16 (12)
III Information about teaching and science popularizing activities (out of cycle)			
Information about promoted doctorates (foreign)	-	5 (3)	5 (3)
Supervision of master's theses (foreign)	-	4 (1)	4 (1)
Supervision of engineering and bachelor's projects	-	16	16
No. teaching classes SUT|UE	-	12|7	12|7
Scientific publications as part of student support (foreign)	-	13 (2)	13 (2)
Popularization and mentoring activities	-	5	5
Prizes and awards	-	8	8
Training and certificates	24	31	55
IV Information about cooperation with the social and economic environment (out of cycle)			
Implementations as part of technological achievements (projects|implementations|patents)	-|-|-	2|4|2	2|4|2
Cooperating institutions from the economic and local government sectors (foreign)	-	7 (3)	7 (3)

4 Information on demonstrating significant scientific activity carried out in more than one university, scientific institution or cultural institution, in particular foreign

The author, fulfilling the requirements of Article 219(3) of the Law on Higher Education, indicates that the degree of habilitated doctor is awarded to a person who demonstrates significant scientific or artistic activity carried out in more than one university, scientific institution or cultural institution, in particular a foreign one. It presents, chronologically from the newest, 12 foreign units, including 8 universities and 4 foreign societies, along with a description of the author's activity in these centers. Then the list is supplemented by 4 national centres and societies, also with a description of the period of stay and activities undertaken in them.

4.1 Foreign research centres and societies

1. Universität zu Lübeck Germany – in February - July 2024, a six-month stay as part of the habilitation grant, the author participated in the "KI-Med-Ökosystem" projects. The aim of the project, funded by the State of Schleswig-Holstein, is to significantly accelerate the development of the originally created artificial intelligence ecosystem in the healthcare system at the University of Lübeck, by, on the one hand, further developing existing approaches and, on the other hand, promoting new activities, especially in the field of completing the necessary computing infrastructure, the active involvement of clinics in application or product innovation projects, in cooperation with companies and servicing start-up initiatives. Appendix No. 9, page 4 – cooperation continues.

2. Fraunhofer IMTE, Germany – February - July 2024, six-month stay as part of the habilitation grant the author participated in the institute's projects in the field of supplementing and testing the necessary computer infrastructure, active involvement of clinics and hospitals in application or product innovation projects, in cooperation with companies and handling start-up initiatives.

3. Université du Québec en Outaouais, Canada. As part of his scientific work, in 2019, at the invitation of Prof. Stéphane Gagnon, for two weeks of his stay, the habilitator participated in projects and lectures related to health market management conducted at the Department of Administrative Sciences. In terms of content, cooperation related to the use of ontologies in diagnostic systems has resulted in, among others, the project "implementation of an application that supports diagnosis of major cardiovascular disease". Appendix No. 9, p.3. - the cooperation continues.

4. Academy for Information Technology (ITE), Halmstad University, Halmstad, Sweden. As part of his scientific work, in 2019, at the invitation of Prof. Stéphane Gagnon, the author supported his doctoral student, Abid Ali Fareedi, in issues related to the management of the European and national health market.

5. Concordia University, Consciousness Research Foundation Canada, cooperation with Prof. Raul Valverde, during his stay in Canada in 2019 ended with a joint publication [RD7] and is still ongoing.

6. Technische Universität München, Germany, cooperation with Prof. Subhamoy Mandal and Prof. Nassir Navab, began during the implementation of a common thesis: "Deformable registration for ar assisted surgery", the measurable result of which is the joint publication [DR27] described in point 2 - from 2020.

7. Universidade de Porto, Portugal, as part of the European project V.I.B.E: Virtual Biomedical and STEM/STEAM Education - ERASMUS+, is to create an educational system that supports the implementation of STEM (Science, Technology, Engineering and Math) skills in parallel with biomedical education based on VR platforms. The results are publications and participation in certificate workshops organized as part of the conference from 01.11.2021 to 31.10.2024.

8. University of Pecs, Hungary as part of the European project V.I.B.E: Virtual Biomedical and STEM/STEAM Education - ERASMUS+ is to create an educational system that supports the implementation of STEM (Science, Technology, Engineering and Math) skills in parallel with biomedical education based on VR platforms. The results are publications and participation in certificate workshops organized as part of the conference from 01.11.2021 to 31.10.2024. Appendix No. 9, page 48.

9. International Society for Telemedicine & eHealth - ISfTeH, Switzerland - association cooperation as part of the activities of the Polish Association of Telemedicine and eHealth, the result is the annual organization of the international conference Telemedicine and eHealth with the participation of invited guests from abroad. Appendix No. 9, page 53 - cooperation continues.

10. IEEE Engineering in Medicine and Biology Society: Piscataway, NJ, US – Certificate Recognized Collaboration Active Participant Mentoring Program for Biomedical Engineering Students in Kenya and Peru – December 2020 – December 2021.

11. The International Institute for Applied Knowledge Management FL, US, - współpraca związana z przygotowaniem wydarzenia związanego z Knowledge Management Conference w 2015.

12. Universität Siegen, Germany – two-year research fellowship (2017-2019), co-investigator under the project, the source of funds was indicated in the publication: German Federal Ministry of Education and Research (BMBF) (grant number: 01IS15048B). The cooperation continued, it was still after the end of the internship. As part of his scientific work, the author participated in the projects: "LEICAR": Lernbasierte multimodalale Interpretation von Sensordaten zur Ereigniserkennung in Carsharing-Flotten. During this scientific internship, he initiated research activities in the field of classification of the context of automated driving using sensors integrated in glasses. This research activity was in line with the LEICAR (Learn-based Multimodal Interpretation of Sensor Data for Event Recognition in Carsharing) project, funded by the German Federal Ministry of Education and Research, and conducted jointly in Siegen by the Research Group on Pattern Recognition and the Research Group on Medical Informatics and Microsystems Design. Thanks to the access to the infrastructure and knowledge of the Research Group on Pattern Recognition and Medical Informatics, the author's publications in scientific journals [RD1], [RD2], RD3], [RD4], [RD8], RD13] and presentation at the 41st International Conference on Engineering in Medicine and Biology, which took place in Berlin from 23 to 27 July 2019 and was announced by the IEEE Engineering in Medicine and Biology Society. As part of the conference, the author presented a paper entitled "Recognition of basic driving scenarios". Confirmation of the above-mentioned activity with references of the above-mentioned Appendix No. 9 page 8,9 – cooperation continues.

4.2 National centres and societies

1. Medical University of Silesia – cooperation in conducting medical and research experiments in accordance with the consent document of the bioethics committee entitled: "The use of modern information and mathematical technologies in order to analyze emotions during various life activities" (Resolution No. KNW/0022/KB1/79/18 of 16.10.2018) – (Appendix No. 9 p.10). The research conducted in the project, with a specification of the author's participation, has received a positive opinion from the bioethics committee. The author of the proposal was responsible for the part related to the delivery of equipment and apparatus along with the analysis, classification and interpretation of data, with the continuation of previous joint work carried out with members of the multidisciplinary research team. The results of the research conducted so far are, among others, publications submitted as part of a scientific achievement by Article 219(1)(2b) of the Law on Intellectual Property and publications in the field of telemedicine and personalized medicine. The cooperation started in 2019 and is still ongoing.

2. University of Economics in Katowice - cooperation with the Department of Knowledge Engineering related to the preparation of joint grant applications and exchange of didactic and educational knowledge since 2014 and continues.

3. Polish Society of Telemedicine and eHealth - cooperation in research related to the analysis of all aspects related to the digitization of the public health market in Poland. In cooperation with the employees of the Health Protection Council of the National Development Council, several interpretations of the law in the field of regulation of the functioning of health services have been developed. Within the framework of the association, cooperation with scientific and medical centers necessary to conduct research has been established. – cooperation at various levels of the organization since 2012 as a member and since 2020 as a member of the board – the cooperation continues. Appendix No. 9, pp. 53 to 57.

4. Polish Society of Biomedical Engineering - cooperation as part of active participation in conferences organized by the society, including in 2010 as a co-organizer of the KKBIB 2011 edition, 11-14 October, Gliwice/Tarnowskie Góry, since 2009 as a member and the cooperation continues. Appendix No. 9, p. 52.

5 Information on didactic, organizational, and popularizing achievements in science or art

The author, fulfilling the requirements of Article 219(3) of the Law on Higher Education, indicates that the degree of habilitated doctor is awarded to a person who demonstrates significant scientific or artistic activity carried out in more than one university, scientific institution or cultural institution, in particular a foreign one. It provides information on didactic, organizational, and popularizing achievements in science or art, chronologically from the most recent lists: 5 doctoral proceedings as an assistant supervisor, of which four have been completed, 20 proceedings ended with the award of a master's degree in engineering or a bachelor's degree, including 4 proceedings for the award of a master's degree with the function of the main supervisor within the discipline of Biomedical Engineering and 16 in the others, also with a description of the topics and functions undertaken in them. In addition, the author of the application reviewed a total of 12 bachelor's projects in the field of Computer Science and Econometrics and engineering projects in the field of Biomedical Engineering. The author demonstrated, together with appendices confirming this, participation in the preparation or teaching of 19 different subjects in 2 academic centres: the Silesian University of Technology in Gliwice and the University of Economics in Katowice, including lectures, laboratories and classes. As part of the function of the scientific supervisor in 2 scientific circles: IEEE EMBS and BioSoft, 14 prepared conference presentations were listed, and the list was supplemented with a report on conducting a mentoring program related to telemedicine and eHealth for 2 students of master's courses in their countries (Kenya and Peru). He performed a similar function as a mentor in 3 national mentoring projects. In addition to the organizational and popularization of science activity, the author listed his participation, along with his function, in 3 organizations, including 2 national ones: the Recruitment Team of the Faculty Recruitment Committee of the Silesian University of Technology, the Faculty of Biomedical Engineering and the Polish Society of Telemedicine and eHealth, where the author has been the secretary of the Main Board since 2020. The author mentioned the European HealthTech Innovation Center (EHTIC) as the coordinator of the project.

5.1 Information about promoted doctorates

In 2021-present, the author of the proposal served as an assistant supervisor in 4 completed doctoral dissertations:

1. "The use of digital signal processing algorithms to analyze selected driving behaviors", carried out at the Silesian University of Technology in Zabrze, by Natalia Piaseczna, MSc, Eng., 2023. Appendix No. 9, page 15.

2. "The effect of smoking electronic and traditional cigarettes on selected parameters of the respiratory and cardiovascular systems of patients, based on the analysis of data vectors obtained from the recording of multimodal biomedical signals.", carried out at the Silesian University of Technology in Zabrze, by Joanna Chwał, MSc, Eng. 2023, Appendix No. 9, p. 14.

3. "Multimodal Sensor Data Analysis for the Investigation of Physical and Mental States Using Machine Learning, realizowana na Institut für Medizinische Informatik, Universität zu Lübeck, przez mgr inż. Muhammad Tausif Irshad, przewód zakończony obroną pracy w dniu 9 kwietnia 2024. Appendix No. 9, p. 11.

4. "Multimodal Sensor Data Analysis for the Investigation of Physical and Mental States Using Machine Learning, carried out at the Institut für Medizinische Informatik, Universität zu Lübeck, by MSc. Muhammad Tausif Irshad, the proceedings ended with the defense of the thesis on April 9, 2024. Appendix No. 9, page 12.

5. "Machine Learning Methods for Pain Investigation Using Physiological Signals", carried out at the Institut für Medizinische Informatik, Universität zu Lübeck, by Philip Johannes Gouverneur, M.Sc., Eng., dissertation completed with thesis defense on 15.04.2024. Appendix No. 9, page 13.

5.2 Supervision of master's theses

In the years 2012-2021, the author of the application was the supervisor of 4 completed master's theses in the field of biomedical engineering:

1. "Development of a classification algorithm for basic and distracting driving activities, based on multimodal signals and (deep) machine learning methods",work in English, carried out at the University of Technology Śląska in Zabrze (completed: 2022).

2. "Deformable registration for AR Assisted Surgery", thesis in English, carried out at the Silesian University of Technology in Zabrze and the Technical University of Munich (completed: 2021).

3. "Benton visual memory test algorithm using AI", implemented at the Silesian University of Technology in Zabrze (completed: 2019).

4. "Development of a classifier algorithm based on machine learning for driving activities", carried out at the Silesian University of Technology in Zabrze (completed 2019).

5.3 Supervision of engineering and bachelor's projects

In the years 2012-2021, the author of the application was the supervisor of 16 completed engineering projects in the field of biomedical engineering:

1. "Development of an educational application supporting the determination of the target group of patients for a selected glucometer model", implemented at the Silesian University of Technology in Zabrze (completed: 2024).

2. "Development of an application supporting sign language recognition based on an EMG wristband and artificial intelligence algorithms, implemented at the Silesian University of Technology in Zabrze, (completed: 2024).

3. "Development of an application for reading speed and assessment of reading comprehension" carried out at the Silesian University of Technology in Zabrze, (completed: 2020).

4. "Database for a medical facility in the MariaDB environment", implemented at the Silesian University of Technology in Zabrze (completed: 2019).

5. "Project of a management system for small enterprises, on the example of a family business: ecological laundry", implemented at the University of Economics in Katowice (completed: 2019).

6. "Application supporting the diagnosis of type 2 diabetes", implemented at the University of Economics in Katowice (completed: 2019).

7. "Analysis and implementation of the system for settling employee business trips.", carried out at the University of Economics in Katowice, (completed: 2019).

8. "Rule database on metabolic diseases", implemented at the University of Economics in Katowice (completed: 2019).

9. "Reporting system using data warehouses to analyze production data" implemented at the University of Economics in Katowice (completed: 2019).

10. "Construction of a discussion forum based on CakePHP technology using Twitter Bootstrap", implemented at the University of Economics in Katowice, (completed: 2019).

11. "Application comparing the prices of laboratory tests with home diagnostic tests", (completed: 2019), implemented at the University of Economics in Katowice.

12. "Mobile application collecting information about e-sports events", implemented at the University of Economics in Katowice, (completed: 2019).

13. "IT system with the functionality of comparing and adding gym and fitness club offers", implemented at the University of Economics in Katowice, (completed: 2019).

14. "Application supporting the selection process for the position of electronic device programmer", implemented at the University of Economics in Katowice (completed: 2018).

15. "Application supporting the analysis of sales data in retail chains based on BI tools", implemented at the University of Economics in Katowice (completed: 2017).

16. "System supporting the organization of mass events as an example of faster and safer functioning of the e-business IT system", implemented at the University of Economics in Katowice, (completed: 2017).

In addition, the author of the application reviewed a total of 12 engineering projects in the field of Biomedical Engineering and bachelor's projects in the field of Computer Science and Econometrics.

5.4 Teaching

W In the years 2013-2023, the author of the application developed lectures with multimedia presentations and demonstration programs as part of the Knowledge Engineering field of study at the University of Economics in Katowice and Biomedical Engineering at the Silesian University of Technology in Gliwice in the following subjects (Appendix No. 8 "Copies of teaching load schedules and pro-student activity records"):

1. Information technology. (University of Economics in Katowice),
2. Metrology (Silesian University of Technology in Gliwice),
3. Python - programming (Silesian University of Technology in Gliwice),
4. Patern Recognition (Silesian University of Technology in Gliwice),
5. Cybersecurity in medical databases and data systems (Silesian University of Technology in Gliwice),
6. Telematics (Silesian University of Technology in Gliwice),
7. Artifical Organs (Silesian University of Technology in Gliwice).

In the years 2013-2023, the author of the application conducted didactic classes and developed a number of laboratory exercises, along with instructions and materials as part of the field of knowledge engineering at the University of Economics in Katowice and biomedical engineering at the Silesian University of Technology in Gliwice in the following subjects: (Appendix No. 8 - you can find details from the hourly load cards):

1. Computer Science in Management — Exercise Instructions, project (University of Economics in Katowice),
2. Computer Science in Logistics — Exercise Instructions, project (University of Economics in Katowice),
3. Computerization of office work — instructions for exercises, project (University of Economics in Katowice),
4. Computer Networks — instructions for seven laboratories, preparation of laboratory stations "from scratch" (University of Economics in Katowice),
5. Local lab databases — instructions for seven laboratories, preparation of laboratory stations "from scratch" (University of Economics in Katowice),
6. Introduction to databases — instructions for seven laboratories, preparation of laboratory stations "from scratch" (University of Economics in Katowice),
7. Metrology. — instructions for seven laboratories, preparation of laboratory stations "from scratch" (Silesian University of Technology in Gliwice),
8. Python - Programming. instructions for seven laboratories, preparation of laboratory stations "from scratch" (Silesian University of Technology in Gliwice),
9. Patern Recognition – instructions for seven labs, preparation of laboratory stations "from scratch" (Silesian University of Technology in Gliwice),
10. Cybersecurity in medical databases and data systems – instructions for seven laboratories, preparation of laboratory workstations "from scratch" (Silesian University of Technology in Gliwice),
11. Automatic and Control Systems — instructions for five laboratories, preparation of laboratory stations "from scratch" (Silesian University of Technology in Gliwice),
12. Artifical Organs — instructions for seven laboratories, preparation of laboratory stations "from scratch" (Silesian University of Technology in Gliwice).

5.5 Scientific publications as part of student supervision

The result of the research carried out in cooperation with students is the publication of thematically related scientific articles, listed in the list of publications [DR10, DR11]. Subsequent conference papers and post-conference publications submitted together with students and members of the IEEE Silesian University of Technology Student Branch and the Biomedical Engineering Student Academic Club "BioSoft" are:

1. Julia Bodak, Marta Piwko, Emilia Skwarek, Piotr Ferst, Kamil Pilarski, Marcin Pieniążek, Julia Mieszczanin, Katarzyna Bryzik, Katarzyna Mocny-Pachońska, Joanna Chwał, Natalia Piaseczna and Rafał Doniec, "The Classifier Algorithm for Recognition of the Secondary Distracting Factors while Driving a Car", HealthTech Innovations Conference 23, Faculty of Biomedical Engineering, Silesian University of Technology, Zabrze, Poland, 9-10th Octoberber, https://www.polsl.pl/rib/htic-23/,

2. Rafał Doniec, Natalia Piaseczna, Eva Odima Berepiki, Muhammad Tausif Irshad, Xinyu Huang, Szymon Sieciński, Marcin Grzegorzek, "Introducing a Non-Invasive App for Cardiovascular Disease Diagnosis Support - (a pilot study.)", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, Institute of Metrology and Biomedical Engineering Faculty of Mechatronics, Warsaw University of Technology, Warsaw, Poland, 7 September 2023. https://www.telemedycyna.org/konferencja/.

3. Wojciech Glinkowski, Tomasz Cedro, Rafał Doniec, Bartłomiej Michalak. "Introducing Polish version of Translating User Version of Mobile Application Rating Scale (uMARS)", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, Institute of Metrology and Biomedical Engineering Faculty of Mechatronics, Warsaw University of Technology, Warsaw, Poland, 7 September 2023. https://www.telemedycyna.org/konferencja/,

4. Rafał Doniec, Natalia Piaseczna, Ewaryst Tkacz, "Road type recognition with smartglasses and machine learning", International Conference of Biomedical Engineering and Innovation - iCBEI 2022, Szentágothai Research Centre, Pécs, Hungary, 24-26th Octoberber 2022, https://icbei.pte.hu,

5. Kruczkowski Adam, Lovell Dominic, Szymczyk Sebastian, Wojtowicz Marcin, Piaseczna Natalia, Doniec Rafał, Tkacz Ewaryst, Mocny-Pachońska Katarzyna, "The influence of sleep duration on the feeling of well-being during the Covid-19 lockdown", HealthTech Innovations Conference 22, Faculty of Biomedical Engineering, Silesian University of Technology, Zabrze, Poland, 10-11th Octoberber, http IEEE EMBS Kruczkowski Adam, Lovell Dominic, Szymczyk Sebastian, Wojtowicz Marcin, Piaseczna Natalia, Doniec Rafał, Tkacz Ewaryst, Mocny-Pachońska Katarzyna, "The influence of sleep duration on the feeling of well-being during the Covid-19 lockdown", HealthTech Innovations Conference 22, Faculty of Biomedical Engineering, Silesian University of Technology, Zabrze, Poland, 10-11th Octoberber 2022, DOI: 10.1007/978-3-031-52382-3_4, Appendix No. 9, page 47,

6. Rafał Doniec, Natalia Piaseczna,"The Database of home tests for rapid diagnosis (pilot study)", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, Institute of Metrology and Biomedical Engineering Faculty of Mechatronics, Warsaw University of Technology, Warsaw, Poland, 1st September 2022. https://www.telemedycyna.org/konferencja/,

7. Duraj Konrad, Sieciński Szymon, Doniec Rafał [et al.], In: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, Piscataway, Institute of Electrical and Electronics Engineers, pp.662-665, ISBN 978-1-7281-2783-5. DOI:10.1109/EMBC48229.2022.9871477,

8. Łach Agnieszka, Kalim Faisal, Heiliger Christian [et al.], In: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, Piscataway, Institute of Electrical and Electronics Engineers, pp.562-565, ISBN 978-1-7281-2783-5. DOI:10.1109/embc48229.2022.9871029,

9. Agnieszka Radziun, Rafał Doniec, Szymon Sieciński, Natalia Piaseczna, Katarzyna Mocny-Pachońska, Marta Cieślik-Wegemund, Konrad Duraj, Marta Tanasiewicz, Ewaryst Tkacz, "Smartphone-Based Color Measurement of Tooth Shade Guide in Clinical Lighting Conditions." In Maria Ganzha, Leszek Maciaszek, Marcin Paprzycki, Dominik Ślęzak (eds.) Pre-proceedings of the 2021 Federated Conference on Computer Science and Information Systems, September 2-5, 2021, Online, pages 421–425. https://annals-csis.org/proceedings/2021/pliks/fedcsis.pdf, Sofia, Bulgaria. https://fedcsis.org/,

10. Antony M. Gitau, Anghelo Danny Romero Parra, Rafał Doniec, "Telemedicine in response to the challenges of Kenia.", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, Poland, 17-18th September 2021., https://www.telemedycyna.org/konferencja/,

11. Anghelo Danny Romero Parra, Antony M. Gitau, Rafał Doniec, "Telemedicine in response to the challenges of Peru.", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, IPPT PAN -Institute of Fundamental Technological Research Polish Academy of Sciences,Warsaw, Poland, 17-18th September 2021. https://www.telemedycyna.org/konferencja/,

12. Rafał Doniec, Antony M. Gitau, Anghelo Danny Romero Parra, "Telemedicine in response to the challenges in Poland and Summary.", Telemedicine and eHealth, Polish Telemedicine and eHealth Society, IPPT PAN -Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, Poland, 17-18th September 2021, https://www.telemedycyna.org/konferencja/,

13. Rafał Doniec, Antony M. Gitau, "Summary of the development of Telemedicine and the development of the provision of health services remotely during the pandemic in Kenya and Poland.", I International Congress of Biomedical Engineering "BIOCON", Student Branch Chapter IEEE EMBS UNMSM of SBC03221E - Universidad Nacional Mayor de San Marcos, EMB18, 2021, 17-19th December 2021. https://students.ieee.org/schedule/i-congreso-internacional-de-ingenieria-biomedica-biocon-2021-el-futuro-de-la-bioingenieria/.

14. R. Doniec, Katarzyna Mocny-Pachońska, Natalia Piaseczna, Szymon Siecinski, Jacek Szymczyk, Marta Wadas, "Recognition of Basic Driving Scenarios", 41st Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), July 23-27, 2019, Berlin, Germany. https://embs.papercept.net/conferences/conferences/EMBC19/program/EMBC19_ContentListWeb_2.html.

5.6 Mentoring program

Mentoring activities for foreign second-cycle students of the Master's degree, Antony M. Gitau from Kenyatta University in Nairobi and Anghelo Danny Romero Parra from Universidad Nacional Mayor de San Marcos in Lima, as part of the IEEE EMBS Students Mentoring Program (SMP). Students participating in this mentoring programme were covered by its activities throughout the duration of their second-cycle studies in their respective countries (https://www.embs.org/students/). The result of joint scientific, research and teaching activities was their presentation at the Telemedicine and e-Health 2021 conference, which took place on September 17-18, 2021, and student care lasted from 2020 to 2022. Subsequently, the IEEE EMBS Student Activities Committee (SAC) invited the postdoctoral student to participate as a speaker on September 8, 2022, for a 30-minute workshop and a 15-minute QA session, on the experience of active participation in academia and telemedicine. In addition, on December 19, 2021, as part of the "I International Congress of Biomedical Engineering BIOCON 2021", I was invited to give a lecture entitled: "Future of Bioengineering", (certificates confirming participation in Appendix No. 9, pages 17 and 18).

5.7 Popularising activities

1. Mentor for students of the Biomedical Engineering Student Academic Club "BioSoft",

2. Mentor in the IEEE EMBS Students Mentoring Programme (SMP) in the years 2022-2023,

3. Secured funding within the VIII competition for project-oriented learning – PBL, as part of the Excellence Initiative – Research University programme, with the project titled "Utilisation of machine learning techniques to create a classification and software application assessing differences in concentration disorders based on EOG signals during simulated driving of a mechanical vehicle" (2022),

4. Participation in promotional activities for the Biomedical Engineering field of study at the Faculty of Biomedical Engineering of the Silesian University of Technology, and signing a letter of intent between Centrumelektroniki.pl and the Biosoft Student Research Club, which resulted in equipping the club with equipment worth PLN 10 thousand (2019). Appendix No. 9, page 19,

5. Mentor in the ALIK project: Academic Laboratory of Innovation and Creativity. The project was co-financed by the European Union under the European Social Fund from the funds of the Young Explorer University Programme, Axis III Higher Education for the Economy and Development, Operational Programme Knowledge Education Development 2014-2020, Measure 3.1 Competences in Higher Education. The project was implemented by the College of Social Sciences and Foreign Philology of the Silesian University of Technology in cooperation with the Department of Education of the City Hall in Bytom in the years 2018-2020. As part of the project, classes were prepared for 192 children aged 6-15 from the city and municipality of Bytom (including children with disabilities). Four cycles of repeated training blocks were carried out as part of the project. Each cycle was addressed to 48 girls and boys divided into 3 age groups (6-9; 10-12; 13-15). Organisation of classes and responsibilities within the project. As part of the four cycles, each participant (children and teenagers) received 8 hours of lectures and 16 hours of laboratory sessions within the mathematics and science module. Topics of classes for children: Computational thinking: anyone can programme (group aged 6-9 years). Participation contracted for the period 11.2018 - 06.2019,

6. Industrial mentor in the project entitled: "ZIP – BECOME AN ENGINEER OF THE FUTURE" implementing topics under the Human Capital Operational Programme. Selection of alarms for teletransmission systems on the example of mobile telecommunications networks. Permanent analysis of the status of DSL, Business Everywhere, and LTE telecommunications services. Configuring access devices for IP VPN services and programming using IP VPN services. Participation contracted for the period 1.1.2011-31.12.2015. Appendix No. 9, page 20.

5.8 Organizational activities

1. Participation in the organizing committee in the annual international scientific conference prepared by the Polish Society of Telemedicine and eHealth: Telemedicine and eHealth (since 2014–present).

2. Participation in the public consultation committee for the draft regulation of the Minister of Health on the pilot program for central electronic registration for selected health care services in the field of outpatient specialist care and health programs.

3. Acting as a coordinator of the construction and equipment process of the European HealthTech Innovation Center (EHTIC), European Center for Innovative Technologies for Health at the Faculty of Biomedical Engineering of the Silesian University of Technology (since 2020).

4. Work in the Recruitment Team of the Faculty Recruitment Committee of the Silesian University of Technology, Faculty of Biomedical Engineering, including participation in the Education Fair in Katowice Spodek (2022).

6 Other information

As part of the remaining information, fulfilling the requirements of Article 219(3) of the Law on Higher Education, it indicates that the degree of habilitated doctor is awarded to a person who demonstrates significant scientific or artistic activity carried out in more than one university, scientific institution or cultural institution, in particular a foreign one. It presents information about other training, certificates, awards, and distinctions in the author's opinion. Listing chronologically from the most recent, 55 stays related to training and professional certification, 4 awards in the form of a grant and 4 distinctions, including 3 markings and one honoration in the form of a publication.

6.1 Information about completed trainings

1. Stay at the University of Lübeck, Germany, exchange under the ERASMUS + program, due to sanitary restrictions, the stay was postponed and divided into the following years (2023). Appendix No. 9, page 5,
2. Stay at the University of Lübeck, Germany, exchange under the ERASMUS + program, due to sanitary restrictions, the stay was postponed and divided into subsequent years (2022),
3. Knowledge and Inspiration certificate from the training "Raising awareness about the needs of people with disabilities" (2022). Appendix No. 9, page 23,
4. Stay at the University of Lübeck, Germany, exchange under the ERASMUS + program, due to sanitary restrictions, the stay was postponed and divided into subsequent years (2020). Appendix No. 9, page 6,
5. Certificate Corruption in Public Administration (2021). Appendix No. 9, page 26,
6. Certificate Corruption in Business (2021). Appendix No. 9, page 27,
7. Anti-corruption certificate (2021). Appendix No. 9, page 25,
8. Certificate Data Scientist with Python Track, (2020),
9. Intensive one-month German course in Siegen https://sps-si.de (2019),
10. Certificate Unsupervised Learning in Python (2019),
11. Stay at the University of Siegen, Germany, ERASMUS+ exchange (2018). Appendix No. 9, page 8,
12. Effective work in Sublime Text course (2018),
13. Workshop introduction to Python programming for data engineers DataCamp (2018),
14. Intermediate Python programming workshop for data engineers DataCamp (2018),
15. Workshop Python programming tools for data engineers DataCamp, (2018),
16. Workshop importing data for programming in Python for data engineers, (2018),
17. Workshop of data import tools in Python for data engineers DataCamp, (2018),
18. Stanford oline workshop "Machine Learnig, (2017). Appendix No. 9, p. 28,
19. Stay at the University of Siegen, Germany, ERASMUS+ exchange (2017). Appendix No. 9, p. 9,
20. Workshop "Service training of Elzab products" - ELZAB license training (2015),
21. Workshop "How to plan promotional activities on the Internet", Zabrze (2015),
22. Workshop "Creating the employer's image" - license training, Warsaw, (2014),
23. Pedagogical course and certificate. Appendix No. 9, p. 30,
24. Cisco CCNA Network Fundamentals certificate, Gliwice (2013). Appendix No. 9, p. 32,
25. Cisco CCNA Routing Protocols and Concepts certificate, Gliwice (2013). Appendix No. 9, p. 33,
26. Cisco CCNA LAN Swiching and Wireless certificate, Gliwice (2013). Appendix No. 9, p. 34,
27. Cisco CCNA Accessing the WAN certificate, Gliwice (2013). Appendix No. 9, p. 31,
28. Workshop "Mentoring in relationally and communicatively demanding times", Warsaw (2013),

29. Workshop "Introduction to project management - Orange license training", Warsaw (2013),
30. Speech improvement workshops, Warsaw (2012),
31. EU project to deepen knowledge "Professional School of Finance", Warsaw (2011). Appendix No. 9, p. 35,
32. Workshop "Innovations day", Warszawa (2009),
33. vocational course and certificate "Land of Blooming Innovation", Krakow (2009). Appendix No. 9, pp. 40 and 41,
34. Workshop & test Cisco "CCNA & CCNP - NetworkTypes – SkillSoft" (2007),
35. Workshop & test Cisco "CCNA & CCNP - Basic Cisco Campus Switching Design – SkillSoft" (2007),
36. Workshop & test "Relation with Client" - Achieve Global, Warsaw (2007). Appendix No. 9, p. 39,
37. Workshop & test "IP VPN Architecture" - Orange Business Services, Warszawa (2007),
38. Workshop & test "Metro Ethernet from Atrica", Warszawa (2006),
39. Workshop "New functionality of Customer Relationship Management system", Kraków (2005),
40. Workshop "Base of NGP 2.1.1 - Geographic Information System", Kraków (2005),
41. Workshop "NGP 2.1.1 - Geographic Information System: analyzes, maps, data", Warszawa, (2005),
42. Workshop "Exploitation of application NGP.2.1.1 – Map Maintenance", Kraków (2005),
43. Workshop"Development Integrated Environment Data Transmission Services of Business Everywhere", Katowice (2005),
44. Workshop & test "Cisco CCNA, CCNP - IP Routing and Addressing – SkillSoft" (2005),
45. Workshop & test "Cisco CCNA, CCNP - Introduction Networking – SkillSoft" (2005),
46. Workshop & certyfikat na dozór i eksploatację sieci do 1kV SEP, Katowice (2004),
47. Workshop "Mission, values and principle of strategic TP group", Katowice (2003),
48. Workshop & certyfikat "Exploitation of SDXC network system from Alcatel 1641SX", Warszawa (2002). Appendix No. 9, p. 42,
49. Workshop & certificate "Exploitation of speech compressor DTX 240", ECI, Poznań (2001). Appendix No. 9, p. 43,
50. Workshop "Chosen problems of network and information systems", Warszawa (2001). Appendix No. 9, p. 44,
51. Workshop "Model of signal time and frequencies in telecommunication. Satellite navigation", Poznan (2000). Appendix No. 9, p. 45,
52. Workshop "Synchronization signal in telecommunication", Poznań (2000). Appendix No. 9, p. 46,
53. Workshop "Hierarchy SDH. Optical networks with WDM systems", Poznań (2000),
54. Workshop "Technique and marketing in telecommunication", Cambrige, GB (2000),
55. Language course & certificate London, Great Britain (1994).

6.2 Awards and distinctions

Rector's awards under the Excellence Initiative – Research University program:

1. Grant for the publication published in the journal TOP10: "Sensor-Based Classification of Primary and Secondary Car Driver Activities Using Convolutional Neural Networks" 2023, 23(12), 5551; https://doi.org/10.3390/s23125551 in collaboration with an author from the University of Lübeck, Germany.", published in the journal "Sensors". Appendix No. 9, page 61–62,

2. Grant for the publication published in the journal TOP10: "A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars." Sensors, 2022, 22(10), 3634; https://doi.org/10.3390/s22103634, published in the journal "Sensors". Appendix No. 9, p. 59,

3. Grant for the publication "Evaluation of the Most Stressful Dental Treatment Procedures of Conservative Dentistry among Polish Dental Students.", published in the journal: Int. J. Environ. Res. Public Health 2021, 18, 4448. https://doi.org/10.3390/ijerph18094448, published in cooperation with scientists from the Medical University of Silesia in Katowice. Appendix No. 9, p. 60,

4. Grant for the publication "Evaluating the stress-response of dental students to the dental school environment.", PeerJ 2020, https://doi.org/10.7717/peerj.8981, issued in cooperation with an industrial partner. Appendix No. 9, p. 63.

6.3 Other awards and distinctions

1. Distinction with the bronze badge of the "Polish Association of Telemedicine and eHealth", 2017. Appendix No. 9, p. 57,

2. Distinction with the silver badge of the "Polish Association of Telemedicine and eHealth", 2018. Appendix No. 9, p. 56,

3. Distinction with the gold badge of the "Polish Association of Telemedicine and eHealth", 2019. Appendix No. 9, p. 55,

4. Honorable mention of the paper "Elements of telemedicine and legal regulations of the International Conference on Telemedicine and eHealth (2020).

7 Other publications by the author

The list below includes a total of 51 publications by the author, 43 after the doctorate and 8 before the doctorate. This part lists those that were not included in the main part of the application, in which the "monothesically related" series was presented. Their indexes are identical to those given in Appendix No. 3 and 4, which results in the continuity of numbering below, but they concern separate research areas such as computer-aided diagnostics of heart and metabolic diseases, as well as telemedicine and eHealth.

7.1 Other data repositories made available with the author's participation

[DR18] Sawaryn Bartłomiej, Piaseczna Natalia, Sieciński Szymon, **Doniec Rafał**, Duraj Konad, Komorowski Dariusz, Tkacz Ewaryst, doi: 10.21227/kqdk-w748. License: CC BY 4.0. A detailed description of the database can be found in the publication [DR23].
Own contribution: Data acquisition and segmentation. Processing of data, which was also made available as part of the repository.
Contribution: 30%.

7.2 Other publications

[DR19] **Doniec Rafał**, Krzepina Tymoteusz, Siecinski Szymon, Irshad Muhammad Tausif, Grzegorzek Marcin, "An Educational App for the Selection of Blood Glucose Meters: A Cross-Sectional Study.", BMT 2024, 58th Annual Conference of the German Society for Biomedical Engineering, 18 - 20 September 2024, Stuttgart, Biomedical Engineering / Biomedizinische Technik, ISSNs: 0013-5585, De Gruyter, Germany 2024.
40 pts MNiSW, **CS = 3.5**; conference proceedings indexed in the SCOPUS database, as of 18-09-2024
Own contribution: Analysis of the current state of knowledge. Concept and development of an algorithm for assessing the quality of glucometers. Preparation of the first and coordination of the last version of the article.
Contribution: 60%.

[DR20] Sieciński Szymon, **Doniec Rafał**, Grzegorzek Marcin, "Linear classification of healthy people and patients with valvular heart diseases based on heart rate variability indices derived from electrocardiograms.", BMT 2024, 58th Annual Conference of the German Society for Biomedical Engineering, 18 - 20 September 2024, Stuttgart, Biomedical Engineering / Biomedizinische Technik, ISSNs: 0013-5585, De Gruyter, Germany 2024.
40 pts MNiSW, **CS = 3.5**; conference proceedings indexed in the SCOPUS database, as of 18-09-2024
Own contribution: Analysis of the current state of knowledge. Preparation of the first and coordination of the last version of the article.
Contribution: 40%.

[DR21] Adam Kruczkowski, Dominic Lovell, Sebastian Szymczyk, Marcin Wojtowicz, Natalia Piaseczna, **Rafał Doniec**, Ewaryst Tkacz & Katarzyna Mocny-Pachońska, "The Influence of Sleep Quality and Duration on the Feeling of Mental Acuity During the COVID-19 Lockdown – A Pilot Study." Innovations in Biomedical Engineering 2023. Lecture Notes in Networks and Systems, vol. 875: 33–40, Springer Cham. 2024, https://doi.org/10.1007/978-3-031-52382-3_4.
20 pts MNiSW, **CS = 0.7**; conference proceedings indexed in the SCOPUS database, as of 03-03-2024
Own contribution: Analysis of the current state of knowledge. Concept and development of an algorithm for assessing sleep quality. Preparation of the first and coordination of the last version of the article.
Contribution: 15%.

[DR22] Natalia Piaseczna, **Rafał Doniec** [i in.]: "Driving Reality vs Simulator: Data Distinctions", Electronics, Basel, 2024, vol. 14, nr 3, s.1-16, Numer artykułu: 1320. DOI:10.3390/app14031320.
100 pts MNiSW, **IF = 2.6**.
Own contribution: Concept of research. Data acquisition. Concept of methodology using machine learning technique. Editing, proofreading an article.
Contribution: 30%.

[DR23] **Rafał Doniec**, Eva Odima Berepiki, Natalia Piaseczna [i in.]: "Cardiovascular disease preliminary diagnosis application using SQL queries: filling diagnostic gaps in resource-constrained environments", w: Applied Sciences-Basel, 2024, vol. 14, nr 3, s.1-16, Article number: 1320. DOI:10.3390/app14031320.
100 pts MNiSW, **IF = 2.7**.
Own contribution: Concept of research. Concept of methodology using the ontology technique. Editing,

proofreading an article.
Contribution: 50%.

[DR24] Rimsha Fatima, Muhammad Adeel Nisar, **Rafał Doniec**, [i in.]: "A systematic evaluation of feature encoding techniques for gait analysis using multimodal sensory data", In: Sensors 2024, 24(1), 75, e-ISSN 1424-8220. DOI: DOI:10.3390/s24010075.
100 pts MNiSW, **IF = 3,847**.
Own contribution: Concept of research. The concept of the methodology of multimodal signal segmentation using the "codebook" technique and the k-means clustering algorithm. Editing, proofreading an article.
Contribution: 30%.

[DR25] **Doniec Rafał**, Piaseczna Natalia, Szymczyk Karen A. [i in.]: Experiences of the telemedicine and eHealth conferences in Poland - a cross-national overview of progress in telemedicine, Applied Sciences-Basel, 2023, vol. 13, nr 1, s.1-19, Numer artykułu:587. DOI:10.3390/app13010587.
100 pts MNiSW, **IF = 2.838**.
Own contribution: Concept and development of a set of features describing the analyzed structures based on cocurrence matrices and wavelet transform, discussion. Overview of existing solutions. Preparing the article.
Contribution: 60%.

[DR26] Duraj Konrad, Sieciński Szymon, **Doniec Rafał** [i in.]: "Heartbeat detection in seismocardiograms with semantic segmentation", W: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, 2022, Piscataway, Institute of Electrical and Electronics Engineers, s.662-665, ISBN 978-1-7281-27835. DOI:10.1109/EMBC48229.2022.9871477.
20 pts MNiSW, chapter in a scientific monograph.
Own contribution: Concept of research. The concept of signal segmentation methodology using deep neural networks. Coordination of work. Editing, proofreading the article. (Supervision of the master's thesis, on the basis of which the article was written).
Contribution: 30%.

[DR27] Łach Agnieszka, Kalim Faisal, Heiliger Christian [i in.]: Local shape preserving deformations for augmented reality assisted laparoscopic surgery, W: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, 2022, Piscataway, Institute of Electrical and Electronics Engineers, s.562-565, ISBN 978-1-7281-2783-5. DOI:10.1109/embc48229.2022.9871029.
20 pts MNiSW, chapter in a scientific monograph.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article (Supervision of the master's thesis, on the basis of which the article was based).
Contribution: 50%.

[DR28] Sawaryn Bartłomiej, Piaseczna Natalia, Sieciński Szymon [i in.]: "The assessment of the condition of knee joint surfaces with acoustic emission analysis", Sensors, 2021, vol. 21, nr 19, s.1-22, Article number:6495. DOI:10.3390/s21196495.
100 pts MNiSW, materials indexed in WoS.
Own contribution: Cooperation in the field of data acquisition using microphone inserts and support for the editing of preliminary and final articles.
Contribution: 15%.

[DR29] Agnieszka Radziun, **Rafał Doniec**, Szymon Sieciński, [i in.]: "Smartphone-based color measurement of tooth shade guide in clinical lighting conditions.", Annals of Computer Science and Information Systems, 2021, vol. 25, Institute of Electrical and Electronics Engineers, s. 409-413, ISBN 978-83-959183-6-0. DOI:10.15439/2021F40.
70 pts MNiSW, conference materials indexed in WoS.
Own contribution: Concept and development of a set of features describing the analyzed structures based on reflectometric matrices, discussion. Overview of existing solutions. Preparation of the article. Cooperation in the field of data acquisition using microphone inserts and support for the editing of preliminary and final articles.
Contribution: 45%.

[DR30] Katarzyna Mocny-Pachońska, Agata Trzcionka, [i in.]: "The influence of gender and year of study on stress levels and coping strategies among Polish dental.", Medicina 2020, 56(10), 531; https://doi.org/10

.3390/medicina56100531.
40 pts MNiSW, conference proceedings indexed in WoS.
Own contribution: Concept and statistical elaboration of a set of features describing the analyzed questionnaires dedicated to determining the level of stress, discussion. Overview of existing solutions. Preparation of the article. Final support for article editing.
Contribution: 15%.

[DR31] **Doniec Rafał**, Mocny-Pachońska K., Piaseczna Natalia [i in.]: "Recognition of basic driving scenarios." W: 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23-27 July 2019, 2019, Institute of Electrical and Electronics Engineers, s.1, ISBN 978-1-5386-1312-2.
20 pts MNiSW, conference materials.
Own contribution: Research concept. Data acquisition. Coordination of work. Development of a part of the methodology related to limiting the area of interest. Preparation, editing, and proofreading of the article. Final support in editing the article.
Contribution: 70%.

[DR32] Mocny-Pachońska K., **Doniec Rafał**, Trzcionka A. [i in.]: "The stress level assessment based on sociodemographic and gender factors among Polish and Taiwanese female and male junior dental students Information and software technologies", 25th International Conference. ICIST 2019, Vilnius, Lithuania, October 10-12, 2019. Proceedings / Damasevicius R., Vasiljeviene G. (red.), Communications in Computer and Information Science, 2019, vol. 1078, Springer, s.553-564, ISBN 978-3-030-30274-0. DOI:10.1007/978-3-030-30275-7_43.
20 pts MNiSW, conference materials indexed in WoS.
Own contribution: Preparation of the article. Final support for article editing.
Contribution: 30%.

[DR33] Meiser Dariusz, Doniec Rafał, W: Projekty lokalne i regionalne - interesariusze projektu / Brandenburg H., Tobor G. (red.), "Projekty wytwórcze a ryzyko", Prace Naukowe Uniwersytetu Ekonomicznego w Katowicach, 2017, Katowice, Wydawnictwo Uniwersytetu Ekonomicznego w Katowicach, s.242-260, ISBN 978-83-7875-365-0.
0 pts MNiSW, conference materials indexed in databases of the University of Economics in Katowice.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR34] **Doniec Rafał**, "Limiting the functionality of IT systems monitoring patients with diagnosed metabolic.", Biomedical engineering 2016: 20th International Conference, Kaunas, Lithuania, 24th-25th November 2016, 2016, [B.m.], [b.w.], s.4-9.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR35] **Doniec Rafał**, Spangler Scott., "The functionality of IT systems monitoring patients with diagnosed metabolic disorders in Poland", Abstracts Proceedings - KM Conference 2016 - Lisbon, Portugal: Refereed Proceedings - Abstracts, 2016, [B.m.], International Institute for Applied Knowledge Management, s.39.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR36] Meiser Dariusz, **Doniec Rafał**, "Ryzyko w projektach wytwórczych.", Projekty regionalne i lokalne - interesariusze projektu. Projets régionaux et locaux - parties prenantes : VI Konferencja naukowa, Radzionków, 13-15 czerwca 2016, 2016, [B.m.], [b.w.], s.31-32.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR37] **Doniec Rafał**, Scheller S.," Establishing best practices in innovation on the basis of elements of cooperation between the government, educational institutions, and a private sector.", OJAKM, 2015, vol. 2, nr 2, s.54-67
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR38] **Doniec Rafał**, Meiser Dariusz. Optymalizacja organizacji prac narzędziowni wydziału mechanicznego.", Projekty regionalne i lokalne - sukces projektu. Projets régionaux et locaux - le succès du projet: V Konferencja naukowa, Radzionków, 9-10 czerwca 2015, 2015, [B.m.], [b.w.], s.20-21.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR39] **Doniec Rafał**, "Development of the educational-research standards based on the cooperation of academic centers with employees of the international corporation on the basis of own research.", Refereed proceedings of KM Conference 2014, Blagoevgrad, Bulgaria [online], 2014, [B.m.], International Institute for Applied Knowledge Management, s. 11-19.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR40] **Doniec Rafał**, "Internetowy dziennik zmian dobowych DiabLab i inne sposoby monitorowania stężenia glukozy we krwi diabetyka.", Telemedicine & eHealth 2014: International conference, Warszawa, 24 September 2014. Book of abstracts, 2014, [B.m.], [b.w.], s.16.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR41] **Doniec Rafał**, "Podnoszenie jakości kształcenia zawodowego poprzez kreatywne rozwijanie umiejętności.", Projekty regionalne i lokalne - najlepsze praktyki. Projets règionaux et locaux - les meilleures pratiques : III Konferencja naukowa, Radzionków, 21 maja 2013, 2013, s. 19
Own contribution: The concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR42] **Doniec Rafał**, "Internetowy dziennik zmian dobowych stężenia glukozy we krwi diabetyka – DiabLab", Biocybernetyka i inżynieria biomedyczna: XVII Krajowa konferencja, Gliwice/Tarnowskie Góry, 11-14 października 2011, 2011, s. 31.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR43] **Doniec Rafał**, Doniec Kalina, "Scenariusz rozwoju systemu zdalnej regulacji poziomu insuliny w organizmie człowieka z wykorzystaniem teorii zbiorów rozmytych.", Biocybernetyka i inżynieria biomedyczna: XVII Krajowa konferencja, Gliwice/Tarnowskie Góry, 11-14 października 2011, 2011, [B.m.], [b.w.], s.48.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 80%.

[DR44] **Doniec Rafał**, "Projekt struktury falkowo-neuronowej odwzorowującej krzywą cukrową, otrzymaną w wyniku pomiaru cukru we krwi pacjentów zarejestrowanych w dedykowanej do tego projektu bazie danych.", W: Biocybernetyka i inżynieria biomedyczna: XVI Krajowa konferencja, Warszawa, 26-29 kwietnia 2010, 2010, Warszawa, IBIB PAN, s.211.
Own contribution: Concept of research. Coordination of work. Development of the entire methodology related to preparing and developing an algorithm based on the wavelet-neuron structure limiting the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR45] **Doniec Rafał**, "The remote control system of the insulin level.", Journal of Medical Informatics and Technologies, 2010, vol. 15, s.201-208.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development, and implementation of a remote insulin control system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR46] **Doniec Rafał**, Doniec Kalina, Doniec-Wolnik Jolanta, Goworek Krzysztof, "Remote control system of the human body insulin level.", Analysis of biomedical signals and images: 19th International Eurasip Conference (Biosignal), Brno, Czech Republic, June 2008. Proceedings paper, Biosignal-Brno, 2008, Brno University of Technology, s. 512-519.
Own contribution: Concept of research. Coordination of work. Concept, development, and implementation

of a remote blood glucose control system. Preparation, editing and proofreading of the article.
Contribution: 65%.

[DR47] **Doniec Rafał**, Doniec Kalina, Doniec-Wolnik Jolanta, Goworek Krzysztof, "Website control system of the human body insulin level", Journal of Medical Informatics and Technologies, 2008, vol. 12, s.103-108.
Own contribution: Concept of research. Coordination of work. Concept, development and implementation of a web system. Preparation, editing and proofreading of the article.
Contribution: 65%.

[DR48] **Doniec Rafał**, "The optimization of closed-loop insulin-blood glucose model with the use of bar dry tests.", The Seventh International PhD Students' Workshop Control and Information Technology: IWCIT'08, Gliwice, 18-19 September 2008, 2008, [Gliwice], [Politechnika Śląska. Wydział Automatyki, Elektroniki i Informatyki], s.136-139.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR49] **Doniec Rafał**, Doniec-Wolnik Jolanta, Doniec Kalina, "System zdalnej regulacji poziomu insuliny w organizmie człowieka.", Biocybernetyka i inżynieria biomedyczna: XV Krajowa konferencja naukowa, Wrocław, wrzesień 2007. Streszczenia prac konferencyjnych, 2007, [Warszawa], [Stowarzyszenie Inżynierów i Techników Mechaników Polskich. Zarząd Główny], s.60.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 80%.

[DR50] **Doniec Rafał**, "The optimization of measuring method of blood glucose from dry bar code tests", The Fifth International Workshop Control and Information Technology: IWCIT'06, Gliwice, 21-22 September 2006, 2006, s. 115-118.
Own contribution: Concept and implementation of the measuring station. The course of experiments Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR51] **Doniec Rafał**, "An optimization measurement of glucose concentration and comparison polynominal with wavelet regression method.", International Workshop Control and Information Technology: IWCIT 2005, Ostrava, Czech Republic, 15-16 September 2005, Ostrava, Vysoka Skola Banska - Technicka Univerzita, s. 363-366.
Own contribution: Concept and implementation of the measuring station. The course of experiments Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

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Rafal Doniec

(Applicant's signature)

Appendix No. 4
to the Application dated August 10th, 2024, for Initiation of Habilitation Procedure

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List of scientific achievements constituting a significant contribution to the development of the discipline

Advanced Methods of Analysis and Recognition of Behavioral and Cognitive Activities Using Eye Movement-Recording Sensors and AI Algorithms

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I INFORMATION ON SCIENTIFIC ACHIEVEMENTS REFERRED TO IN ARTICLE 219(1)(2) OF THE ACT

Within each category, the items are arranged in chronological order of publication—from the most recent to the oldest. The numbering of the publications is consistent with that presented in Annex 2 to the Application dated 10 July 2024 for the habilitation procedure. For each publication, any quantitative indicators (awarded number of MNiSW points or impact factor) are provided, and in the case of multi-author works, a brief description of the author's contribution is given. Additionally, the percentage contribution to the research and the creation of the work is provided. All the works included in this section were produced after obtaining the doctoral degree.

1 Thematic Series of Scientific Articles, in Accordance with Article 219(1)(2b) of the Act

1.1 Publications with IF or CS:

[DR1] **Doniec Rafał,** Piaseczna Natalia, Duraj Konrad, Sieciński Szymon, Irshad Muhammad Tausif, Ilona Karpiel, Mirella Urzeniczok, Huang Xinyu, Piet Artur, and Grzegorzek Marcin, The Detection of Alcohol Intoxication Using Electrooculography Signals from Smart Glasses and Machine Learning Techniques. Systems and Soft Computing, Volume 6, December 2024, 200078, https://doi.org/10.1016/j.sasc.2024.200078.

20 pts of the Ministry of Science and Higher Education (MNiSW), **SJR**[1] **IF = 0.288**, Scopus **CS = 2.2**, as of 12-06-2024.

Own contribution: Concept and methodology. Software implementation, formal analysis, validation and data visualization. Preparation of the first and final version of the article. Project management[2].

Contribution: 70%.

Detailed description of the contribution constituting a scientific achievement: as first author, I was the principal investigator of the project whose results are described in the article. I prepared the concept of the experiments and the software for their interpretation. I developed an evaluation method to evaluate the collected and selected data, subjected the selected signal channels to normalisation and filtering. I then calculated the desired features and applied machine learning using different classifiers. I prepared a working and approved final version of the article.

[DR2] **Doniec Rafał**, Konior Justyna, Sieciński Szymon, Piet Artur, Irshad Muhammad Tausif, Piaseczna Natalia, Hasan Md Abid, Li Frédéric, Nisar Muhammad Adeel, Grzegorzek Marcin. Sensor-based classification of primary and secondary car driver activities using convolutional neural networks. Sensors, MDPI, 2023, 23(12), 5551, https://doi.org/10.3390/s23125551.

100 pts MNiSW, **JCR IF = 3.7**, Scopus **CS = 6.8**, **TOP10**, as of 12-06-2023.

Own contribution: Conceptualization of a system to enable selection of relevant data among all signals recorded with JINS MEME ES_R glasses (manufacturer JINS Holdings, Inc., Tokyo, Japan), during driver testing. Development and implementation of a methodology for classifying accelerometer, electrooculogram and gyroscope signals using trained convolutional neural network models. Analysis, evaluation and processing of data. Article preparation. Management of the project starting from the acquisition of funds to enable data acquisition until the publication of the results obtained.

Contribution: 65%.

A detailed description of the scientific contribution: As the first author, I was the principal investigator of a project in which I defined from scratch and configured a data acquisition and flagging workstation for primary and secondary driver activities using JINS MEME ES_R glasses, on a driving simulator. I conducted an analysis of expert annotations in terms of consistency with their descriptions and a literature review of the application of 1D CNN[3] in identifying behavioral and cognitive activities of drivers. As part of the research work, I tested the feasibility of using the sliding window segmentation (SWS)[4] technique to segment the data based on the experiments described in previous publications. I tested various settings to select the length T and step size ΔS of the time window, and determined the most effective values empirically. I substantively and visually processed the results obtained and numerically verified the proposed approach. I prepared the initial and subsequent evaluations of the article, then completed and defined the final concluding version of the solution to the classification problem presented in the article.

[1] SCImago Journal Rank (SJR) is an alternative to IF (WoS) bibliometric indicator in the Scopus database.

[2] The term "Project Management" in cases where the actual project no. is not indicated, refers to the management of the research task under the project from which the article was funded, or the postdoctoral grant of the author of the paper.

[3] For abbreviations, see the detailed description of the achievement.

[4] For abbreviations, see the detailed description of the achievement.

[DR3] **Doniec Rafał**, Piaseczna Natalia, Li Frédéric, Duraj Konrad, Pour Hawzhin Hozhabr, Grzegorzek Marcin, Mocny-Pachońska Katarzyna, Tkacz Ewaryst, Classification of roads and types of public roads using EOG smart glasses and an algorithm based on machine learning while driving a car. Electronics, MDPI, 2022, 11(18), 2960, https://doi.org/10.3390/electronics11182960
100 pts MNiSW, **JCR IF = 2.6**, Scopus **CS = 4.7**, as of 18-09-2022.
Own contribution: Defining the current state of knowledge. Data acquisition and evaluation. Conceptualization of the classification algorithm. Development and implementation of methodology for segmentation of accelerometer, electrooculogram and gyroscope signals using trained models: classification trees, kernel, Gaussian, polynomial, k-nearest neighbor predictors, support vectors and mixed models. Project management.
Contribution: 65%.
A detailed description of the contribution constituting a scientific achievement: as the first author, I was the pcincipal investigator of the project, in which I defined from scratch and configured the station for the acquisition and flagging of activity during real journeys with a vehicle specially prepared for such experiments, which received permission to conduct research in cooperation with the driving school "Proteko". I performed analyses of the available solutions in terms of selecting the best model for classifying signals from the academic version of the JINS MEME ES_R device. I developed processing variants, taking into account/not taking into account the limitation of the ROC curve. I optimized the ROC-AUC curve evaluation method using machine learning techniques and all the calibration steps of the classifier algorithm (including the selection of input parameters, weights and selected standard evaluation metrics calculated from the classifier confusion matrix). I prepared all partial results using selected machine learning models. I prepared a draft and co-edited the final version of the paper with a final discussion describing the advantages and limitations of the designed classifier system. I developed and shared the database of data obtained during the experiments.

[DR4] Pour Hozhabr Hawzhin, Li Frédéric, Wegmeth Lukas, Trense Christian, **Doniec Rafał**, Grzegorzek Marcin, Wismüller Roland, A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars. Sensors, MDPI, 2022, 22(10), 3634, https://doi.org/10.3390/s22103634.
100 pts MNiSW, **JCR IF = 3.7**, Scopus **CS = 6.8**, **TOP10** as of 10-05-2022.
Own contribution: The current state of the art and the concept of the system. The research and development activities leading to publishing this article were supported by the German Federal Ministry of Education and Research (BMBF) as part of the LEICAR project (grant number: 01IS15048B) and the German Federal Ministry for Economic Affairs and Climate Action (BMWK) as part of the GEMIMEG-II project (grant number: 01MT20001L).
Contriubution: 8%.
Detailed description of the scientific contribution: as an author, based on previous participation and experience gained in the LEICAR project, I supported the development of the concept of a collision avoidance system on roads based on the analysis of data from JINS MEME ES_R glasses, I was a corresponding author and co-edited the last version of the article.

[DR5] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Wójcik Sylwia, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Tkacz Ewaryst. Evaluation of the most stressful dental treatment procedures of conservative dentistry among Polish dental students, International Journal of Environmental Research and Public Health, 2021, 18(9), 4448; https://doi.org/10.3390/ijerph18094448.
140 pts MNiSW, **JCR IF = 4.799**, Scopus **CS = 4.5**, **TOP10** as of 22-04-2021.
Own contribution: Software development. Preparation and editing of the manuscript. Funding acquisition.
Contribution: 15%.
A detailed description of the contribution constituting a scientific achievement: as an author, I was the second beneficiary of the project, and I developed a comprehensive review of the literature. I was a corresponding author and co-edited the first and published version of the article related to the statistical interpretation of the results along with the selection of adequate supplementary literature for this part.

[DR6] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Pachoński Marek, Tkacz Ewaryst, The relationship between stress levels measured by a questionnaire and the data obtained by smart glasses and finger pulse oximeters among Polish dental students, Applied Sciences, 2021, 11(18), 8648; https://doi.org/10.3390/app11188648.
100 pts MNiSW, **JCR IF = 2.7**, Scopus **CS = 3.7**, **TOP10** a of 21-09-2021.
Own contribution: Development of the concept and implementation of the measurement system for signals recorded with JINS MEME ES_R glasses. Funding acquisition.
Contribution: 25%.
Detailed description of the scientific contribution: as an author, I was the second beneficiary of the project,

I developed a literature review and methodologies for experiments using JINS MEME ES_R glasses. I was a corresponding author, I took part in the preparation of the first and published version of the article.

[DR7] **Doniec Rafał**, Wójcik Sylwia, Valverde Raul, Piaseczna Natalia, Szymon Sieciński, Duraj Konrad, Tkacz Ewaryst. Extreme situation experienced by dental students of the Medical University of Silesia due to the SARS-CoV-2 epidemic during the first lockdown, Healthcare 2021, 9(11), 1513; https://doi.org/10.3390/healthcare9111513.
40 pts MNiSW, **JCR IF = 2.5**, Scopus **CS = 2**, as of 5-11-2021.
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of an assessment algorithm and stress scale, including a scale for assessing pattern imitation. Preparation of the first and editing of the final version of the article. Project management. Funding acquisition.
Contribution: 55%.
A detailed description of the contribution constituting a scientific achievement: as the first author, I was the principal investigator of the project, I reviewed the literature, and proposed an algorithm for assessing stress during dental students' classes in the COVID-19 pandemic based on the PSS-10 test and the dedicated questionnaire. I performed statistical interpretation and visualization of the results. I participated in the preparation of the first and published version of the article.

[DR8] **Doniec Rafał**, Sieciński Szymon, Duraj Konrad, Piaseczna Natalia, Mocny-Pachońska Katarzyna, Tkacz Ewaryst, Recognition of drivers' activity based on 1D convolutional neural network. Electronics, MDPI, 2020, 9(12), 2002, https://doi.org/10.3390/electronics9122002.
100 pts MNiSW, **JCR IF = 2.6**, Scopus **CS = 2.7**, as of 25-11-2020.
Own contribution: System concept development and implementation. Data acquisition. Verification of results. Preparation of the manuscript. Project management.
Contribution: 65%.
Detailed description of the contribution constituting a scientific achievement: as the first author, I was the primary investigator of the project which results are described in the article. I participated in the development of the multi-modal data acquisition system. I participated in the conceptual work of building the station in the vehicle where the experiments were carried out. Finally, I developed a data visualization tool, which is described in the article. This tool, along with the database, is publicly available as part of IEEE DataPort. I participated in the work of verifying the next steps of the analysis, the implementation of a one-dimensional convolutional neural network. I prepared the first version of the article, edited the entire text, which led to its publication.

[DR9] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Trzcionka Agata, Pachoński Marek, Piaseczna Natalia, Sieciński Szymon, Osadcha Oleksandra, Łanowy Patrycja, Tanasiewicz Marta. Evaluating the stress-response of dental students to the dental school environment, PeeJ 2020, 8, e8981; https://doi.org/10.7717/peerj.8981.
100 pts MNiSW, **JCR IF = 2.8**, Scopus **CS = 1.036**, as of 6-05-2020.
Own contribution: Analysis of the current state of the art. Implementation of a measurement system for signals recorded with JINS MEME ES_R glasses. Conceptualization and development of a test evaluation algorithm dedicated to dental students, together with the development of a scale for evaluating pattern imitation. Preparation of the first and approval of the final version of the article. Coordination of the publication process.
Contribution: 15%.
Detailed description of the scientific contribution: as the author, I was the second beneficiary of the project, I developed the literature review, proposed and designed experiments based on the recording of the EOG signal, analyzed the data, authored or co-edited the first drafts of the article and approved the final version.

1.2 Other publications scored and indexed by the Ministry of Science and Higher Education and Sports or Scopus

[DR10] Grabny Łukasz, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, The application for reading comprehension and reading speed test. Innovations in Biomedical Engineering. Lecture Notes in Networks and Systems, vol. 409: 245–254, Springer Cham. 2023, https://doi.org/10.1007/978-3-030-99112-8_25.
20 pts MNiSW, **CS = 0.7**; conference materials indexed in WoS, as of 03-03-2024
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of the algorithm. Preparation of the first and coordination of the final version of the article.
Contribution: 45%.
Detailed description of the contribution constituting a scientific achievement: as an author, I developed a

literature review, set up the measurement system, and proposed an algorithm for assessing reading speed along with evaluating reading comprehension based on the technique of approximate inference using fuzzy sets, enabling the definition of parameters of segmented structures for the EOG signal.

[DR11] Gabor Dominika, **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Tkacz Ewaryst, Automatic assessment of Benton Visual Retention test results: a pilot study. Biocybernetics and Biomedical Engineering - Current Trends and Challenges Proceedings of the 22nd Polish Conference on Biocybernetics and Biomedical Engineering, Warsaw, Poland, May 19-21, 2021, vol. 293: 1–8, Springer Cham. 2023, https://doi.org/10.1007/978-3-030-83704-4_1.
20 pts MNiSW, **CS = 0.7**; conference materials indexed in WoS, as of 3-03-2024.
Own contribution: Analysis of the current state of knowledge. Conceptualization and development of the algorithm. Preparation of the first and coordination of the final version of the article.
Contribution: 45%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed a literature review, set up a data acquisition system, and proposed an evaluation algorithm for Benton's visual memory test, along with the development of a pattern imitation evaluation scale based on a graphical similarity grouping method in ten prepared patterns.

[DR12] **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Mocny-Pachońska Katarzyna, Lang Marta, Szymczyk Jacek, The classifier algorithm for recognition of basic driving scenarios. Information Technology in Biomedicine, Advances in Intelligent Systems and Computing, vol. 1186, 2021, Springer, 337 p., ISBN 978-3-030-49665-4, https://doi.org/10.1007/978-3-030-49666-1_28.
20 pts MNiSW, chapter of the monograph, Scopus **CS = 0.9**, as of 12-06-2023.
Own contribution: Current state of the art. System concept. Development of the segmentation algorithm. Development of the preprocessing algorithm. Proposing modifications to the input data. Implementation. Preparation of the article. Project management.
Contribution: 80%.
Detailed description of the contribution constituting a scientific achievement: Based on a detailed analysis of available solutions, I tested the feasibility of various models for building BSF feature dictionaries, in terms of supporting feature extraction for real-world motor vehicle transit scenarios. I developed a proprietary model for building and flagging signals from the academic version of the JINS MEME ES_R device. Using the BSF dictionary method, I developed a mobile signal segmentation architecture with a variable window size, which, based on the entropy principle, determines the optimal window size for a specific signal feature corresponding to a selected activity. I proposed the use of clustering of probability values and changing the size of BSF dictionaries, which further improved the segmentation results. I conducted an analysis of the effect of the selected learning parameters and the restriction of the region of interest on the segmentation result. I compiled the obtained results, performed their visualization and prepared a working version of the article. I determined the final version for discussion describing the advantages and limitations of the designed system.

[DR13] **Doniec Rafał**, Sieciński Szymon, Piaseczna Natalia, Duraj Konrad, Chwał Joanna, Gawlikowski Maciej, Tkacz Ewaryst, Classification of Recorded Electrooculographic Signals on Drive Activity for Assessing Four Kind of Driver Inattention by Bagged Trees Algorithm: A Pilot Study. The latest developments and challenges in biomedical engineering. Proceedings of the 23rd Polish Conference on Biocybernetics and Biomedical Engineering, Lodz, Poland, September 27-29, 2023 / Strumiłło Piotr [i in.] (red.), Lecture Notes in Networks and Systems, 2024, vol. 746, Cham, Springer, s.225-236, ISBN 978-3-031-38429-5, https://doi.org/10.1007/978-3-031-38430-1_18.
20 pts MNiSW, chapter in the monograph, Scopus **CS = 0.7**; as of 12-06-2023.
Own contribution: Current state of the art. Conceptualization of the system. Development of measurement methodology. Development of the pre-processing algorithm. Proposing modifications to the input data. Implementation of the algorithm. Preparation of the article. Project management.
Contribution: 80%.
A detailed description of the contribution constituting a scientific achievement: as the author, based on the bioethics committee's approval, I prepared the experiments so as to enable the extraction of the characteristics of the selected scenarios simulating the passage of a motor vehicle. I developed a proprietary model for building flagging and then filtering data for recorded signals from the JINS MEME ES_R device. Based on statistical methods, I extracted the characteristics of the monitored signals. I performed experiments using the MATLAB environment and, based on decision tree rules, implemented the final classification system. I compiled the obtained results, made their visualization and prepared a working version of the article. I set the final version for discussion describing the advantages and limitations of the designed system.

[DR14] Piaseczna Natalia, Duraj Konrad, **Doniec Rafał**, Tkacz Ewaryst, Evaluation of Intoxication Level with EOG Analysis and Machine Learning: A Study of a Driving Simulator. Institute of Electrical and Electronics Engineers: 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Sydney, Australia 24-27 July 2023, 2023, Piscataway, Institute of Electrical and Electronics Engineers, 1500 s.1-4, ISBN 979-8-3503-2448-8, https://doi.org/10.1109/EMBC40787.2023.10340736.
20 pts MNiSW, Scopus **CS = 2.1**; chapter in a scientific monograph indexed in WoS.
Own contribution: Concept and preparation of the article.
Contribution: 5%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed the course of experiments using alco-goggles and a driving simulator. As a corresponding author, I contacted the publisher, edited the initial version, and accepted the final version of the article.

[DR15] Mocny-Pachońska Katarzyna, **Doniec Rafał**, Trzcionka Agata, Lang Marta, Pachoński Marek, Piaseczna Natalia, Sieciński Szymon, Twardawa Henryk, Tanasiewicz Marta. The Stress Level Assessment Based on Socio-demographic and Gender Factors Among Polish and Taiwanese Female and Male Junior Dental Students. Information and Software Technologies. ICIST 2019. Communications in Computer and Information Science, vol 1078. Springer, Cham. https://doi.org/10.1007/978-3-030-30275-7_43.
20 pts MNiSW, Scopus **CS = 0.7**; conference materials indexed in WoS.
Own contribution: Current state of the art. Development of the algorithm. Verification of the results. Preparation of the article.
Contribution: 10%.
A detailed description of the contribution constituting a scientific achievement: as an author, I developed a literature review and an algorithm to classify stress levels in a multimodal data set using statistical methods. The algorithm allows comparison of stress levels based on EOG, ACC, GYRO and pulse signals in Polish and English-speaking student groups, which has a direct impact on the insertion and guidance of the dental tool during the practice procedure of filling dental cavities. The final result of the study was the development of the dedicated stress scale.

[DR16] **Doniec Rafał**, Piaseczna Natalia Li Frédéric "A dataset for classification of road and types using eog smart glasses", own data repository IEEE DataPort, 2022, License: CC BY 4.0, doi: 10.21227/4yte-5s06.
Own contribution: Acquisition of multimodal data related to the simulation of car journeys, description, and development of data analysis methodology. Prepare the repository.
Contribution: 85%.

[DR17] **Doniec Rafał**, Duraj Konrad, Mocny-Pachońska Katarzyna, Piaseczna Natalia, Sieciński Szymon, Tkacz Ewaryst, "Drivers' activity tracking with jins meme smart glasses", own data repository IEEE DataPort, V2, 2020, License: CC BY 4.0, doi: 10.21227/q163-w472.
Own contribution: Acquisition of multimodal data related to actual car trips, Data description, and processing. Development of a methodology for data analysis. Prepare the repository.
Contribution: 85%.

II INFORMATION ABOUT SCIENTIFIC ACTIVITY

2 List of publications not listed in point I.

The author has published a total of 48 results of his work as part of monographs or journal articles and to verify his results, he has made available 3 data repositories with the effects of his experiments. Before his doctorate, the author published 8 results of his work, mostly devoted to monitoring and supporting the diagnosis of type I or type II diabetes mellitus.

2.1 List of publications not mentioned in section I, after obtaining a doctoral degree

Repository

[DR18] Sawaryn Bartłomiej, Piaseczna Natalia, Sieciński Szymon, **Doniec Rafał**, Duraj Konad, Komorowski Dariusz, Tkacz Ewaryst, doi: 10.21227/kqdk-w748. License: CC BY 4.0. A detailed description of the database can be found in the publication [DR23].
Own contribution: Data acquisition and segmentation. Processing of data, which was also made available as part of the repository.
Contribution: 30%.

Publications with an impact factor

[DR19] **Doniec Rafał**, Krzepina Tymoteusz, Siecinski Szymon, Irshad Muhammad Tausif, Grzegorzek Marcin, "An Educational App for the Selection of Blood Glucose Meters: A Cross-Sectional Study.", BMT 2024, 58th Annual Conference of the German Society for Biomedical Engineering, 18 - 20 September 2024, Stuttgart, Biomedical Engineering / Biomedizinische Technik, ISSNs: 0013-5585, De Gruyter, Germany 2024.
40 pts MNiSW, **CS = 3.5**; conference proceedings indexed in the SCOPUS database, as of 18-09-2024
Own contribution: Analysis of the current state of knowledge. Concept and development of an algorithm for assessing the quality of glucometers. Preparation of the first and coordination of the last version of the article.
Contribution: 60%.

[DR20] Sieciński Szymon, **Doniec Rafał**, Grzegorzek Marcin, "Linear classification of healthy people and patients with valvular heart diseases based on heart rate variability indices derived from electrocardiograms.", BMT 2024, 58th Annual Conference of the German Society for Biomedical Engineering, 18 - 20 September 2024, Stuttgart, Biomedical Engineering / Biomedizinische Technik, ISSNs: 0013-5585, De Gruyter, Germany 2024.
40 pts MNiSW, **CS = 3.5**; conference proceedings indexed in the SCOPUS database, as of 18-09-2024
Own contribution: Analysis of the current state of knowledge. Preparation of the first and coordination of the last version of the article.
Contribution: 40%.

[DR21] Adam Kruczkowski, Dominic Lovell, Sebastian Szymczyk, Marcin Wojtowicz, Natalia Piaseczna, **Rafał Doniec**, Ewaryst Tkacz & Katarzyna Mocny-Pachońska, "The Influence of Sleep Quality and Duration on the Feeling of Mental Acuity During the COVID-19 Lockdown – A Pilot Study." Innovations in Biomedical Engineering 2023. Lecture Notes in Networks and Systems, vol. 875: 33–40, Springer Cham. 2024, https://doi.org/10.1007/978-3-031-52382-3_4.
20 pts MNiSW, **CS = 0.7**; conference proceedings indexed in the SCOPUS database, as of 03-03-2024
Own contribution: Analysis of the current state of knowledge. Concept and development of an algorithm for assessing sleep quality. Preparation of the first and coordination of the last version of the article.
Contribution: 15%.

[DR22] Natalia Piaseczna, **Rafał Doniec** [i in.]: "Driving Reality vs Simulator: Data Distinctions", Electronics, Basel, 2024, vol. 14, nr 3, s.1-16, Numer artykułu: 1320. DOI:10.3390/app14031320.
100 pts MNiSW, **IF = 2.6**.
Own contribution: Concept of research. Data acquisition. Concept of methodology using machine learning technique. Editing, proofreading an article.
Contribution: 30%.

[DR23] **Rafał Doniec**, Eva Odima Berepiki, Natalia Piaseczna [i in.]: "Cardiovascular disease preliminary diagnosis application using SQL queries: filling diagnostic gaps in resource-constrained environments", w:

Applied Sciences-Basel, 2024, vol. 14, nr 3, s.1-16, Article number: 1320. DOI:10.3390/app14031320.
100 pts MNiSW, **IF = 2.7**.
Own contribution: Concept of research. Concept of methodology using the ontology technique. Editing, proofreading an article.
Contribution: 50%.

[DR24] Rimsha Fatima, Muhammad Adeel Nisar, **Rafał Doniec**, [i in.]: "A systematic evaluation of feature encoding techniques for gait analysis using multimodal sensory data", In: Sensors 2024, 24(1), 75, e-ISSN 1424-8220. DOI: DOI:10.3390/s24010075.
100 pts MNiSW, **IF = 3,847**.
Own contribution: Concept of research. The concept of the methodology of multimodal signal segmentation using the "codebook" technique and the k-means clustering algorithm. Editing, proofreading an article.
Contribution: 30%.

[DR25] **Doniec Rafał**, Piaseczna Natalia, Szymczyk Karen A. [i in.]: Experiences of the telemedicine and eHealth conferences in Poland - a cross-national overview of progress in telemedicine, Applied Sciences-Basel, 2023, vol. 13, nr 1, s.1-19, Numer artykułu:587. DOI:10.3390/app13010587.
100 pts MNiSW, **IF = 2.838**.
Own contribution: Concept and development of a set of features describing the analyzed structures based on cocurrence matrices and wavelet transform, discussion. Overview of existing solutions. Preparing the article.
Contribution: 60%.

Other publications

[DR26] Duraj Konrad, Sieciński Szymon, **Doniec Rafał** [i in.]: "Heartbeat detection in seismocardiograms with semantic segmentation", W: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, 2022, Piscataway, Institute of Electrical and Electronics Engineers, s.662-665, ISBN 978-1-7281-27835. DOI:10.1109/EMBC48229.2022.9871477.
20 pts MNiSW, chapter in a scientific monograph.
Own contribution: Concept of research. The concept of signal segmentation methodology using deep neural networks. Coordination of work. Editing, proofreading the article. (Supervision of the master's thesis, on the basis of which the article was written).
Contribution: 30%.

[DR27] Łach Agnieszka, Kalim Faisal, Heiliger Christian [i in.]: Local shape preserving deformations for augmented reality assisted laparoscopic surgery, W: 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, United Kingdom, 11-15 July 2022, 2022, Piscataway, Institute of Electrical and Electronics Engineers, s.562-565, ISBN 978-1-7281-2783-5. DOI:10.1109/embc48229.2022.9871029.
20 pts MNiSW, chapter in a scientific monograph.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article (Supervision of the master's thesis, on the basis of which the article was based).
Contribution: 50%.

[DR28] Sawaryn Bartłomiej, Piaseczna Natalia, Sieciński Szymon [i in.]: "The assessment of the condition of knee joint surfaces with acoustic emission analysis", Sensors, 2021, vol. 21, nr 19, s.1-22, Article number:6495. DOI:10.3390/s21196495.
100 pts MNiSW, materials indexed in WoS.
Own contribution: Cooperation in the field of data acquisition using microphone inserts and support for the editing of preliminary and final articles.
Contribution: 15%.

[DR29] Agnieszka Radziun, **Rafał Doniec**, Szymon Sieciński, [i in.]: "Smartphone-based color measurement of tooth shade guide in clinical lighting conditions.", Annals of Computer Science and Information Systems, 2021, vol. 25, Institute of Electrical and Electronics Engineers, s. 409-413, ISBN 978-83-959183-6-0. DOI:10.15439/2021F40.
70 pts MNiSW, conference materials indexed in WoS.
Own contribution: Concept and development of a set of features describing the analyzed structures based on reflectometric matrices, discussion. Overview of existing solutions. Preparation of the article. Cooperation in the field of data acquisition using microphone inserts and support for the editing of preliminary and

final articles.
Contribution: 45%.

[DR30] Katarzyna Mocny-Pachońska, Agata Trzcionka, [i in.]: "The influence of gender and year of study on stress levels and coping strategies among Polish dental.", Medicina 2020, 56(10), 531; https://doi.org/10.3390/medicina56100531.
40 pts MNiSW, conference proceedings indexed in WoS.
Own contribution: Concept and statistical elaboration of a set of features describing the analyzed questionnaires dedicated to determining the level of stress, discussion. Overview of existing solutions. Preparation of the article. Final support for article editing.
Contribution: 15%.

[DR31] **Doniec Rafał**, Mocny-Pachońska K., Piaseczna Natalia [i in.]: "Recognition of basic driving scenarios." W: 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23-27 July 2019, 2019, Institute of Electrical and Electronics Engineers, s.1, ISBN 978-1-5386-1312-2.
20 pts MNiSW, conference materials.
Own contribution: Research concept. Data acquisition. Coordination of work. Development of a part of the methodology related to limiting the area of interest. Preparation, editing, and proofreading of the article. Final support in editing the article.
Contribution: 70%.

[DR32] Mocny-Pachońska K., **Doniec Rafał**, Trzcionka A. [i in.]: "The stress level assessment based on sociodemographic and gender factors among Polish and Taiwanese female and male junior dental students Information and software technologies", 25th International Conference. ICIST 2019, Vilnius, Lithuania, October 10-12, 2019. Proceedings / Damasevicius R., Vasiljeviene G. (red.), Communications in Computer and Information Science, 2019, vol. 1078, Springer, s.553-564, ISBN 978-3-030-30274-0. DOI:10.1007/978-3-030-30275-7_43.
20 pts MNiSW, conference materials indexed in WoS.
Own contribution: Preparation of the article. Final support for article editing.
Contribution: 30%.

[DR33] Meiser Dariusz, Doniec Rafał, W: Projekty lokalne i regionalne - interesariusze projektu / Brandenburg H., Tobor G. (red.), "Projekty wytwórcze a ryzyko", Prace Naukowe Uniwersytetu Ekonomicznego w Katowicach, 2017, Katowice, Wydawnictwo Uniwersytetu Ekonomicznego w Katowicach, s.242-260, ISBN 978-83-7875-365-0.
0 pts MNiSW, conference materials indexed in databases of the University of Economics in Katowice.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR34] **Doniec Rafał**, "Limiting the functionality of IT systems monitoring patients with diagnosed metabolic.", Biomedical engineering 2016: 20th International Conference, Kaunas, Lithuania, 24th-25th November 2016, 2016, [B.m.], [b.w.], s.4-9.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR35] **Doniec Rafał**, Spangler Scott., "The functionality of IT systems monitoring patients with diagnosed metabolic disorders in Poland", Abstracts Proceedings - KM Conference 2016 - Lisbon, Portugal: Refereed Proceedings - Abstracts, 2016, [B.m.], International Institute for Applied Knowledge Management, s.39.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR36] Meiser Dariusz, **Doniec Rafał**, "Ryzyko w projektach wytwórczych.", Projekty regionalne i lokalne - interesariusze projektu. Projets régionaux et locaux - parties prenantes : VI Konferencja naukowa, Radzionków, 13-15 czerwca 2016, 2016, [B.m.], [b.w.], s.31-32.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR37] **Doniec Rafał**, Scheller S.," Establishing best practices in innovation on the basis of elements of cooperation between the government, educational institutions, and a private sector.", OJAKM, 2015, vol. 2, nr

2, s.54-67
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR38] **Doniec Rafał**, Meiser Dariusz. Optymalizacja organizacji prac narzędziowni wydziału mechanicznego.", Projekty regionalne i lokalne - sukces projektu. Projets régionaux et locaux - le succès du projet: V Konferencja naukowa, Radzionków, 9-10 czerwca 2015, 2015, [B.m.], [b.w.], s.20-21.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 50%.

[DR39] **Doniec Rafał**, "Development of the educational-research standards based on the cooperation of academic centers with employees of the international corporation on the basis of own research.", Refereed proceedings of KM Conference 2014, Blagoevgrad, Bulgaria [online], 2014, [B.m.], International Institute for Applied Knowledge Management, s. 11-19.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR40] **Doniec Rafał**, "Internetowy dziennik zmian dobowych DiabLab i inne sposoby monitorowania stężenia glukozy we krwi diabetyka.", Telemedicine & eHealth 2014: International conference, Warszawa, 24 September 2014. Book of abstracts, 2014, [B.m.], [b.w.], s.16.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR41] **Doniec Rafał**, "Podnoszenie jakości kształcenia zawodowego poprzez kreatywne rozwijanie umiejętności.", Projekty regionalne i lokalne - najlepsze praktyki. Projets règionaux et locaux - les meilleures pratiques : III Konferencja naukowa, Radzionków, 21 maja 2013, 2013, s. 19
Own contribution: The concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR42] **Doniec Rafał**, "Internetowy dziennik zmian dobowych stężenia glukozy we krwi diabetyka – DiabLab", Biocybernetyka i inżynieria biomedyczna: XVII Krajowa konferencja, Gliwice/Tarnowskie Góry, 11-14 października 2011, 2011, s. 31.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR43] **Doniec Rafał**, Doniec Kalina, "Scenariusz rozwoju systemu zdalnej regulacji poziomu insuliny w organizmie człowieka z wykorzystaniem teorii zbiorów rozmytych.", Biocybernetyka i inżynieria biomedyczna: XVII Krajowa konferencja, Gliwice/Tarnowskie Góry, 11-14 października 2011, 2011, [B.m.], [b.w.], s.48.
Own contribution: Concept of research. Coordination of work. Development of a part of the methodology related to the limitation of the region of interest. Preparation, editing and proofreading of the article.
Contribution: 80%.

2.2 List of publications not listed in point I, before obtaining the doctoral degree

[DR44] **Doniec Rafał**, "Projekt struktury falkowo-neuronowej odwzorowującej krzywą cukrową, otrzymaną w wyniku pomiaru cukru we krwi pacjentów zarejestrowanych w dedykowanej do tego projektu bazie danych.", W: Biocybernetyka i inżynieria biomedyczna: XVI Krajowa konferencja, Warszawa, 26-29 kwietnia 2010, 2010, Warszawa, IBIB PAN, s.211.
Own contribution: Concept of research. Coordination of work. Development of the entire methodology related to preparing and developing an algorithm based on the wavelet-neuron structure limiting the region of interest. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR45] **Doniec Rafał**, "The remote control system of the insulin level.", Journal of Medical Informatics and Technologies, 2010, vol. 15, s.201-208.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development, and implementation of a remote insulin control system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR46] **Doniec Rafał**, Doniec Kalina, Doniec-Wolnik Jolanta, Goworek Krzysztof, "Remote control system of the human body insulin level.", Analysis of biomedical signals and images: 19th International Eurasip Conference (Biosignal), Brno, Czech Republic, June 2008. Proceedings paper, Biosignal-Brno, 2008, Brno University of Technology, s. 512-519.
Own contribution: Concept of research. Coordination of work. Concept, development, and implementation of a remote blood glucose control system. Preparation, editing and proofreading of the article.
Contribution: 65%.

[DR47] **Doniec Rafał**, Doniec Kalina, Doniec-Wolnik Jolanta, Goworek Krzysztof, "Website control system of the human body insulin level", Journal of Medical Informatics and Technologies, 2008, vol. 12, s.103-108.
Own contribution: Concept of research. Coordination of work. Concept, development and implementation of a web system. Preparation, editing and proofreading of the article.
Contribution: 65%.

[DR48] **Doniec Rafał**, "The optimization of closed-loop insulin-blood glucose model with the use of bar dry tests.", The Seventh International PhD Students' Workshop Control and Information Technology: IWCIT'08, Gliwice, 18-19 September 2008, 2008, [Gliwice], [Politechnika Śląska. Wydział Automatyki, Elektroniki i Informatyki], s.136-139.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR49] **Doniec Rafał**, Doniec-Wolnik Jolanta, Doniec Kalina, "System zdalnej regulacji poziomu insuliny w organizmie człowieka.", Biocybernetyka i inżynieria biomedyczna: XV Krajowa konferencja naukowa, Wrocław, wrzesień 2007. Streszczenia prac konferencyjnych, 2007, [Warszawa], [Stowarzyszenie Inżynierów i Techników Mechaników Polskich. Zarząd Główny], s.60.
Own contribution: Concept and implementation of research. Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 80%.

[DR50] **Doniec Rafał**, "The optimization of measuring method of blood glucose from dry bar code tests", The Fifth International Workshop Control and Information Technology: IWCIT'06, Gliwice, 21-22 September 2006, 2006, s. 115-118.
Own contribution: Concept and implementation of the measuring station. The course of experiments Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

[DR51] **Doniec Rafał**, "An optimization measurement of glucose concentration and comparison polynominal with wavelet regression method.", International Workshop Control and Information Technology: IWCIT 2005, Ostrava, Czech Republic, 15-16 September 2005, Ostrava, Vysoka Skola Banska - Technicka Univerzita, s. 363-366.
Own contribution: Concept and implementation of the measuring station. The course of experiments Coordination of work. Concept, development and implementation of the system. Preparation, editing and proofreading of the article.
Contribution: 100%.

3 List of design, construction, and technological achievements (marking items not listed in point I.)

Information on participation in the work of research teams implementing projects financed through domestic or foreign competitions, divided into completed and ongoing projects, and including information on the function performed within the teams' work.

The author of the application participated in the implementation of a total of 6 tasks listed below for scientific and research projects. Including 1 before obtaining a doctoral degree.

3.1 Scientific and research projects financed from external funds, after obtaining a doctoral degree

1. During the period 01.11.2021 - 31.10.2024, as part of the European project 2021-1-HU01-KA220-HED-000032251. V.I.B.E: Virtual Biomedical and STEM/STEAM Education - ERASMUS+
   Contribution: Development of an educational system that supports the implementation of STEM (Science, Technology, Engineering, and Mathematics) skills alongside biomedical education based on VR and AR platforms.

2. During the period 2017 - 12.2019, as part of the LEICAR project (grant number: 01IS15048B), supported by the German Federal Ministry of Education and Research (BMBF).
   Role: Contributor.
   Contribution: Establishing the current state of knowledge and conceptualising the system. Research and development activities leading to the creation of a system for defining insurance component amounts based on multimodal data as part of the GEMIMEG-II project (grant number: 01MT20001L).

3. During the period 11.2014 - 11.2015, the author coordinated and managed the project: "Innovative workstation for retail". In the context of the operation and distribution of EU funds, project number POIG.01.04.00-24-275/13. Support for targeted projects. Specialised implementation of custom IT services."
   Role: Project coordinator, patent: FLASH FILE SYSTEM, application EP15001857, exclusive right number: EP3109764.
   Contribution: Supervisory and substantive oversight for the method of data compression and recording in the memory module.

3.2 Scientific and research projects financed from external funds, before obtaining a doctoral degree

1. In the period from November 11, 2007, to December 2014, as part of the project, the author was involved in the NGP GIS Platform - Development and Maintenance of Network Information Systems of Polish Telecommunications.
   Contribution: Managerial and substantive supervision for the implementation and concept of IT services in the key areas of passporting and implementation of IT services for Telekomunikacja Polska, in which Sygnity S.A. is the supplier.

3.3 Scientific and research projects financed from funds for the statutory activities of the Silesian University of Technology, after obtaining a doctoral degree

1. 2018 -2020. Operational Program Knowledge Education Development 2014-2020, POWR.03.01.00-00-U146/17, ALIK: Academic Laboratory of Innovation and Creativity. Project co-financed by the European Union under the European Social Fund from the Young Explorer University program, Axis III Higher education for the economy and development, Operational Program Knowledge Education Development 2014-2020, Measure 3.1 Competences in higher education. The project was implemented by the College of Social Sciences and Foreign Languages of the Silesian University of Technology in cooperation with the Education Department of the City Hall in Bytom in 2018-2020. Contribution: Organization of classes and responsibilities within the project. Within four cycles, 8 hours of lectures and 16 hours of laboratory were prepared for each participant (children and youth) as part of the mathematics and science module. Topics of classes for children: Computational thinking: everyone can program (group 6-9 years old).

2. 1/1/2011 - 31/12/2015 of the Human Capital Operational Program, No. D992-0CEB-8CA9-9390 Project entitled: "ZIP - ZOSTAŃ INŻYNIEREM PRZYSZŁOŚCI.

Nature of participation: contractor, industrial mentor.
Contribution: development of a method for automatic selection of alarms in teletransmission systems on the example of a cellular telecommunications network. Permanent analysis of the state of DSL, Business Everywhere, and LTE telecommunications services. Configuring access devices for IP VPN services and programming using IP VPN services.

3.4 Scientific and research projects financed from funds for the statutory activities of the Silesian University of Technology, before obtaining a doctoral degree

No items to list.

4 Information about presentations at national or international scientific or artistic conferences, including invited lectures and plenary lectures

The author of the proposal participated in a total of 39 different conferences and presented the following topics during the conference. Including 7 years before obtaining a doctoral degree.

4.1 Information about presentations at national or international scientific or artistic conferences, including invited lectures and plenary lectures, after obtaining a doctoral degree

1. HealthTech Innovations Conference, Faculty of Biomedical Engineering, Silesian University of Technology, Zabrze, Poland, 2023. 9-10th October: "The Classifier Algorithm for Recognition of the Secondary Distracting Factors while Driving a Car".
2. Polish Conference on Biocybernetics and Biomedical Engineering (PCBBE) 2023, Institute of Electronics, Lodz University of Technology, Poland, 2023, 27-29th September: "Classification of recorded EOG on-drive activity for assessing four kinds of driver inattention by bagged trees algorithm: A Pilot Study".
3. Series of invited lectures at the conference Telemedicine and eHealth, Polish Telemedicine and eHealth Society, Institute of Metrology and Biomedical Engineering, Faculty of Mechatronics, Warsaw University of Technology, Warsaw, Poland, 2023, 7th September: "Profiling Humans Using Pattern Recognition Algorithms for Personalised Healthcare".
4. The Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2023, International Convention Centre Sydney, Australia, 24-27th July: "Evaluation of intoxication level with EOG analysis and machine learning: a study on the driving simulator: A Pilot Study".
5. International Conference of Biomedical Engineering and Innovation - iCBEI 2022, Szentágothai Research Centre, Pécs, Hungary, 24-26th October: "Road type recognition with smartglasses and machine learning".
6. HealthTech Innovations Conference 2022, Faculty of Biomedical Engineering, Silesian University of Technology, Zabrze, Poland, 10-11th October: "The influence of sleep duration on the feeling of well-being during the Covid-19 lockdown".
7. IEEE EMBS Summer Camp 2022, 8th September: "Pattern detection and data transmission in medicine".
8. Telemedicine and eHealth, Polish Telemedicine and eHealth Society, Institute of Metrology and Biomedical Engineering, Faculty of Mechatronics, Warsaw University of Technology, Warsaw, Poland, 1st September 2022: "The Database of home tests for rapid diagnosis (pilot study)".
9. 22nd Polish Conference on Biocybernetics and Biomedical Engineering, Warsaw, Poland, 2021, May 19-21: "Automatic Assessment of Benton Visual Retention Test Results".
10. Federated Conference on Computer Science and Information Systems, September 2-5, 2021, Online, pages 421–425: "Smartphone-Based Color Measurement of Tooth Shade Guide in Clinical Lighting Conditions".
11. Series of invited lectures at the conference Telemedicine and eHealth, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, Poland, 2021, 17-18th September: "Telemedicine in response to the challenges in Kenya, Peru and Poland".
12. International Congress of Biomedical Engineering "BIOCON", Student Branch Chapter IEEE EMBS UNMSM of SBC03221E - Universidad Nacional Mayor de San Marcos, EMB18, 2021, 17-19th December: "Summary of the development of Telemedicine and the development of the provision of health services remotely during the pandemic in Kenya and Poland".
13. 8th International Conference Information Technology in Biomedicine ITiB 2020, June 15-17, Kamien Slaski near Opole, Poland: "The Classifier Algorithm for Recognition of Basic Driving Scenarios - a pilot study".
14. Series of invited lectures at the conference "Telemedicine and eHealth", 2020, 18th September, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, PL: "Elements of telemedicine and dental law regulation dedicated to a mobile application as a student project".

15. Scientific Conference "Innovations in Biomedical Engineering - IiBE'2020", Faculty of Biomedical Engineering, Silesian University of Technology, 2020, October 8-9, Zabrze, PL: "The method for recording the reading comprehension and reading speed with smart glasses".

16. 41st Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), July 23-27, Berlin, Germany: "Recognition of Basic Driving Scenarios".

17. Series of invited lectures at the conference Telemedicine and eHealth, 2019, 22-23th November, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw: "Design of an educational stand for modeling a digital artificial pancreas".

18. Telemedicine and eHealth, 2018, 14-15th December, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, PL: "Comparison of cognitive drivers' patterns with driving school students".

19. Telemedicine and eHealth, 2017, 8th September, Polish Telemedicine and eHealth Society, IPPT PAN - Institute of Fundamental Technological Research Polish Academy of Sciences, Warsaw, PL: "Rule-based expert systems in medical decision support".

20. "Be a #trendhunter – Promotion of few words", Conference on 2016, 5-6th May, The Economy University in Katowice: "3 trends, that changed the IT industry".

21. VI International Conference on Local - Stakeholders of the Project, Radzionków, 2016, 13-15th June, PL: "The risk in project production".

22. KM Conference 2016, 22-25th June, ISEG - University of Lisbon, Portugal: "The functionality of IT systems monitoring patients with diagnosed metabolic disorders in Poland".

23. V International Conference on Local and Regional Projects with Cooperation of Science - Business - Local Government, 2015, 9-10th June, Radzionków: "The optimization of work organization by the aspect of distribution of mechanical tools".

24. Knowledge Management Conference 2015, The University of Economics in Katowice, 24-27th June, Katowice: "Establishing the best practices in innovation based on elements of cooperation between the government, educational institutions, and a private sector".

25. Series of invited lectures at the conference International Conference of Telemedicine and e-Health 2015, 29-30th September, Warsaw, PL: "Telemedicine in monitoring diabetes".

26. Biomedical Engineering 2015, The Kaunas University of Technology, 26th-27th November 2015, Kaunas, LT: "Limiting the functionality of IT systems monitoring patients with diagnosed metabolic disorders".

27. Knowledge Management Conference 2014, The American University in Bulgaria, 25-28th June, Blagoevgrad, BL: "Development of the educational-research standards based on the cooperation of academic centers with employees of the international corporation based on own research".

28. Conference "Telemedicine and eHealth 2014", 24th September 2014, Warsaw, PL: "Internet daily diary of blood glucose levels in diabetics DiabLab and other methods of monitoring blood glucose levels".

29. Fourth International Conference on Local and Regional Projects with Cooperation of Science - Business - Local Government, 2014, 10-11th June, Radzionków, PL: "Competences in managing a telecommunications project".

30. Third International Conference on Local and Regional Projects with Cooperation of Science - Business - Local Government, 2013, 11th May, Radzionków: "Improving the quality of vocational training by the development of creative skills".

31. Second International Conference on Local and Regional Projects with Cooperation of Science - Business - Local Government, 2012, 8th May, Radzionków: "Land of the Rising Innovation - active e-learning as individual career paths with the support of European Community Funds".

32. KKBIB 2011, 11-14th November, Gliwice/Tarnowskie Góry: "Scenario for the development of a remote insulin regulation system in the human body".

4.2 Information about presentations at national or international scientific or artistic conferences, including invited lectures and plenary lectures presented before obtaining a doctoral degree

1. KKNBIB 2010, 26-29th April 2010, Warsaw: "Projekt struktury falkowo – neuronowej odwzorowującej krzywą cukrową, otrzymaną w wyniku pomiaru cukru we krwi pacjentów zarejestrowanych w dedykowanej do tego projektu bazie danych".
2. 6th International Workshop Control & Information Technology IWCIT08, Ostrava, CZ: "The Optimization of Close-Loop Model of Insulin-Blood Glucose with Use of Dry Tests - a pilot study".
3. BIOSIGNAL 2008, Brno: "The Optimization of Closed-Loop Insulin-Blood Glucose Model with the use of Bar Dry Test".
4. KKNBIB07, 2007, Wrocław: "System zdalnej regulacji poziomu insuliny w organizmie człowieka".
5. 5th International Workshop Control & Information Technology IWCIT08, Ostrava, CZ: "The Optimization of Reflection Measuring Method for Blood Glucose from Dry Bar Code Tests".
6. 10th International Conference MIT 2005, October 20-22, 2005, Ustroń – Jaszowiec: "Modeling of glucose concentration curve and comparison of polynomial with wavelet regression method".
7. 4th International Workshop Control & Information Technology IWCIT05, Ostrava: "An optimization measurement of glucose concentration and comparison of polynomial with wavelet regression methods".

5 Information about participation in organizational and scientific committees of national or international conferences, including the function held

The author participated in 11 conferences as an organizer or session chairman. Before his doctorate, he had not taken on such functions at conferences.

5.1 Information about participation in organizational and scientific committees of national or international conferences, specifying the function held, after obtaining a doctoral degree

1. International Conference of Telemedicine and e-Health 2023, 7th September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, member of the organizational team and session chair.
2. International Conference of Telemedicine and e-Health 2022, 1st September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, member of the organizational team and session chair.
3. International Conference of Telemedicine and e-Health 2021, 17-18th September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, member of the organizational team and session chair.
4. International Conference of Telemedicine and e-Health 2020, 18th September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, member of the organizational team and session chair.
5. International Conference of Telemedicine and e-Health 2019, 22-23rd November, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, session chair.
6. International Conference of Telemedicine and e-Health 2018, 2-3rd September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, session chair.
7. International Conference of Telemedicine and e-Health 2017, 8-9th September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, session chair.

8. International Conference of Telemedicine and e-Health 2016, 2-3rd September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, session chair.
9. Knowledge Management Conference 2015, The University of Economics in Katowice, 24-27th June, Katowice - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants, session chair.
10. International Conference of Telemedicine and e-Health 2015, 29-30th September, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants.
11. Conference "Telemedicine and e-Health 2014", 24th September 2014, Warsaw, PL - preparation of conference materials, preparation of promotional materials, graphic design, on-site registration of participants.

5.2 Information about participation in organizational and scientific committees of national or international conferences, specifying the function held, before obtaining a doctoral degree

No items to list.

6 Membership in international or national scientific organizations and societies, including information on functions held

The author is a member of four international or national organizations, two of which he joined before his Ph.D.

6.1 Membership in international or national scientific organizations and societies, including information on functions performed, after obtaining a doctoral degree

1. Member of the Institute of Electrical and Electronics Engineers since 2018 - membership number — 95693065.
2. Since 2014 — a member of the Polish Society of Telemedicine and eHealth.

6.2 Membership in international or national scientific organizations and societies, including information on functions held, before obtaining a doctoral degree

1. Since 2007, member of the Polish Society of Biomedical Engineering — membership number 44 (Appendix No. 9, p. 52).
2. Since 1997, member of the Polish Association of Electrical Engineers.

7 Information about internships completed in scientific or artistic institutions, including foreign ones, including the date, place and the nature of the internship

The author participated in 2 foreign internships after his Ph.D.

7.1 Information about internships completed in scientific or artistic institutions, including foreign ones, including the date, place and the nature of the internship, after obtaining a doctoral degree

1. 1.03.2024 – 30.06.2024, Universität zu Lübeck and Fraunhofer IMTE, Germany. The author participated in projects within the "KI-Med-Ökosystem" group. The aim of the project, funded by the federal state of Schleswig-Holstein, is to significantly accelerate the development of the originally established artificial intelligence ecosystem in the healthcare system at the University of Lübeck. KI-Med brings together experts from companies, universities, and hospitals to discuss various topics related to artificial intelligence in healthcare. This includes, among other things, data acquisition, compliance/standards and guidelines, ethical aspects, explainable artificial intelligence, anonymisation, validation and verification, as well as transparency and high-performance computing. The author's involvement also includes associated projects such as KI-SIGS, AnoMed, ZKIL (KI-Med ecosystem), Gaia-X-Med, MCEA, KI-Transfer-Hub SH, PASBADIA, LIROS, MDZ-SH, EDIH-SH, and IKAPP.

2. 2017 - 2019, Universität Siegen, Germany. A 2-year post-doctoral fellowship funded by the German Federal Ministry of Education and Research (BMBF) (grant number: 01IS15048B). The collaboration continued even after the completion of the fellowship. As part of the research work, the author participated in the "LEICAR" projects: Lernbasierte multimodale Interpretation von Sensordaten zur Ereigniserkennung in Carsharing-Flotten. During this research fellowship, the author initiated research activities in the area of context classification for automated driving using sensors integrated into smart glasses. This research activity was aligned with the LEICAR project (Learn-based Multimodal Interpretation of Sensor Data for Event Recognition in Carsharing), funded by the German Federal Ministry of Education and Research, conducted in Siegen jointly by the Pattern Recognition Research Group and the Medical Informatics and Microsystems Design Research Group. With access to the infrastructure and expertise of the Pattern Recognition and Medical Informatics Research Group, the author developed the idea of the LEICAR project towards a sensor-based support system for driving schools. During the fellowship, the author supervised doctoral students, conducted teaching activities, scientific research, and participated in promotional activities related to the project.

7.2 Information about internships completed in scientific or artistic institutions, including foreign ones, including the date, place and the nature of the internship, before obtaining a doctoral degree

No items to list.

8 Information about peer-reviewed scientific or artistic works, especially those published in international journals

8.1 Information about peer-reviewed scientific or artistic works, especially those published in international journals, after obtaining a doctoral degree

The author of the proposal reviewed a total of 23 papers for the following journals and conferences.

8.1.1 Journals from the Journal Citation Reports list

Table 1: Summary of the number of reviews in magazines

Name of the magazine	Impact Factor	Number of reviews
Applied Sciences, MDPI	2.838	4
IEEE Access	3.476	4
Sensors, MDPI	3.847	6

8.1.2 International conferencese

Table 2: Summary of the number of reviews in conference materials

Conference name	Rok	Number of reviews
International Conference Telemedicine & eHealth	2023	2
International Conference Telemedicine & eHealth	2022	1
International Conference Telemedicine & eHealth	2021	1
International Conference Telemedicine & eHealth	2020	1
International Conference Telemedicine & eHealth	2019	2
International Conference Telemedicine & eHealth	2018	2

8.2 Information about peer-reviewed scientific or artistic works, especially those published in international journals, before obtaining a doctoral degree

No items to list.

III INFORMATION ABOUT COOPERATION WITH THE SOCIAL AND ECONOMIC ENVIRONMENT

9 List of technological achievements

9.1 Projects completed with implementation

The author of the application, after obtaining a doctoral degree, participated in 2 projects that have already been implemented.

9.1.1 Projects completed with implementation, after defending the doctorate

1. National Centre for Research and Development in Poland, POIG.01.04.00-24-275/13. Implemented in 2017, "Specialist Implementation of Non-standard IT Services." Role: Project coordinator, patent: FLASH FILE SYSTEM, application EP15001857, exclusive right number: Contribution: Expert and substantive supervision for the data compression and recording method in the memory module.
   Contractor: Elzab, SA (Appendix No. 7).
   Role: Project coordinator.
   Contribution: The author coordinated research and development work related to the concept of services and their implementation in the fiscal cash module.

2. German Federal Ministry of Education and Research, 01IS15048B. Implemented in 2016, LEICAR: Learn-based Multimodal Interpretation of Sensor Data for Event Recognition in Carsharing Fleets.
   Contractor: INVERS GmbH Siegen, Germany.
   Role: Project executor.
   Contribution: The author coordinated research and development work related to the concept of insurance services where the premium calculation was based on machine learning and multimodal interpretation of sensor data for event detection in carsharing fleets.

9.1.2 Projects completed with implementation, before the defense of the doctorate.

No items to list.

9.2 Information about cooperation with the economic and local government sectors

As part of the implemented scientific projects, the author of the application cooperated with 7 economic and local government entities.

1. DEX INNOVATION CENTRE, Czech Republic – within the V.I.B.E: Virtual Biomedical and STEM/STEAM Education project - ERASMUS+;

2. Centrumelektroniki.pl sp. z o.o – within student projects, supporting student associations – Appendix No. 9, p. 19;

3. Elzab S.A. – within the NCBiR project "Innovative Retail Sales Position";

4. Orange S.A - industry mentor in the project "Increasing Professional Competence of Students in the EiT Programme at Silesian University of Technology in Gliwice";

5. INVERS GmbH Siegen, Germany – within the LEICAR project, machine learning-based multimodal interpretation of sensor data for event detection in carsharing fleets;

6. Orange S.A Institute of Experimental Psychophysiology, Duesseldorf – within the NCBiR project – Appendix No. 9, p. 59;

7. City Hall, Education Department of Bytom City Hall - within ALIK: Academic Laboratory of Innovation and Creativity.

Summary

Table 3: Summary of publications and other activities of the author of the application (as of July 10, 2024) WoS - total number of citations to publications in the Web of Science Core Collection database, CS - total number of citations to publications in the Scopus database, GS - total number of citations to publications in the database Google Scholar

I Information about scientific achievements referred to in Article 219(1) 1. point 2 of the Act. (cycle)			
Applicant's Activities	Pre-doctoral	Post-doctoral	Overall
Publications from the WoS database submitted as part of the habilitation cycle (first or corresponding author)	-	8 (7)	8 (7)
Chapters in monographs submitted as part of the habilitation cycle	-	7	7
Data repositories	-	2	2
List of project, design, and technological achievements	-	1	1
Citations (WoS|SC|GS)	2|-|-	78|110|230	80|110|230
Citations without self-citations (WoS|SC|GS)	2|-|-	58|-|-	60|-|-
II Information about scientific activity (outside the cycle)			
Publications indexed in the database WoS	1	9	10
Data repositories	-	1	1
Monographs and others	-	25	25
List of design, construction and technological achievements	1	5	6
Cooperation in national or international scientific conferences (foreign)	7 (4)	32 (7)	39 (11)
Information about participation in the conference organizing committees	-	11	11
Membership in international or national organizations (foreign)	2 (0)	2 (1)	4 (1)
Information about internships completed in foreign scientific institutions	-	2	2
Information about peer-reviewed scientific works (journals|conferences)	-	14|9	14|9
Scientific activity in research institutions (foreign)	1 (0)	15 (12)	16 (12)
III Information about cooperation with the social and economic environment (outside the cycle)			
Implementations as part of technological achievements (projects|implementations|patents)	-|-|-	2|4|2	2|4|2
Cooperating institutions from the economic and local government sectors (foreign)	-	7 (3)	7 (3)

IV SCIENTIFIC INFORMATION

In the table 4 the publications for which at least one of the used metrics applies have been compiled. An empty cell in the table indicates that a given metric does not apply to the bibliographic item. Column designations: Pkt. – number of MNiSW points (according to the year of publication), IF – impact factor (according to the year of publication), WoS – total number of citations of the publication in the Web of Science Core Collection database, WoS_{ba} – total number of citations of the publication in the Web of Science Core Collection database excluding self-citations, Scopus – total number of citations of the publication in the Scopus database, GS – total number of citations of the publication in the Google Scholar database.

In Tables5–6 the scientometric data collected in the Table are summarized in detail4. In Table 7 a summary of the percentage contribution of the author of the proposal to published scientific works is presented.

Table 4: List of bibliometric data for individual publications (as of March 30 2024).

Item	Pts. MNiSW	IF	WoS (WOS_{ba})	Scopus	GS
[DR1] Doniec et al., 2024	20	-	0 (0)	0	2
[DR2] Doniec et al., 2023	100	3,7	0 (0)	2	0
[DR3] Doniec et al., 2022	100	2,6	3 (1)	7	11
[DR4] Hozhabr et al., 2022	100	3,7	12 (10)	17	37
[DR5] Mocny-Pachońska et al., 2021	140	4.799	10 (8)	8	12
[DR6] Mocny-Pachońska et al., 2021	100	2,7	3 (3)	3	5
[DR7] Doniec et al., 2021	40	2,5	2 (1)	3	2
[DR8] Doniec et al., 2020	100	2,6	10 (7)	16	21
[DR9] Mocny-Pachońska et al., 2020	100	2,8	15 (11)	16	31
[DR10] Grabny et al., 2023	20	-	0 (0)	-	-
[DR11] Gabor et al., 2021	20	-	0 (0)	-	-
[DR12] Doniec et al., 2021	20	-	-	-	-
[DR13] Doniec et al., 2024	20	-	-	-	-
[DR14] Piaseczna et al., 2023	20	-	-	-	-
[DR15] Mocny-Pachońska et al., 2019	20	-	-	-	-
[DR16] Doniec et al., 2022	-	-	-	-	-
[DR17] Doniec et al., 2022	-	-	-	-	-
Total habilitation cycle	**920**	**25,399**	**55(40)**	**72**	**121**
[DR18] Sawaryn et al., 2021	-	-	-	-	-
[DR19] Doniec et al., 2024	-	1,7	-	-	-
[DR20] Sieciński et al., 2024	-	1,7	-	-	-
[DR21] Kruczkowski et al., 2024	20	-	-	-	-
[DR22] Piaseczna et al., 2024	100	2,6	-	-	-
[DR23] Doniec et al., 2024	20	0,9	-	-	-
[DR24] Rimsha et al., 2024	100	3,847	-	-	-
[DR25] Doniec et al., 2023	100	2,838	2 (0)	-	3
[DR26] Duraj et al., 2022	20	-	-	2	-
[DR27] Łach et al., 2022	20	-	-	-	-
[DR28] Sawaryn et al., 2021	100	3,847	2 (0)	-	3
[DR29] Radziun et al., 2021	70	-	-	-	-
[DR30] Mocny Pachońska et al., 2020	20	2,6	15 (3)	-	20
[DR31] Doniec et al., 2019	20	-	-	-	-
[DR32] Mocny Pachońska et al., 2019	20	-	1 (1)	2	4
[DR33] Meiser & Doniec, 2017	-	-	4 (4)	3	5
[DR34] Doniec, 2016	-	-	-	-	-
[DR35] Doniec, 2016	-	-	-	11	13
[DR36] Meiser & Doniec, 2016	-	-	4 (4)	5	7
[DR37] Doniec & Scheller, 2015	-	-	6 (4)	6	9
[DR38] Doniec & Meiser., 2015	-	-	14 (9)	14	21
[DR39] Doniec, 2014	-	-	12 (8)	14	11
[DR40] Doniec, 2014	-	-	-	1	2
[DR41] Doniec, 2013	-	-	11 (9)	11	15
[DR42] Doniec, 2011	-	-	-	-	1

[DR43] Doniec & Doniec, 2011	-	-	-	-	-
[DR44] Doniec, 2010	-	-	-	-	-
[DR45] Doniec, 2010	-	-	-	-	-
[DR46] Doniec & Doniec et al., 2008	-	-	1 (1)	-	-
[DR47] Doniec & Doniec et al., 2008	-	-	-	-	-
[DR48] Doniec, 2008	-	-	-	-	-
[DR49] Doniec & Doniec et al., 2007	-	-	-	-	-
[DR50] Doniec, 2006	-	-	-	-	-
[DR51] Doniec, 2005	-	-	-	-	-

Table 5: List of citation indicators for the author's publications (as of July 10, 2024).

	WoS (WOS_{ba})	Scopus	GS
Number of citations of publications	80 (60)	110	230
Hirsch index	5	7	8

Table 6: Summary of selected bibliometric data of the author of the application (as of July 10, 2024).

Indicator	In total	After obtaining a Ph.D
Total impact factor	42,27	42,27
Number of points of the MNiSW	1630	1630
Number of points of the MNiSW weighted by percentage. author's contribution	545	545

Table 7: Summary of publications and percentage contribution of the author of the proposal (as of July 10, 2024).

Publication time	Number of positions	Author's average IF
Before obtaining a Ph.D. (WoS)	8 (1)	88,8%
After obtaining his Ph.D (WoS)	43 (18)	51,0%
In total (WoS)	**51 (19)**	**69,7%**

Rafal Doniec

(Applicant signature)

Appendix No. 5
to the Application dated August 10th, 2024, for Initiation of Habilitation Procedure

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Copies of publications in the discussed cycle, originals in English

Advanced Methods of Analysis and Recognition of Behavioral and Cognitive Activities Using Eye Movement-Recording Sensors and AI Algorithms

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Contents

Copies of publications

1 Publication [DR1] doi.org/10.1016/j.sasc.2024.200078 . . . 2
2 Publication [DR2] doi.org/10.3390/s23125551 . . . 15
3 Publication [DR3] doi.org/10.3390/electronics11182960 . . . 34
4 Publication [DR4] doi.org/10.3390/s22103634 . . . 54
5 Publication [DR5] doi.org/10.3390/ijerph18094448 . . . 75
6 Publication [DR6] doi.org/10.3390/app11188648 . . . 88
7 Publication [DR7] doi.org/10.3390/healthcare9111513 . . . 107
8 Publication [DR8] doi.org/10.3390/electronics9122002 . . . 120
9 Publication [DR9] doi.org/10.7717/peerj.8981 . . . 137
10 Publication [DR10] doi.org/10.1007/978-3-030-99112-8_25 . . . 156
11 Publication [DR11] doi.org/10.1007/978-3-030-83704-4_1 . . . 166
12 Publication [DR12] doi.org/10.1007/978-3-030-49666-1_28 . . . 174
13 Publication [DR13] doi.org/10.1007/978-3-031-38430-1_18 . . . 184
14 Publication [DR14] doi.org/10.1109/EMBC40787.2023.10340736 . . . 196
15 Publication [DR15] doi.org/10.1007/978-3-030-30275-7_43 . . . 200

Rafal Doniec

(Applicant signature)

Systems and Soft Computing 6 (2024) 200078

Contents lists available at ScienceDirect

Systems and Soft Computing

journal homepage: www.elsevier.com/locate/soft-computing-letters

The detection of alcohol intoxication using electrooculography signals from smart glasses and machine learning techniques

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ARTICLE INFO

Keywords:
Electrooculography
Smart glasses
Driving
Alcohol
Human intoxication
Machine learning

ABSTRACT

The operation of a motor vehicle under the influence of alcohol poses a significant risk to the safety of the driver, passengers, and other road users. Electrooculographic (EOG) signal analysis can be used to understand the movements and behavior of the eyes while driving. In our study, we used smart glasses to collect EOG data from nine participants who used a driving simulator. Their level of alcoholic intoxication was simulated by drunk vision goggles at three different levels of inebriation (0, 1, 2, and 3‰ blood alcohol content). We used machine learning algorithms (decision trees, support vector machines, nearest-neighbor classifiers, boosted trees, bagged trees, subspace discriminant classifier, subspace k nearest-neighbor classifier, and RUSBoosted Trees) to analyze the data. The Bagged Trees achieved the highest accuracy of 79%. The most important features to detect simulated alcohol intoxication were the blink rate and the velocity of the saccade, a rapid simultaneous movement of both eyes in the same direction. Our study shows the potential of using smart glasses and machine learning for the automated detection of alcohol intoxication, even when alcohol consumption is simulated.

1. Introduction

According to the legal definition, driving involves operating a motor vehicle while in motion on an active roadway, including being stationary due to traffic, stop signs or traffic lights [1,2]. Distracted driving has become a major concern in recent years, with the increasing use of mobile devices and other technologies behind the wheel [3,4]. This seriously threatens road safety, as distracted drivers are more likely to be involved in accidents. As a result, there is a growing need for advanced detection systems that can identify distracted drivers and alert them to potential hazards [5–7].

One promising approach to this problem is the use of electrooculography (EOG) signals from smart glasses to detect the state of human intoxication. EOG signals can provide valuable information on the driver's level of intoxication by analyzing their eye movements, which are directly related to impaired motor and cognitive functions [8,9]. By integrating EOG signals with machine learning techniques, it is possible to develop an automated system that can accurately detect the level of intoxication and alert the driver to take the appropriate action.

An alternative to smart glasses equipped with EOG (electrooculographic) sensors as a non-invasive method to measure the electrical activity of the eyes may be the use of a camera that tracks eye movements. Eye tracking technology is becoming more and more advanced, enabling precise monitoring of where and how quickly the eyes of a user move [10,11]. It is worth mentioning other alternatives similar to the presented method. The first common method that is used on a

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https://doi.org/10.1016/j.sasc.2024.200078
Received 22 September 2023; Received in revised form 28 November 2023; Accepted 23 January 2024
Available online 30 January 2024
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daily basis is electroencephalography (EEG). It measures the electrical activity of the brain. Although more invasive than EOG, there are non-invasive solutions available based on electrodes placed on the scalp [12–15]. Next, electromyography (EMG), which measures the electrical activity of muscles, including eye muscles. It can be used to monitor eye movements. Imaging with a thermal camera is also increasingly used, which can record changes in temperature around the eyes, which may be related to electrical activity of the eye muscles [16–21]. Additionally, less popular pupilometry is based on the measurement of pupil dilation, which can provide information on the intensity of light stimuli and the level of interest in a given object problem [22,23]. Magnetic resonance imaging, specifically functional magnetic resonance imaging (fMRI), is also used as an alternative method. A complex and expensive method that can provide information on brain activity related to areas responsible for controlling eye movement. This method is becoming more and more common throughout the world, but the availability of this method in the form of medical staff, equipment and knowledge remains a problem [24,25]. A less medically, but still an alternative solution is the so-called eye tracker, which can help monitor the direction and duration of gaze without directly measuring electrical activity [11,22]. It should be noted that each of these methods has its advantages and limitations and the choice depends on the specific application, the precision required in the measurement, the comfort of the user and other factors [11,26].

The aforementioned approaches also have limitations. For example, eye tracking involves the need for calibration, interference with head movements, and differences between different people in the way they move their eyes. Infrared oculography requires maintaining the camera's line of sight in the field of view, which may be difficult in practice, while, for example, accelerometers that measure changes in eye movement speed may be less precise than other methods. More invasive methods, such as electroretinography (ERG), which is based on measuring the electrical activity of the retina, are limited to the use of electrodes on the surface of the eye, which can be a burden and potentially uncomfortable for the user [11,27–29]. The effectiveness of each method may depend on the specific application and context of use. Therefore, the choice of the appropriate method depends on the specificity of the test and the requirements for precision and non-invasiveness. Although EOG is not a direct tool for detecting alcohol intoxication, it could potentially be used as part of a system to monitor alcohol-related behaviors and physiological responses. Alcohol affects the ability to maintain eye stability, which can manifest itself in irregular eye movements. EOG can be used to monitor these changes, which may indicate possible intoxication [30]. Driving under the influence of alcohol can affect the ability to maintain visual focus on a given object, where the use of EOG can help monitor visual focus and possible difficulties maintaining it at one point. In addition, alcohol may affect the reaction time to visual stimuli. Monitoring the speed of eye movements using EOG in response to stimuli can provide information on the level of alcohol intoxication. And in turn, it can be used in tests to assess eye–hand coordination, because driving a vehicle requires precise visual and motor coordination [31]. The effectiveness of EOG in detecting alcohol intoxication may depend on many factors, such as individual differences in physiological reactions. Therefore, in practice, various techniques and methods can be combined to obtain a more comprehensive assessment of driver sobriety.

In this context, the main objective of this study is to investigate the feasibility of using JiNS MEME (JINS Inc., Tokyo, Japan) smart glasses EOG signals to detect human intoxication using machine learning-based methods (decision trees, support vector machines, nearest-neighbor classifiers, ensemble classifiers) [32]. To achieve this objective, we propose a novel approach based on the fusion of deep learning and causal reasoning, which can effectively capture the complex relationships between EOG signals and intoxication levels. By testing our system in a driving simulator with simulated intoxication, our objective is to demonstrate the potential of our approach for real-world applications in road safety [33–35].

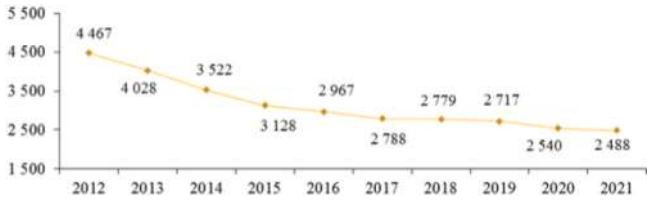


Fig. 1. Statistic of accidents involving drunk drivers over the years 2012–2021 in Poland.
Source of data: [47].

Detecting driver impairment due to alcohol intoxication is a critical issue to ensure road safety. In recent years, there have been increasing efforts to develop automated systems to detect driver impairment using various physiological signals, including electrooculography (EOG) signals [36–41]. Smart glasses equipped with EOG sensors offer a non-invasive method of measuring electrical activity in the eyes, which can be used as a reliable indicator of a person's level of intoxication, according to the findings of [42,43].

1.1. Drunk driving

Alcohol is a substance that alters brain function, leading to impaired thinking, reasoning, and muscle coordination, and also slows reaction time. These abilities are crucial for safe driving, so it is not recommended to drive a vehicle under the influence [44]. As the World Health Organization (WHO) states, there are several measures available for national governments, such as:

- strictly established limits for blood-alcohol concentration for drivers,
- sobriety checkpoint and random breath-testing,
- mandatory driver education, appropriate, and for repeat offenders [45].

WHO reports that approximately 1.3 million people die each year in accidents on the world's roads. Between 20 and 50 million people are injured in the aftermath of these incidents and many experience disability as a result of the injuries sustained. In the European Union (EU), 1.5%–2% km have been traveled by people under the influence of alcohol and about 25% fatal accidents are related to alcohol. 21% of drivers admitted to have driven after drinking alcohol and 13% to have driven while exceeding the legal alcohol limit [46].

In Poland, 2488 road accidents were caused by people under the influence of alcohol in 2021. This number is equivalent to 10.9% of all road accidents in that year. 331 people were killed (14.7% of all people killed in road accidents) and 2805 were injured (10.6% of all people injured in road accidents) [47]. Fig. 1 presents the official statistics of the Polish Police Department, Bureau of Road Traffic.

1.2. Our contribution

The main objective of this study is to investigate the feasibility of using EOG signals recorded from participants wearing smart glasses while simulating varying levels of alcohol intoxication and machine learning-based classifiers (decision trees, support vector machines, nearest-neighbor classifiers, ensemble classifiers) to detect alcohol intoxication in humans. The analysis involved the application of machine learning techniques (decision trees, support vector machines, nearest-neighbor classifiers, and ensemble classifiers) to classify EOG signals and determine the level of alcohol intoxication. This study contributes to the development of automated systems for detecting

impairment of drivers, which could potentially reduce the number of accidents and deaths on the road [48,49].

The paper is structured as follows. Section 2 presents previous studies on the use of electrooculography to detect human intoxication, the limitations of existing methods, and we underline the novelty of the proposed approach. In Section 3 we describe the study group, the data set, and the methods. Section 4 presents the results of the study, including the accuracy, sensitivity and specificity of the proposed approach, comparisons of the performance of different feature extraction and classification methods, and visualizations of the EOG signals and selected features to help interpret the results. Section 5 provides a discussion of the relative advantages and disadvantages of our methods compared to similar studies, and Section 6 summarizes our findings, limitations, and indications for future studies.

2. Related work

Rapid progress in intelligent devices with capabilities for physical, chemical, and biological sensing, as well as multimodal sensing, has significantly expanded the range of applications of wearable electronics, particularly wireless monitoring of an individual's health status [50–60].

In this context, sensors capable of detecting the concentration of ethanol (alcohol) in the human body have gained considerable significance due to the potential risks associated with excessive ethanol consumption, including vehicle accidents, violence, and adverse health effects [60,61]. Consequently, wearable transdermal ethanol monitors have been commercially developed to detect ethanol gas concentration without the need for skin perspiration detection [59].

Driver monitoring systems typically include a combination of various sensors, an LCD module to present the result, and a microcontroller, algorithms, and data processing techniques to accurately detect drowsiness or alcohol consumption, and machine learning can play a key role in achieving high detection accuracy [62]. In [62], the main objective remains the same: to develop a system that can detect typical signs of the progression of alcohol drowsiness in drivers and issue warnings against them if driving behavior becomes unsafe, but is available without additional certification checks.

The European Union Regulation 2019/2144/EU requires car manufacturers to install a standardized interface that facilitates the installation of a blood alcohol measurement system in each vehicle, including an alcohol sensor, to detect driver drowsiness and alcohol consumption in real time to prevent road accidents [63–66].

Several studies have focused on the development of unobtrusive sensor-based methods to estimate the level of intoxication in drivers. For example, Varghese et al. [67] presented a low-cost, non-intrusive real-time system for the detection of driver drowsiness and blood alcohol level (BAL) that was based on a webcam, Raspberry Pi 3, and Arduino UNO and has achieved an accuracy of 86%.

Li et al. [2] described BAL with a smartphone camera and bidirectional long-short-term memory (Bi-LSTM) and a convolutional neural network (CNN). The proposed Bi-LSTM and CNN architectures achieved an RMSE of 0.0167 and 0.0168, respectively, and outperformed Bayesian regularized multilayer perceptrons (MLP) (RMSE of 0.017) and Random Forest (RF), with hand-crafted features.

Nassi et al. [68] estimated the BAL from gait analysis with Microsoft Band, Samsung Galaxy S4, Gradient Boosting Machine (GBM), and AdaBoost. The area under curve (AUC) was 0.97 and 0.04 false positive rate (FPR), given a fixed true positive rate (TPR) of 1.0.

Ljungblad et al. [69] proposed a system to measure the level of alcohol in the breath with a CO_2 sensor based on infrared spectroscopy installed in a vehicle, video camera, and signal fusion. The reported results showed that alcohol in the breath could be detected with such a system.

Murata et al. [70] presented a system for non-invasive measurement of blood alcohol level based on frequency domain analysis of finger photoplethysmograms, namely LF/HF and HF. An increase in blood alcohol level is correlated with an increase in LF/HF and a decrease in HF. However, the detection of alcohol intoxication with heart rate variability analysis is difficult.

An example is the empirical mode decomposition (EMD) method, which has been proposed as a signal decomposition tool for EOG data analysis. EMD is a technique commonly used to analyze natural and non-stationary processes. By applying EMD to the EOG data, the researchers aim to isolate relevant features and patterns associated with drowsiness [71].

Table 1
Description of the study group.

Number	Age	Gender	Driving license	Abstinent
1	21	Male	Yes	No
2	21	Female	No	No
3	23	Male	Yes	No
4	22	Male	Yes	No
5	20	Male	Yes	No
6	20	Male	Yes	No
7	21	Male	Yes	No
8	21	Male	Yes	Yes
9	20	Female	No	Yes

3. Materials and methods

3.1. Study group

The study group consists of 9 people, male (77.8%) and female (22.2%) of which only 22% are abstinent. Most subjects have driving experience, but only 22.2% had no experience operating a mechanical vehicle. The age of the participants ranges from 20 to 23 years, with the mean and median equal to 21 years. The description of the study group is presented in Table 1.

3.2. Experimental setup

The car driving simulator consisted of: a computer with Windows 10 (central unit equipped with an Intel Core i7 processor and a graphics card with an NVIDIA graphics processor and the 3D VISION system, additionally standard computer peripherals and LED backlight), a spatial structure made of steel (2-layer painting + primer) and a chair adjustable in 2 ranges with 5.1 sound, a Logitech set: steering wheel, pedals and gearbox, three 27 inch LED monitors adapted to long work, dedicated software, including routes in the city and highways, and maneuvering area. The experimental setup is presented in Fig. 2.

Nine driving routes were prepared, which were used as stages in the driving simulator, namely:

1. driving left through the intersection,
2. driving straight through the intersection,
3. driving right through the intersection,
4. driving right at the roundabout,
5. driving straight at the roundabout,
6. driving left at the roundabout,
7. perpendicular parking,
8. parallel parking,
9. diagonal parking.

During driving, the driver always wore JiNS MEME smart glasses (see Fig. 3a) connected to a laptop with a data collection program. Furthermore, drunk vision goggles were used that simulated driving with a blood alcohol content of 1 per mil, 2 per mil, and 3 per mil (see Fig. 3 b).

The driver was supposed to drive the nine routes described in Section 3.2 in the first place only wearing EOG glasses. Later, in addition to



Fig. 2. Experimental setup.



(a) JiNS MEME smart glasses (b) Drunk vision goggles

Fig. 3. Glasses and goggles used during examination.

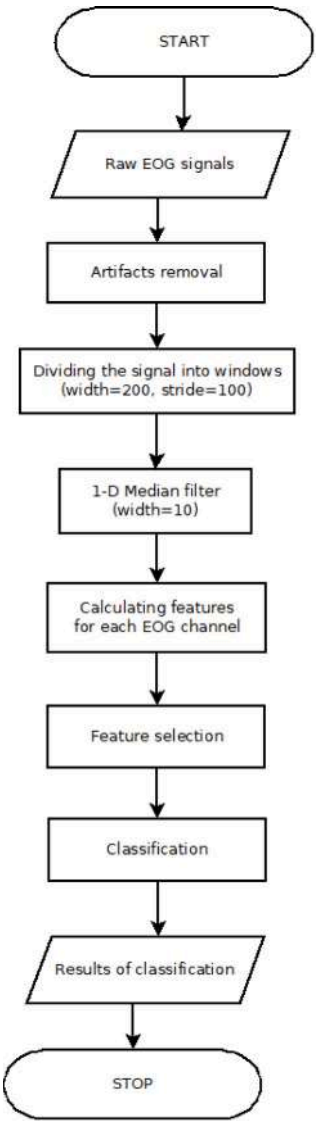


Fig. 4. EOG signal processing flowchart.

the EOG glasses, he put on the goggles with the weakest level of inebriation and repeated the previous steps. Then he did the same in drunk vision goggles with two per mil and finally in the strongest goggles. Before each route, the program was started and stopped immediately after completion. In this way, 9 files were obtained from each state of inebriation (at levels 0, 1, 2 or 3‰ of blood alcohol content) and then saved for analysis. The overview of EOG signal processing and classification of simulated alcohol intoxication is shown in Fig. 4.

3.3. Data processing

The first step was to remove incorrectly classified signal samples after manual inspection. After combining the signals into separate channels: EOG_L, EOG_R, EOG_H, EOG_V, they were normalized with the use of global extremes. The next step was to apply a 1-D median filter with a window length of 10. Then, each feature was calculated on the signal divided into several windows of size 200. The window was moving along the signal with a stride of 100. Finally, all collected data were saved in a table that was then used for further processing.

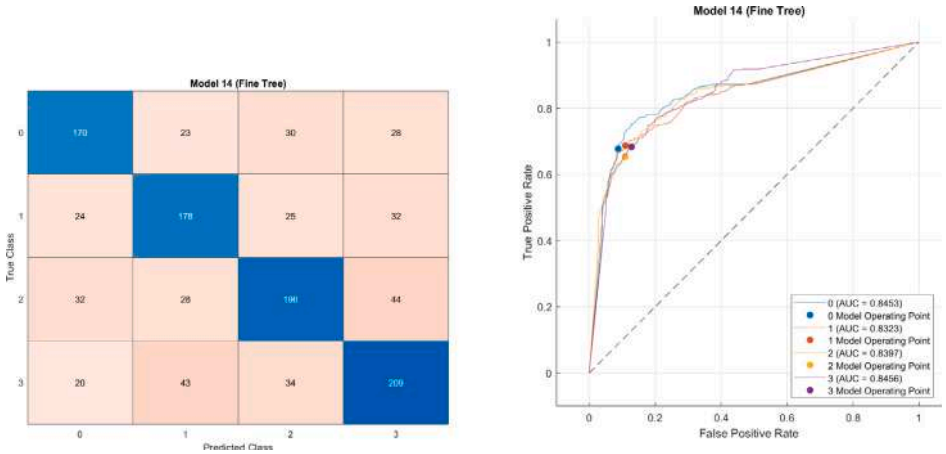
3.4. Feature engineering

After the preprocessing step, we choose the optimal set of features consisting of kurtosis, standard deviation, variance, quadratic regression, area under the density curve of the power spectrum, interquartile range, mean, percentile, most frequent value, mean time between consecutive saccadic movements, and linear regression coefficients.

A total of 44 features, derived from 11 features extracted from each of the four EOG channels (EOG_L, EOG_R, EOG_H, EOG_V), were used in the machine learning analysis. This resulted in a feature matrix with dimensions of $44 \times 11\,649$.

3.5. Feature selection

ANOVA, conceived by Ronald Fisher, extends the t-test by assessing the equality of means between multiple groups. It relies on the assumptions of data normality and the absence of outliers. Feature selection in machine learning poses a major challenge, aiming to retain only response-dependent attributes [72]. For optimal results, the ANOVA F-test is recommended. This method suits this purpose due to its ability to investigate the impact of variance through the F distribution,



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 5. Fine tree, 30 features.

assuming hypotheses such as H_0: equal variances and H_1: unequal variances. In particular, ANOVA also accommodates comparisons between categorical and numerical variables [73].

In this study, we used ANOVA analysis to determine the significance of the 44 calculated features. For this, we took into consideration the subsequent 5, 10, 15, 20, 25, 30, and 35 features that were most important according to the analysis. We performed a series of tests for each classifier using all the features sets to establish the optimal number of features needed for this specific problem. We summarize the classification results for different feature sets in Section 4. For each classifier, a different set of features produced the best result.

4. Results

Classification results were obtained using different classifiers implemented in a Matlab Classification Learner app and expressed as accuracy, confusion matrices, and ROC curves. Each class (0–3) corresponds to the simulated blood alcohol level.

4.1. Decision trees

Only Medium and Fine trees were considered for further analysis. All trees have undergone an initial test in which the Coarse Tree has given the worst results. Table 2 shows the best results obtained for the fine tree and the medium tree, together with the number of features and accuracy.

The best results were obtained for the Fine Tree with 30 features (see Fig. 5) and the Medium Tree with 35 features (see Fig. 6).

Table 2
Decision trees with respective hyperparameters, number features and accuracy.

Method	Number of features	Maximum number of splits	Split criterion	Surrogate decision splits	Accuracy [%]
Fine tree	25	100	Gini's diversity index	Off	53.3
Fine tree	30	1000	Max deviance reduction	On, max 10	67.5
Fine tree	40	100	Gini's diversity index	Off	54.4
Medium tree	25	20	Gini's diversity index	Off	43.8
Medium tree	35	2000	Max deviance reduction	On, max 10	67.5

Table 3
Support vector machine with respective number of features and accuracy.

Method	Number of features	Accuracy [%]
Linear SVM	44	31.6
Quadratic SVM	35	46.3
Cubic SVM	30	56.8
Fine Gaussian SVM	25	**71.4**
Medium Gaussian SVM	44	49.8
Coarse Gaussian SVM	44	31.6

4.2. Support vector machines

The Table 3 shows highest achieved test accuracy and amount of features for each of the available SVM methods.

The Fine Gaussian SVM model gave the best results. To visualize these results, a confusion matrix is shown in Fig. 7(a). This matrix shows the true positive rate (TPR), the false positive rate (FPR), and the accuracy of the model. A receiver operating characteristic curve (ROC curve) is also shown in Fig. 7(b). This curve shows the trade-off between TPR and FPR for different thresholds of the model.

The parameters of the best classifier preset are presented in Table 4.

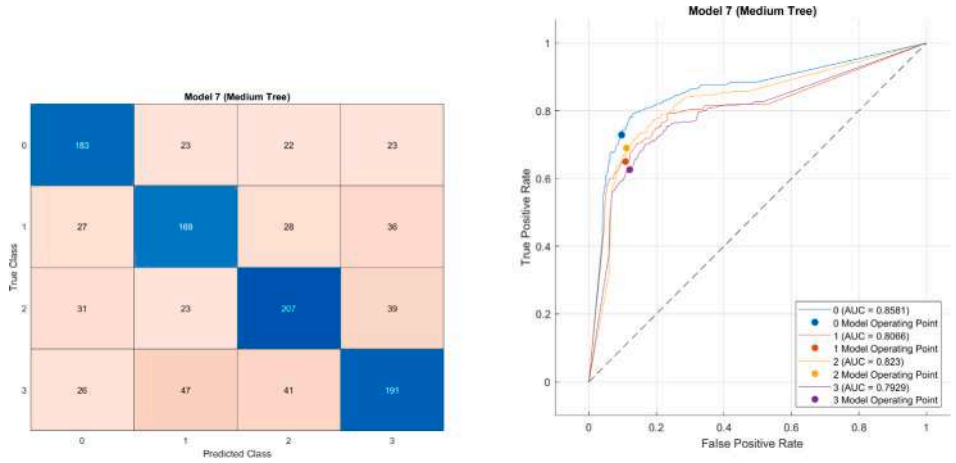
After finding the optimal SVM preset, some additional tests were performed to find a better solution. The results of these tests are shown in Table 5.

Table 4
Parameters of best classifier.

Preset	Fine Gaussian SVM
Kernel function	Gaussian
Kernel scale	1.7
Box constraint level	1
Multiclass method	One-vs-One
Standardize data	Yes

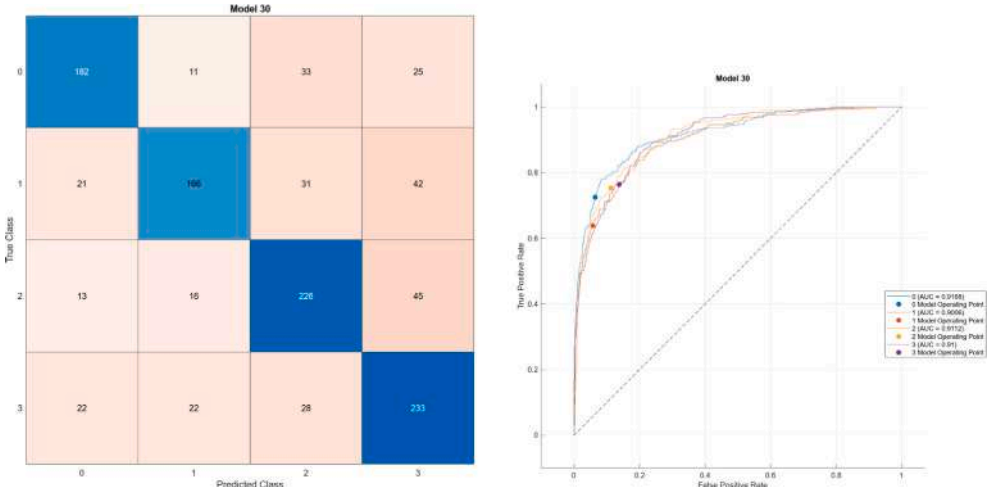
4.3. Nearest neighbor classifiers

After checking all the possible variants of the KNN classifiers provided by MATLAB, and training them, three with the best accuracy were chosen (see Table 6).



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 6. Medium tree, 35 features.



(a) Test Confusion Matrix (b) Test ROC curve

Fig. 7. Fine Gaussian SVM, 25 features.

Table 5
Analysis of chosen classification preset.

Method	Number of features	Accuracy [%]
Fine Gaussian SVM	25	72.3
Fine Gaussian SVM	30	68.5
Fine Gaussian SVM	20	67.8
Fine Gaussian SVM	35	67.1
Fine Gaussian SVM	15	66.8
Fine Gaussian SVM	10	62.0

Table 6
K nearest neighbors with the respective number of features and accuracy.

Method	Number of features	Accuracy [%]
Fine KNN	25	73.3
Medium KNN	25	71.4
Weighted KNN	25	**74.2**

From these, the Weighed KNN provided the best result using the parameters shown in Table 7.

Fig. 8 is the result of the optimal number of features, and the results of the tests that use all of them are presented in Fig. 9.

Table 7
Parameters of the best KNN classifier.

Preset	Weighted KNN
Number of neighbors	10
Distance metric	Euclidean
Distance weight	Squared inverse
Standardize data	Yes

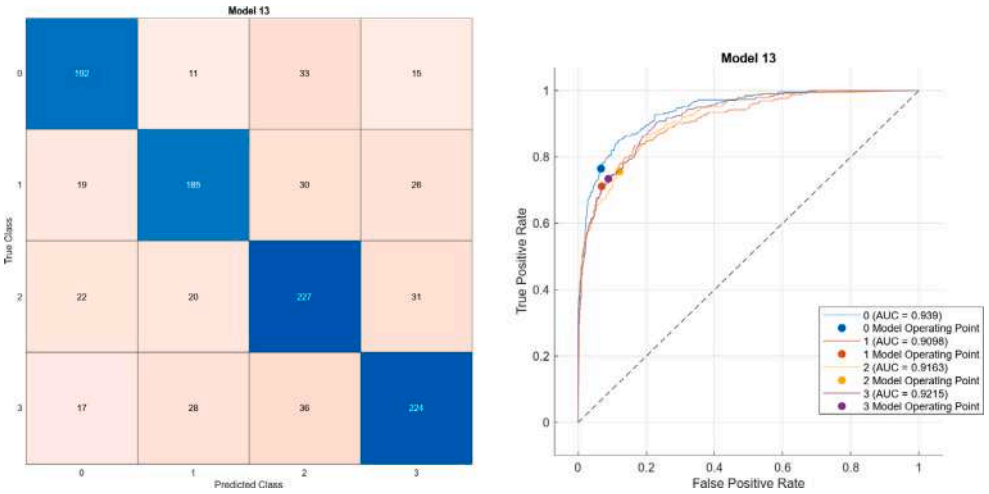
4.4. Ensemble classifiers

Table 8 shows the names of the methods along with the highest test accuracy achieved and the corresponding number of features. During each learning session, the number of learners was set at 30.

For a better visualization of the performance of the Bagged Trees method for 25 features, an error matrix is shown in Fig. 10a. A receiver operating characteristic curve is depicted in Fig. 10b.

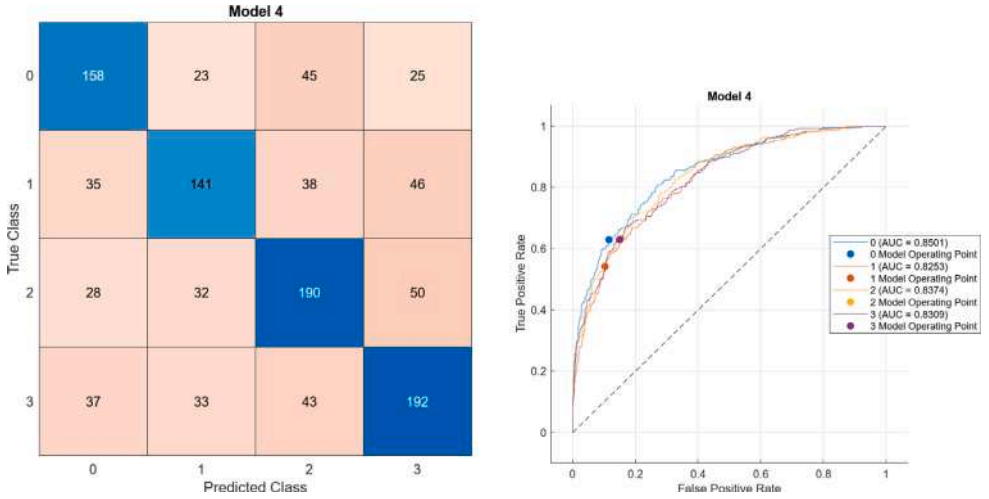
For comparison, the performance of the Bagged Trees method for all features (ANOVA was not involved), an error matrix is shown in Fig. 11a. A receiver operating characteristic curve is depicted in Fig. 11b.

The best output accuracy was observed for the Bagged Trees with 25 features. In this case, the Model Hyperparameters were as in Table 9.



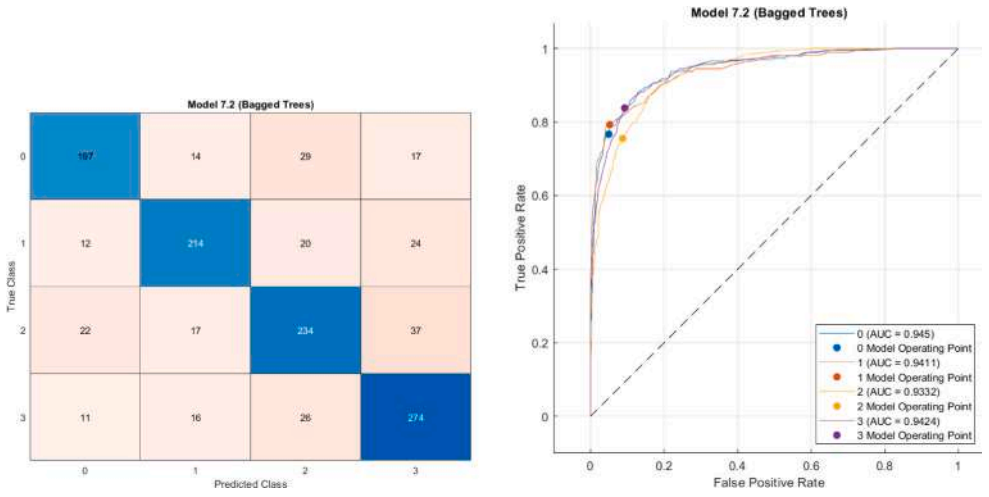
(a) Test Confusion matrix (b) Test ROC curve

Fig. 8. Weighted KNN, 25 features.



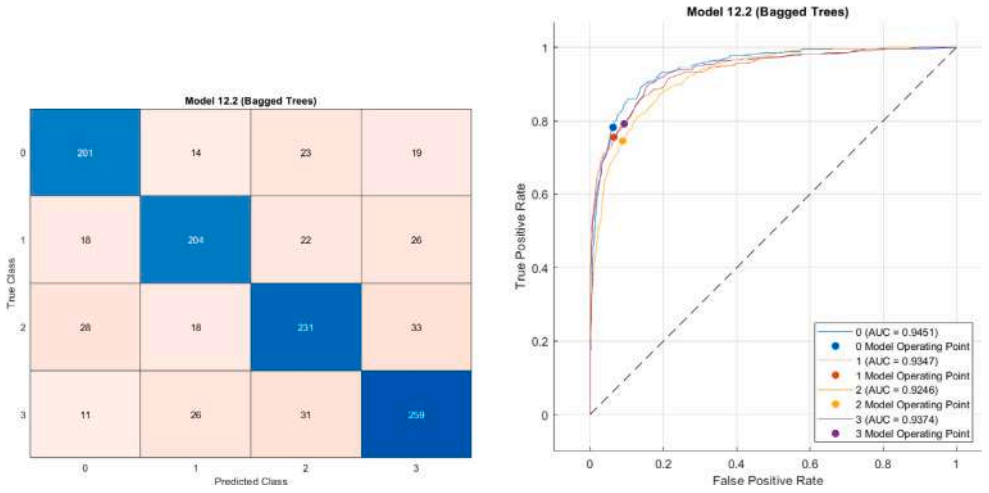
(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 9. Weighted KNN, 44 features.



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 10. Bagged tree results, 25 features.



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 11. Bagged tree results, 44 features.

Table 8
Gradient boosting methods with the respective number of features and accuracy.

Method	Number of features	Accuracy [%]
Boosted trees	25	42.7
Bagged trees	25	**79.0**
Subspace discriminant	35, 44	32.0
Subspace KNN	5	60.1
RUSBoosted trees	35	43.7

Table 9
Hyperparameters for bagged trees, 25 features.

Preset	Bagged Trees
Ensemble method	Bag
Learner type	Decision tree
Maximum number of splits	10 484
Number of learners	30
Number of predictions to sample	Select all

Table 10
Bagged trees for 50, 100, and 200 learners with respective accuracy.

Number of features	Number of learners	Accuracy [%]
25	50	78.4
25	100	78.4
25	200	78.5

To analyze the desired model even more deeply, a different number of learners was considered. The model hyperparameters were set as above 9 except for the number of learners. Therefore, the results shown in Table 10 were obtained.

4.5. Neural network classifiers

Table 11 shows the best results for neural network classifiers for each category (Narrow, Medium, Wide, Optimizable). Each model achieved the best accuracy during training, with 20 features chosen with the ANOVA ranking mentioned in Section 3.5. The columns **Layer 1, Layer 2, and Layer 3** show the number of neurons per layer.

4.5.1. Detailed results for each neural network

Figs. 12 to 15 contains confusion matrices and ROC curves for the test groups. Both are graphical representations of the performance of the model.

Comparison of the best-performing models from all the chosen classifiers clarifies that the Bagged Tree is the best classifier for determining the intoxication level based on the EOG signal. A detailed comparison of performance that determines the best classifier for each group (see Fig. 16) confirms the result mentioned above.

Table 11
Comparison of neural network models.

Preset	Number of features	Layer 1	Layer 2	Layer 3	Accuracy [%]
Narrow NN	20	1000	500	100	71.8
Medium NN	20	1000	1000	1000	73.1
Wide NN	20	50	100	500	71.5
Optimizable NN	20	17	228	228	71.9

5. Discussion

In our study, we proved that machine learning-based techniques are useful for estimating the level of blood alcohol based on EOG signals.

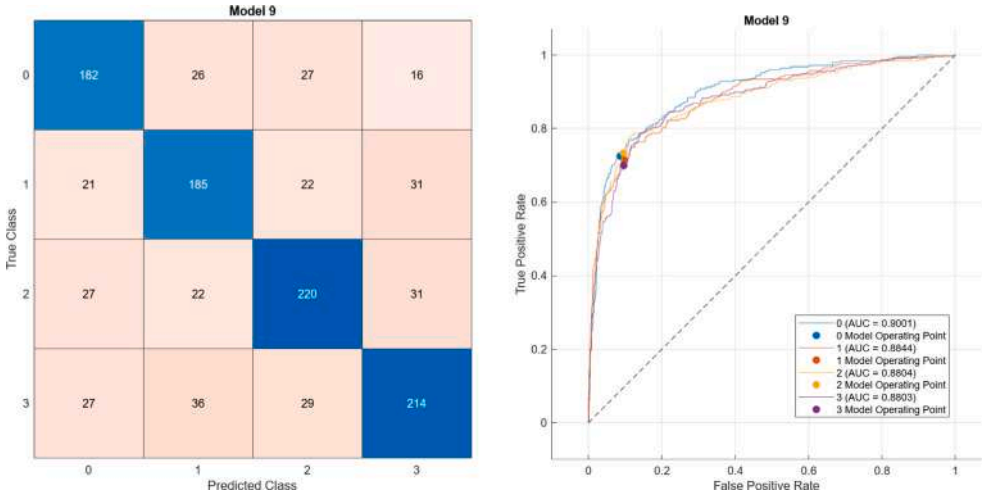
The accuracy of examined methods is slightly lower than that reported in [67,74,75]: 86% versus 96.2% in the best case in [67] and 98% versus 96.2% in the best case in [67,75], respectively. However, Varghese et al. [67] and Koch et al. [74,75] use cameras and alcohol sensors. Our approach uses electrooculography and drunk vision goggles with a driving simulator. In the previous study [76], the overall accuracy was higher than reported in this study (86% vs. 94.57%).

The importance of ethanol intoxication detection methods is unquestionable, especially in places like Europe, which is one of the heaviest drinking regions in the world. Such methods allow for the early detection and prevention of accidents caused by intoxication with ethanol, which is especially important for road safety [63,67,77].

It is believed that by using machine learning and integrating these technologies, the number of accidents caused by these two main factors can be reduced. It should be noted that, while such a system can improve road safety, it would require thorough testing, validation, and compliance with relevant regulations and standards before it could be deployed on a larger scale [77].

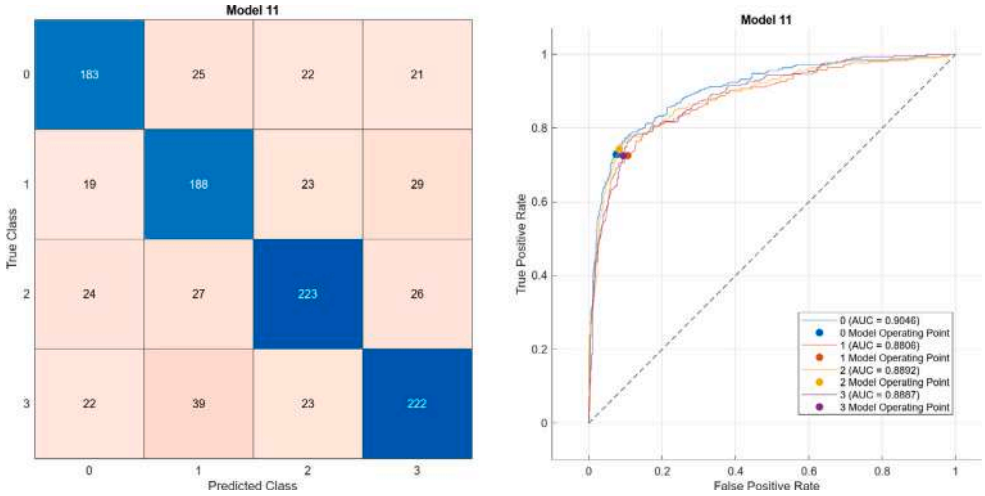
After thorough research, we have concluded that machine learning is a useful tool to indicate the level of intoxication based on EOG data. We also believe that greater accuracy can be attained by:

1. using more thorough procedures, MATLAB software only permits minor integration in model hyperparameters,
2. better optimization of learning models performed on machines with greater computing power,
3. more diverse population of subjects,



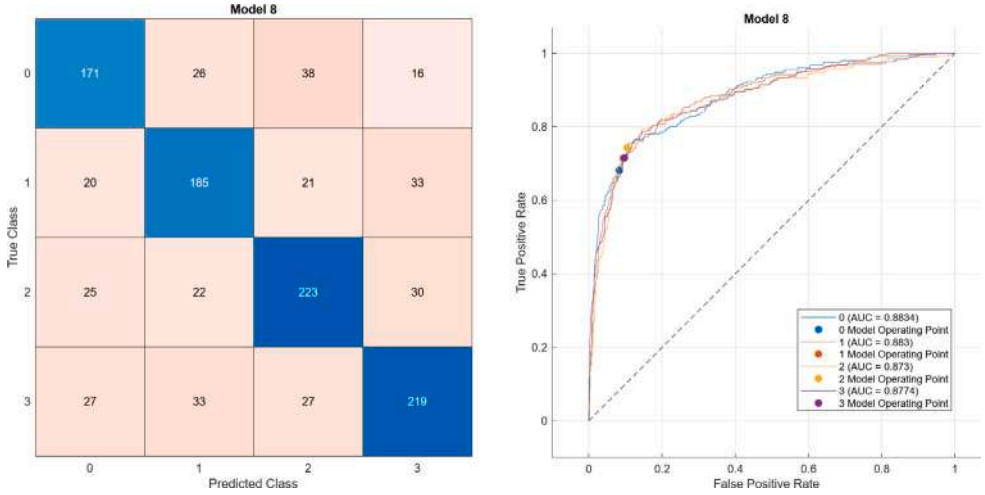
(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 12. Narow neural network.



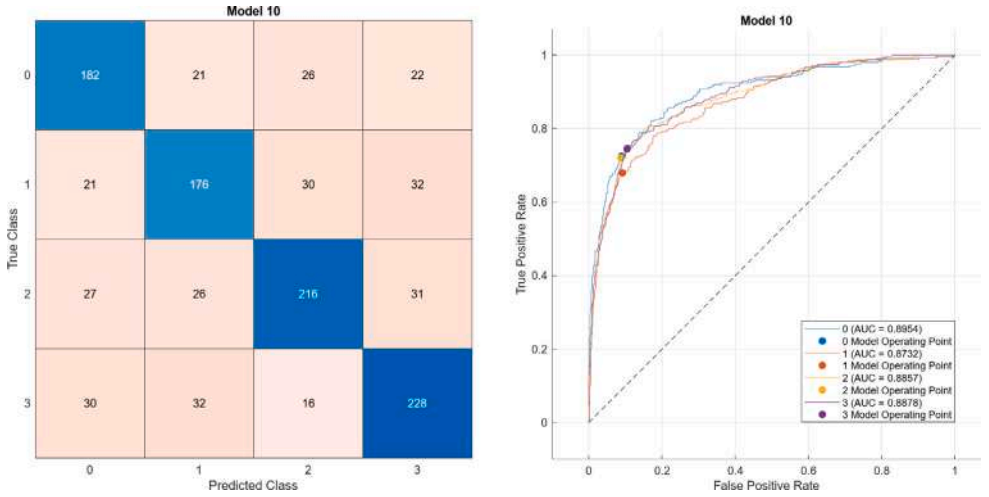
(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 13. Medium neural network.



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 14. Wide neural network.



(a) Test Confusion Matrix (b) Test ROC Curve

Fig. 15. Optimizable neural network.

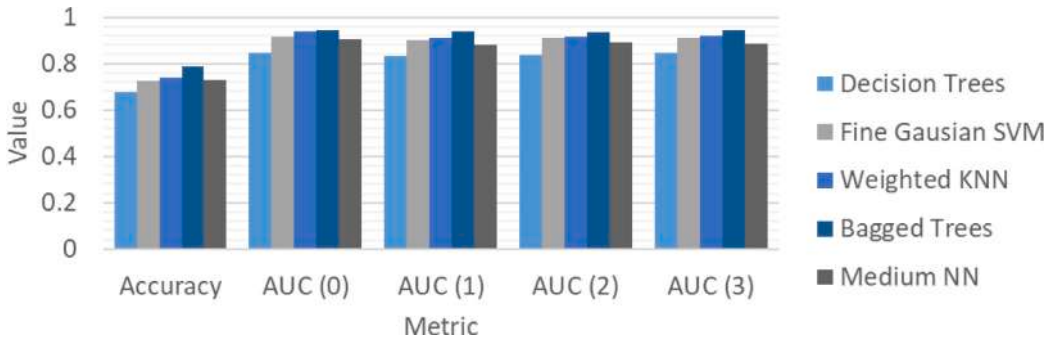


Fig. 16. Comparison of the best performing classifiers in each group regarding accuracy and area under the receiver operating characteristic curve for each class.

4. considering the age, body mass, medical history of subjects.

Undoubtedly, the limitation of our study is definitely a small sample size, as it consists of only seven males in the age range of 20 to 23 years, with a driving license. Only one person from this group is abstinent.

It is assumed that in the next stage the research should include a larger and more variety data set with the same number of men and women from different age ranges. The instructor should also consider being more active in the group to determine if there is a difference in behavior while driving under simulated intoxication. In the future, it may be interesting to combine the EOG signal with other physiological signals, such as the ECG or EMG. The effects of other stimulants on driving can also be the next stage of investigation, through a combination of EOG measurements and simulations, such as drugs. Other stages may include the effects of various distractions on the driver, such as the presence of screens in the vehicle that display, for example, the current route.

No studies have been found using EOG specifically in alcohol intoxication detection; however, existing studies confirm the possibility of using EOG and artificial intelligence to recognize and classify unsafe behaviors among drivers, such as driving while tired or drowsy [36,37,39]. Based on these studies and this presented in this paper, it seems possible to create a system to recognize dangerous driver activity based on the use of smart glasses and machine-processing methods. Such a solution would be cost-effective as it would not require the installation of additional sensors in the vehicle and safe, as it would not interfere in any way with driver comfort. Further studies should focus on validating the algorithm presented both under simulated conditions and later under real conditions, so that it becomes possible to use it in everyday situations.

6. Conclusion

Motor vehicles under the influence of an alcohol-drunk driver can present a significant risk not only to the safety of the driver but also to passengers and other road users. In this context, this article demonstrates the utility of machine learning-based techniques to estimate blood alcohol levels using electrooculographic (EOG) signals. Although the accuracy of the examined methods is inferior to those reported in previous studies with cameras and alcohol sensors, the importance of detecting ethanol intoxication using unobtrusive wearable technology remains paramount, particularly in high-drinking regions such as Europe. In general, the following are the main scientific contributions of this study:

- We investigated the use of wearable sensor technology and state-of-the-art machine learning algorithms to detect driver ethanol intoxication without unobtrusive detection.
- We provide a comparative analysis of machine learning algorithms, which helped to achieve high accuracy (79%) and future directions.
- We also investigated feature selection in this field because redundant and noisy data can influence the precision of prediction models.

Such methods can enable the early detection and prevention of road accidents caused by alcohol intoxication, which is crucial for road safety. Integration of machine learning and these technologies is believed to reduce accidents caused by these factors. However, deploying such a system on a larger scale requires rigorous testing, validation, and adherence to relevant regulations.

The study concludes that machine learning models can effectively indicate intoxication levels based on wearable EOG data. Nevertheless, the accuracy of the implemented model can be improved by employing more comprehensive procedures, such as optimizing learning models on more powerful machines, recruiting a more diverse population of subjects, and considering their age, body mass, and medical history, which is part of our future research.

Funding

This research was carried out under the initiative "Involving students in scientific research through scientific clubs and project-based learning", in connection with the participation of the Silesian University of Technology, Poland in the Excellence Initiative - Research University program (contract No. 08/IDUB/2019/84 of December 16, 2019).

CRediT authorship contribution statement

Rafał J. Doniec: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Natalia Piaseczna:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing, Validation. **Konrad Duraj:** Conceptualization, Data curation, Formal analysis, Methodology, Resources. **Szymon Sieciński:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Visualization. **Muhammad Tausif Irshad:** Conceptualization, Writing – original draft, Writing – review & editing. **Ilona Karpiel:** Writing – review & editing. **Mirella Urzeniczok:** Writing – review & editing. **Xinyu Huang:** Conceptualization, Writing – review & editing. **Artur Piet:** Conceptualization, Writing – original draft, Writing – review & editing. **Muhammad Adeel Nisar:** Supervision, Writing – original draft. **Marcin Grzegorzek:** Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Sensor-Based Classification of Primary and Secondary Car Driver Activities Using Convolutional Neural Networks

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Abstract: To drive safely, the driver must be aware of the surroundings, pay attention to the road traffic, and be ready to adapt to new circumstances. Most studies on driving safety focus on detecting anomalies in driver behavior and monitoring cognitive capabilities in drivers. In our study, we proposed a classifier for basic activities in driving a car, based on a similar approach that could be applied to the recognition of basic activities in daily life, that is, using electrooculographic (EOG) signals and a one-dimensional convolutional neural network (1D CNN). Our classifier achieved an accuracy of 80% for the 16 primary and secondary activities. The accuracy related to activities in driving, including crossroad, parking, roundabout, and secondary activities, was 97.9%, 96.8%, 97.4%, and 99.5%, respectively. The F1 score for secondary driving actions (0.99) was higher than for primary driving activities (0.93–0.94). Furthermore, using the same algorithm, it was possible to distinguish four activities related to activities of daily life that were secondary activities when driving a car.

Keywords: driving a car; driving behavior; electrooculography; convolutional neural networks

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Citation: Doniec, R.; Konior, J.; Sieciński, S.; Piet, A.; Irshad, M.T.; Piaseczna, N.; Hasan, M.A.; Li, F.; Nisar, M.A.; Grzegorzek, M. Sensor-Based Classification of Primary and Secondary Car Driver Activities Using Convolutional Neural Networks. *Sensors* **2023**, *23*, 5551. https://doi.org/10.3390/s23125551

Academic Editors: Umar Iqbal and Michael J. Korenberg

Received: 25 April 2023
Revised: 6 June 2023
Accepted: 9 June 2023
Published: 13 June 2023

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1. Introduction

To drive safely, the driver must be sufficiently aware of his/her surroundings, pay constant attention to the road and traffic, and be alert enough to react to unexpected circumstances [1–4]. Tasks that are directly related to maneuvering a vehicle are called basic driving activities [5].

The lack of concentration of drivers remains one of the crucial factors that contribute to serious accidents and deaths on the road and continues to be a problem for international road safety measures, as they affect not only the driver but also everyone else on the road [6,7]. Approximately 324,000 people were injured due to driver inattention in the United States in 2020 and more than 3000 lost their lives, representing 8.1% of all fatal accidents in the country [8,9].

The term "driver fatigue" refers to a particular type of inattention that occurs when a driver removes his/her focus from basic vehicle navigation tasks to focus on another activity [10]. These distractions may come from common activities, such as talking to other passengers and eating, as well as using mobile phones and systems [11]. These activities can have different effects on drivers. From the point of view of support by measurement technologies, existing research indicates two main areas:

1. Detect anomalies in driver behavior to prevent an accident, with personalized behavior measures of driving style through face detection or Internet of Things (IoT) technologies [12–16];
2. Monitor correct cognitive and safe driver behaviors with intelligent sensors and IoT to monitor the face, eyes, or movements of a driver's entire body for a novel driver education process [17].

Although there are two distinct categories, they have a lot in common; for example, they are recorded and classified within the framework of currently available technologies, and many activities can be assigned into more than one of them. The use of a device requires participation in all of these distractions, also known as secondary driving activities. The cognitive distraction that occurs in the driver's brain is the most difficult to identify. This phenomenon is also known as "looking but not seeing". Attention requirements for distracting work and the prevalence of multitasking among drivers are two fundamental elements of the problem of distributed driving safety [18–20].

Task demand is the total amount of visual, physical, and cognitive resources required to perform the activity. The second issue is the frequency with which the drivers perform the task. Even a task that is small, but performed frequently, can pose a safety concern [2,3,19,21,22].

According to [23,24], the results suggest that activities that require the driver to look away from the road or perform manual tasks significantly increase the probability of a collision. The risk of a traffic accident increases by 2.05 when using a mobile phone, especially when dialing ($\times$12) and sending messages ($\times$6).

The long time spent looking away from the road also has a significant impact. According to some studies, removing your eyes from the road for more than two seconds significantly increases the probability of safety-critical events [25]. In fact, the U.S. Department of Transportation advises against taking your eyes off the road repeatedly in 12 s while operating a motor vehicle [26]. Recognition of human activity based on preconstructed groups of activities is a commonly used approach [27–30].

There are many well-described activities, mainly related to basic needs and daily life, e.g., breathing, eating, sleeping, and walking [31–35]. Among the recognition of these activities, some were divided into even more detailed (complex) activities, e.g., food was divided into food preparation, and food preparation was even more separated for the preparation of breakfast, lunch, and dinner. Using this convention, we decided to analyze and recognize the activities and scenarios that accompany driving a vehicle.

To explore more deeply the research problem, our objective was two-fold: to identify the prevailing road conditions during a trip and to determine whether individuals exhibited improved parking skills after the journey. Accomplishing this required the acquisition of a substantial volume of data. This paper outlines the integration of data and fundamental principles of physics into sensors embedded within JINS MEME ES_R glasses, as well as the methodology employed to acquire and analyze the collected data for classification purposes [3,36–40].

To summarize, we make the following contributions:

1. We investigate the use of JINS MEME ES_R (smart glasses) sensor data and develop a state-of-the-art machine learning model that learns patterns related to the primary and secondary activities of drivers and classifies them into their respective classes.
2. We perform a comparative analysis of wearable sensor data consisting of nine activities of the first driver and four activities of the second driver.
3. We provide a brief review of related approaches.

The rest of the article is structured as follows: Section 2 presents the current state of the art in the field of recognition of vehicle driver activities. Section 3 describes the materials and methods used to analyze signals to assess these activities. Section 4 presents the experimental results. Section 5 provides a discussion and, finally, Section 6 concludes this work.

2. Related Works

When looking for examples of similar studies to compare, it should be noted that, in a ratio of four to one, articles were found dedicated to searching for anomalies such as drowsiness, fatigue, lack of driver concentration, and external factors associated with vehicle damage and atmospheric factors associated with driving conditions [41–43].

In another study based on data tracking the head and eyes in driving simulation conditions, the activity of 73 people who performed various secondary tasks while driving was recorded. The results of this research improved performance classification through the development of new functions, in particular to assess the context of autonomous driving [44]. Algorithms for the classification of eye movements were divided into methods based on statistical thresholds and probabilistic methods. Algorithms based on static thresholds are usually selected for the classification of tasks assigned to the person who performs them; in other words, they are limited in quantity.

Probabilistic methods were introduced to meet the challenge of automatic adaptation of many people as a result of various behaviors, for example, individual visual cues. Drowsiness while driving is a critical issue in the context of road safety. Several approaches have been developed to reduce the risk of driver drowsiness. Fatigue and drowsiness detection techniques are divided into three broad strategies, namely vehicle-based, physiological, and driver-based approaches. This article discusses the latest research on diagnosing driver drowsiness based on behavior, in particular changes in eye movements and facial features.

2.1. Drowsiness in Drivers

Another research project turned to a traffic surveillance system developed to detect and warn the driver of a degree of drowsiness or stress [45–47]. A smartphone with a mobile application, using the Android operating system, was used to implement a human–computer interaction system. To detect drowsiness, the most important visual indicators that reflect the driver's condition are the behavior of the eyes, the side and front of the head, and yawning. The system works well under natural light conditions and regardless of the use of accessories supplied by the driver, such as glasses, hearing aids, or a cap.

Due to the large number of road accidents in which drivers fall asleep, this project was implemented to develop methods to prevent napping by providing a non-invasive system that is easy to operate and without the need to purchase additional specialized equipment. This method was able to detect drowsiness with an efficiency of 93.4% [48].

Another significant educational research experiment evaluated how an educational program affected the fatigue and conduct of teenage and adult drivers, as well as their performance and behavior during simulated driving at night. A 4-week sleep program and a 4-week driving program were randomly assigned to 34 volunteers (aged 18 to 26). The findings imply that the educational program increases people's awareness of sleepiness. Sleep and driving instruction can reduce the risk that young drivers become fatigued and suffer accidents related to fatigue, but this requires a more comprehensive evaluation of their real driving abilities [49].

2.2. Wireless Sensor Networks

Next, we consider a second group of studies related to eliminating typical driver behavior and IoT-based traffic management to increase road safety. IoT is an innovative design paradigm designed as a network of billions to trillions of tiny sensors communicating with each other to offer innovative solutions to problems in real time [50]. These sensors form a network called a wireless sensor network (WSN) to monitor the physical environment and distribute the collected data back to the base station via multiple hops.

WSN has the ability to collect and report data for a specific application. Location information plays an important role in various wireless sensor network applications. Therefore, such systems can improve driving safety. However, real-time monitoring of

driving behavior and conditions is linked to various issues, including dizziness caused by long journeys, drastic changes in lighting, and reflections in a driver's glasses.

2.3. Deep Learning and Driver's Gaze

A deep learning approach was presented in [51–54] to address this problem, where the authors used a near-infrared (NIR) camera sensor to detect glances, as well as head and eye movements, without the need for user calibration at first. The proposed system was evaluated on a dedicated database, as well as on Columbia's open dataset (The Face Tracer CAVE-DB database).

A comprehensive solution was introduced in previous works [51–54] to address the aforementioned issue by employing deep learning models. This approach used a near-infrared (NIR) camera sensor to accurately identify glances, head movements, and eye movements, all without the need for initial user calibration. The efficacy of the proposed system was assessed on a specialized database and additionally validated using Columbia University's publicly accessible dataset, known as The Face Tracer CAVE-DB database.

The driver's gaze turned out to be an excellent way to create a system for driving intelligent vehicles. Due to the fashion for highly autonomous vehicles, the driver's view can be useful in determining the time of transmission of the gesture from the driver to the traffic management system. Although there have been significant improvements in the personalization of driver vision assessment systems, a universal generalized system that is immutable for different perspectives and scales has not yet been developed. We are taking a step towards this general system using convolutional neural networks (CNNs).

The utilization of the driver's gaze has emerged as a promising avenue for developing intelligent driving systems. In the context of the rising popularity of highly autonomous vehicles, leveraging the driver's perspective becomes crucial in accurately timing the transmission of gestures to the traffic management system. Despite notable advances in tailoring driver vision assessment systems to individual users, a universally applicable and adaptable system, capable of accommodating diverse perspectives and scales, remains an open problem. To address this challenge, we are progressing towards the development of a comprehensive framework using convolutional neural networks (CNNs), aiming to establish a generalized solution.

In [55,56] four prominent convolutional neural network (CNN) architectures specifically designed for this purpose were used to conduct detailed comparisons of their performance. Additionally, various modifications were applied to the input images and the influence of the image size on the effectiveness of the models was examined.

To facilitate network training and evaluation, a substantial dataset was collected comprising 11 extended driving activity recordings. This dataset encompassed the driving behaviors of 10 individuals in two distinct vehicles. The most successful models achieved a recognition accuracy of 95.2% during the comparative testing phase.

Subsequently, the highest performing model was subjected to a comparison with the publicly available Columbia Gaze dataset. This dataset consisted of images showing 56 individuals displaying various head positions and viewing directions. Interestingly, even without any specific training on this particular dataset, the model effectively interpreted different perspectives from disparate datasets [57].

3. Materials and Methods

This section presents details on the sensor modalities that were used for data acquisition, discusses the data acquisition process, and explains the experimental settings. Figure 1 shows all the steps in the process from data acquisition to evaluation, which has been extensively described in [40,58,59].

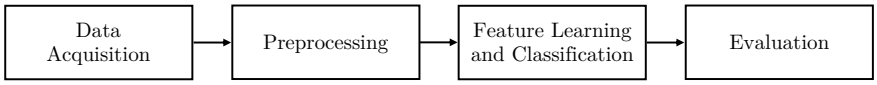


Figure 1. Standard approach to developing a deep learning model. Each step in the chain should be optimized in parallel to achieve the best possible performance.

3.1. Data Acquisition

We acquired the dataset using JINS MEME smart glasses, which have a six-axis inertial measurement unit (IMU) that incorporates EOG, an accelerometer and a gyroscope [60,61]. Participants volunteered for the study and gave their informed consent.

The experiments were carried out in a simulated environment [11,62] as presented in Figure 2.



Figure 2. Driving simulator setup used for the data acquisition.

The simulator consists of the following components:

- A central unit equipped with:
  - An Intel Core i7 processor;
  - XFX RADEON HD 5770 1 GB graphic card with NVIDIA processor and 3D VISION system;
  - 4 GB memory;
  - Gigabyte's Ultra Durable 3 motherboard;
- A special construction made of steel;
- A two-way adjustable seat;
- A Logitech set: steering wheel, pedals, and gearbox;
- Three LED 27 monitors suitable for long operation;
- A sound system;
- Dedicated software "Nauka jazdy" (English: Driver training).

The study consisted of two independent experiments that were conducted separately. Both were completed using the JINS MEME ES_R software with the default settings. The EOG sampling rate was 200 Hz, the accelerometer sampling frequency was 100 Hz, and the accelerometer measurement range was ± 2 g. We synchronized all frequencies to 50 Hz. The signals were recorded simultaneously for each subject while they received voice commands during the driving simulation.

Nine subjects in total (five men and four women) volunteered to participate in the study. Six individuals, all graduate students in their 20s, four men and two women, performed the fundamental driving tasks. In total, we collected 1200 samples of primary driver activities, evenly divided into classes that represent a different activity. Half of

the samples were created by one participant, while the remaining samples were evenly distributed among the other subjects.

For the secondary driver activities, we recorded 700 samples that were distributed equally among all classes. Four subjects, one male and three female, with ages ranging from 23 to 57 years, participated. One participant provided 100 samples, while the other participants each contributed 25. None of the subjects had vision problems. One subject participated in both data acquisitions (primary and secondary driver activities). All participants agreed to participate in this study and use the results for research purposes. In total, 2100 samples were collected for this investigation.

3.1.1. Scenarios

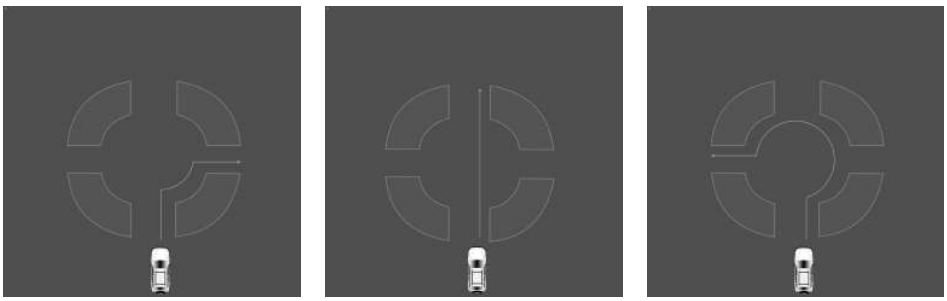
The tests consisted of scenarios that serve as good representations of basic and distracting driving behaviors. Primary activity scenarios were chosen as recommended by the local Driving Exam Center (WORD) and were evaluated while the driving test was administered.

As stated in Tables No. 2 and No. 7, Appendix No. 2 of the Regulation of the Minister of Infrastructure of the Republic of Poland [63], these activities include:

- Passing through uncontrolled intersections (three- and four-way);
- Passing through intersections marked with signs establishing priority of passage;
- Drive through intersections with traffic lights;
- Drive through intersections where traffic flows around a traffic island;
- Perform one of the following parking maneuvers: perpendicular, angle, and parallel.

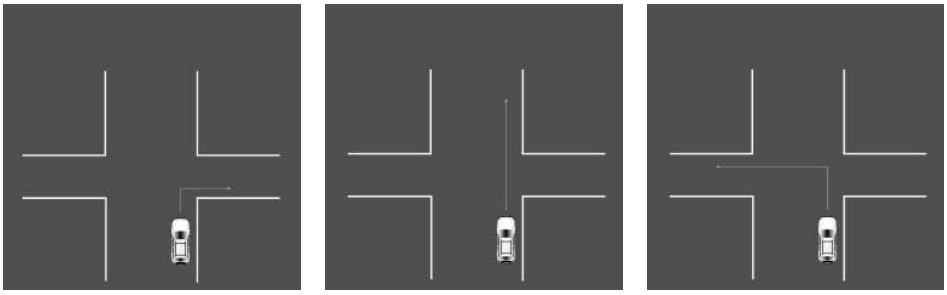
3.1.2. Basic Driving Activities

The driving simulator was used to carry out this experiment. To familiarize themselves with the machinery, each participant began with a test ride. Once they felt comfortable, a scenario was given and they were asked to complete the action while wearing JINS MEME ES_R Eyewear. To allow participants to concentrate solely on driving, the supervisor was in charge of managing the computer program and issuing voice commands. Three types of situation were created, each of which was performed in an appropriate setting. There were a total of 12 scenarios in this section. The first set of tasks was carried out in a roundabout. It involved making a left turn, a right turn, or going straight ahead, choosing the first, second, or third exit. The actions are illustrated in Figure 3. The second set of actions was executed at an intersection. The scenarios are similar to the roundabout. The second series of actions was carried out at a crossroad. The situations resemble those of a roundabout and are illustrated in Figure 4. The final set of situations comprises various parking methods, specifically, angle, parallel, and perpendicular parking. Each action was carried out twice, on each side of the street. All scenarios are illustrated in Figure 5.



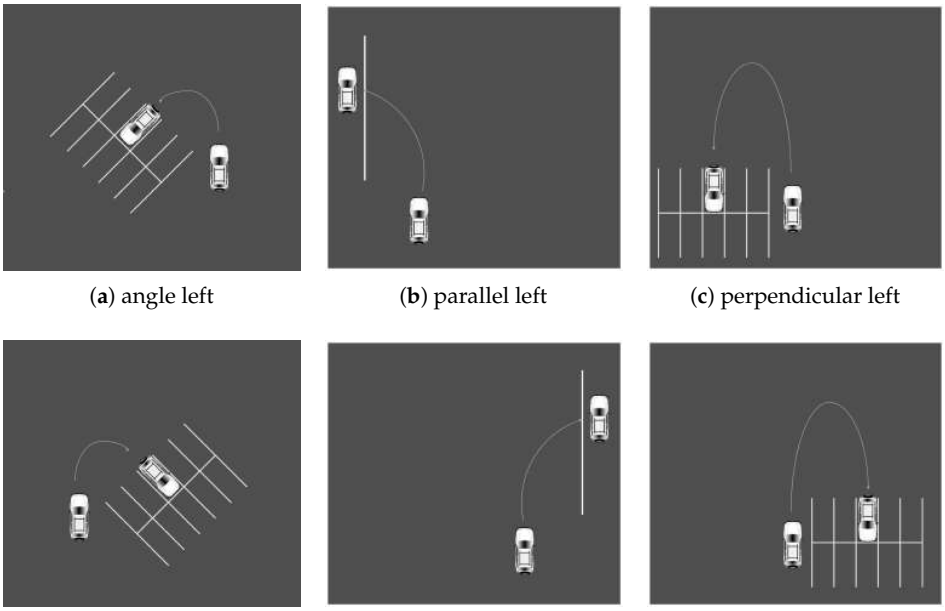
(**a**) Right (**b**) Straight (**c**) Left

Figure 3. Roundabout scenarios such as 'right', 'straight', and 'left', (**a**–**c**), respectively.



(**a**) Right (**b**) Straight (**c**) Left

Figure 4. Crossroad scenarios such as 'right', 'straight', and 'left', (**a**–**c**), respectively.



(**a**) angle left (**b**) parallel left (**c**) perpendicular left

(**d**) angle right (**e**) parallel right (**f**) perpendicular right

Figure 5. Parking scenarios such as 'angle left', 'parallel left', 'perpendicular left', 'angle right', 'parallel right', and 'perpendicular right', (**a**–**f**), respectively.

3.1.3. Distracting Driving Activities

The second investigation focused on secondary or distracting driving activities. They represent all actions that are performed when operating a vehicle that are not related to actual driving. However, they affect performance quality. These actions were carried out in a setting similar to sitting behind a wheel because they do not require being in a vehicle. This section of the study introduced four scenarios: eating, drinking, turning, and bending. Actions are explained in detail in Table 1.

Table 1. Secondary driving activities scenarios.

Eating	Drinking	Turning	Bending
Taking a bite of any food.	Taking a sip of water.	Turning back and reaching to a passenger's seat.	Bending and picking up a fallen object.

3.1.4. Data Format and Label Information

First, the data acquisition parameters are presented, followed by the header describing the content of each column that contains the sample number, the date in the format: dd.mm.rrrr:hh:mm:ss, and then the 3 channel accelerometer components:

- $ACC_{X,Y,Z}$:= acceleration on the X, Y, and Z axes.

Followed by the EOG sensor components:

- $EOG_{L,R}$:= raw EOG signal from the left and right eye, respectively;
- EOG_H := the difference between the left and right eye potential ($EOG_L - EOG_R$);
- EOG_V := negative arithmetical mean of the left and right eye potential $-$ (EOG_L + EOG_R)/2.

A list of dataframes comprising one sample signal is created by successively reading the data from the relevant path by folders. To accurately describe all signals, the rows containing the parameter specifications are removed, and the header is fixed. The labels for the primary activities are presented in Table 2.

Table 2. List of activities for which data were collected in this study (driving activities), using JINS MEME ES_R Smart Glasses.

Label	Activity
0	P_Crossroad_Left
1	P_Crossroad_Right
2	P_Crossroad_Straight
3	P_Parking_Diagonal_Left
4	P_Parking_Diagonal_Right
5	P_Parking_Parallel_Left
6	P_Parking_Parallel_Right
7	P_Parking_Perpendicular_Left
8	P_Parking_Perpendicular_Right
9	P_Roundabout_Left
10	P_Roundabout_Right
11	P_Roundabout_Straight
12	S_Bending
13	S_Drinking
14	S_Eating
15	S_Turning_Back

3.2. Preprocessing

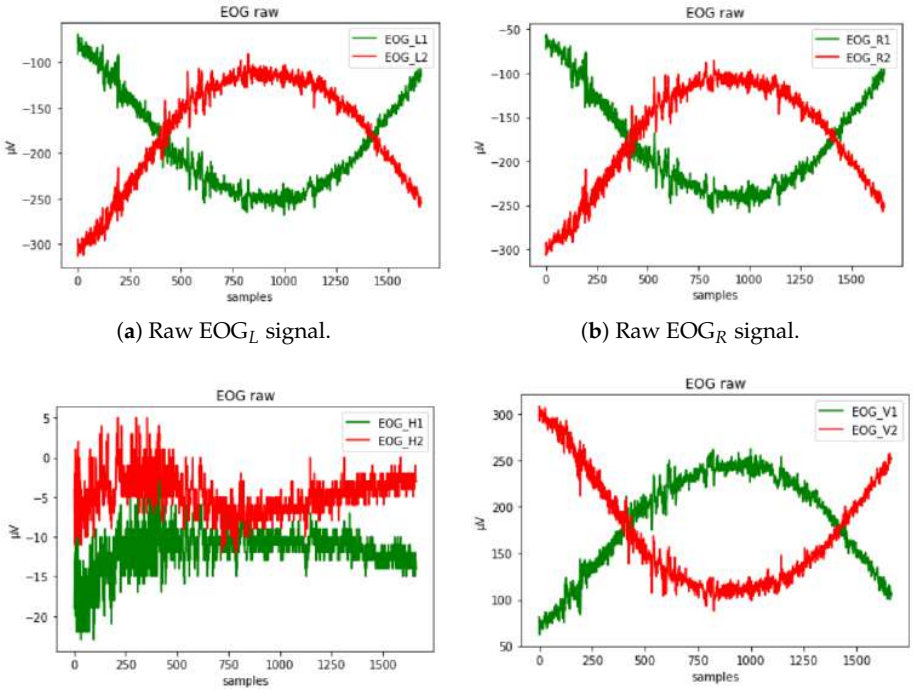
The data collected by smart glasses include signals from the four EOG channels (EOG_L, EOG_R, EOG_H, and EOG_V), three axes of the accelerometer (ACC_X, ACC_Y, and ACC_Z) and three axes of the gyroscope ($GYRO_X$, $GYRO_Y$, and $GYRO_Z$).

The signals collected by these sensors are often contaminated by noise and artifacts. For example, EOG channels can pick up electrical signals from the surrounding environment, which can cause baseline drift and power line noise. Linear and angular acceleration can be affected by vibrations or other disturbances, which can cause errors in measurements. To address these issues, various preprocessing techniques were applied to the data, which involves applying mathematical operations to the signals to remove unwanted components.

The first step of preprocessing was to apply a low-pass filter to remove power line noise (50 or 60 Hz, depending on the country) and baseline wandering. The next step was to use a band-pass filter to remove DC components of the EOG signal caused by electrode polarization.

After preprocessing the data, they can finally be analyzed using the statistical analysis and machine learning technique. Clean data provide valuable associations of changes in the EOG signal in the recognition of human behavior or cognition.

The raw EOG signal presented in Figure 6 contains different types of artifacts that must first be filtered out. To reduce the noise from electricity lines and other potential types of noise, a second-order low-pass Butterworth filter is used to filter the EOG signal. It is applied to the signal twice: once forward and once backward. Such a filter has twice the order of the initial filter and zero phase. In addition, a slow unrelated alteration that is superimposed on the EOG signal, known as a baseline drift, might appear. It could be caused by a variety of things, including electrode polarization or interference with background signals [64]. To eliminate this effect, we have applied detrending by differentiating.



(**a**) Raw EOG_L signal. (**b**) Raw EOG_R signal.

(**c**) Raw EOG_H signal. (**d**) Raw EOG_V signal.

Figure 6. Raw EOG signal in channels EOG_L, EOG_R, EOG_H, and EOG_V shown in (**a**–**d**), respectively.

Linear acceleration signal in three axes undergoes preprocessing that consists of applying a median filter and a low-pass filter. The purpose of the median filter is to remove short irregular peaks. Since vigorous voluntary head rotations typically have frequencies below 20 Hz, a low-pass filter is applied to remove components with lower frequencies. However, this type of filter can introduce unwanted distortions while preserving low frequencies. To make the most of both techniques, they are combined by first applying the median filter and then passing the resulting signal through a low-pass filter with a Hamming window. A disadvantage of this approach is the potential weakening of values at the signal edges. However, these values were excluded due to the potential presence of noise caused by human control.

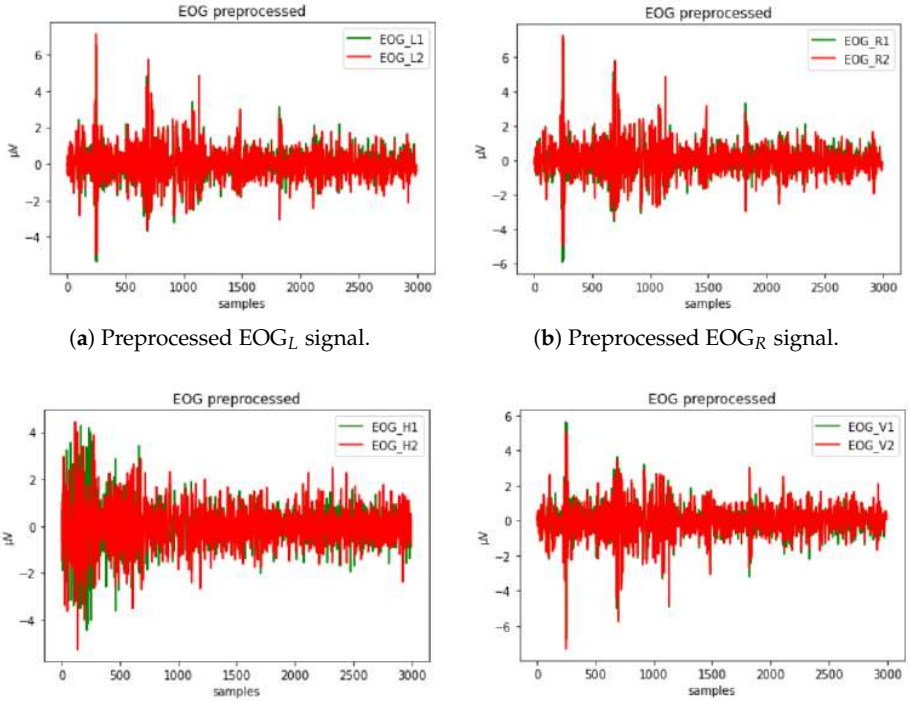
The entire dataset was then independently normalized using Z-score normalization. Z-score normalization helps distinguish the rest values and the values related to activities. The mean and standard deviation of each signal are calculated, and the samples values are replaced with the newly determined values using the following formula:

$$x' = (x - \mu)/\sigma, \tag{1}$$

where μ is the mean of the signal, σ is the standard deviation, x is the current value of a sample, and x is the new value, so that the new mean of all values is 0 and the standard deviation is 1.

A sliding time window technique was used to segment all normalized sensor signals, with a window length of 5.6 s (280 samples) and a 50% stride (140 samples). Final samples were eliminated if the signal length was not divisible by 140.

Completing some tasks required more time than for the others. Also, depending on the precision of the driver, the acquired signals had different lengths. The shortest one was obtained for secondary activity Turning back and lasted 103 samples (2.06 s); the longest one was for primary activity, while taking a left turn at a roundabout was 3013 samples (60.26 s) long. To train the model, the signal data were resampled at a rate of 3000. The results of signal preprocessing are shown in Figure 7.



(**a**) Preprocessed EOG_L signal. (**b**) Preprocessed EOG_R signal.

(**c**) Preprocessed EOG_H signal. (**d**) Preprocessed EOG_V signal.

Figure 7. Preprocessed EOG signal in channels EOG_L, EOG_R, EOG_H, and EOG_V shown in (**a**–**d**), respectively.

3.3. Classification

In this study, we used 1D CNN for feature learning and classification. Multiple convolutional operators in CNN allow automatic recognition of important features from a higher-dimensional input [65–68]. Convolutions offer the advantage of taking into account the spatial organization of the data. In doing so, additional information about the position in relation to other samples is expected to be taken into account.

The 1D CNN can be used to analyze time series with one or more variables. The latter scenario involves combining two or more concurrent signals. On the basis of our previous experiments, we segmented the data using the sliding window segmentation technique (SWS). Different settings were tested to select the length T and stride size ΔS of a time window and the best values were chosen empirically. In 1D CNN, the only samples with an inherent ordering are those along the time dimension. The channels for the various variables do not have this, in contrast to the most popular 2D CNN.

The basic architecture of a CNN model is shown in Figure 8 and the parameters used in the 1D CNN are shown in Table 3. The first dimension of the input and output data is the batch size, the second dimension is the length of the sequence, and the third dimension is the number of features. The batch size was 32, the number of epochs was 100, and the learning rate (lr) was set to 2×10^{-4}.

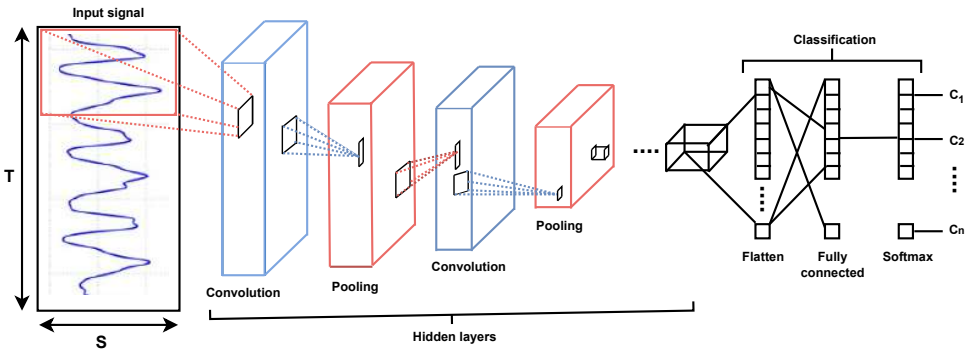


Figure 8. General architecture of a convolutional neural network for time series data classification. T represents time window, S represents the number of sensor channels, c represents a class, and n represents the number of classes.

Table 3. CNN architecture with a fixed dropout rate of 0.4 and a minimum learning rate of 2×10^{-4}.

Layer Name	No. Kernels (Units)	Kernel (Pool) Size	Stride Size	Activation
Convolution	128	5	1	ReLU
Batch norm	-	-	-	-
Max pooling	-	3	-	-
Convolution	128	5	1	ReLU
Batch norm	-	-	-	-
Convolution	128	5	1	ReLU
Batch norm	-	-	-	-
Global avg. pooling	-	-	-	-
Dense	2	-	-	Softmax

In terms of functionality, the model can be divided into two parts. The first component, common for this type of network, acts as a feature extractor. It matches templates using convolutional filtering techniques. To create the so-called "feature maps", it uses layers and functions that include a convolutional layer, a batch normalization layer, a ReLU activation function, and a pooling layer. The network can learn higher-level features by being trained on a large dataset using a suitable number of epochs and a learning rate.

The second component is the categorization into one of the output classes. The input vector values are first reshaped using the global average pooling layer, a further dropout layer to prevent the model from overfitting, and a dense layer with the "softmax" activation function, which assigns the final label representing the predicted class value by performing a matrix vector multiplication. This process results in a new vector at the output.

3.4. Evaluation

The performance of the classifier was expressed in the form of tables with with the numbers of accuracy, precision, recall, and F1 score and confusion matrix.

Accuracy presents the percentage of correct predictions relative to all predictions made.

$$\text{Accuracy} = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \times 100\%, \tag{2}$$

where:

- True positive (t_p)—correctly classified trials;
- False positive (f_p)—incorrectly classified trials;
- True negative (t_n)—correctly classified nonevent trials;
- False negative (f_n)—incorrectly classified nonevent trials.

Precision is a metric that identifies the successful predictions of all predictions made in favor of the event.

$$\text{Precision} = \frac{t_p}{t_p + f_p} \tag{3}$$

Recall presents the fraction of correctly classified predictions of a particular activity with respect to all predictions made in favor of the activity.

$$\text{Recall} = \frac{t_p}{t_p + f_n} \tag{4}$$

The F1 score is a harmonic mean of precision and recall, which, compared to accuracy, should provide a more realistic model assessment in multiclass predictions with unbalanced classes.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

Categorical cross-entropy loss measures the model performance by comparing the actual and predicted labels according to the formula:

$$\text{CE} = -\sum_{i=1}^{N} t_i \times log(p_i), \tag{6}$$

where t is the true label, p the predicted label, and N the number of scalar values in the model output.

Linear acceleration and EOG signals that had already been analyzed were used to train and assess the network. A 9:1 ratio was used to divide the data into subsets for training and testing. A further division with 8:2 ratio was used on the training set to divide it into training and validation sets. Since the signals were sorted, the data had to be shuffled to train the model on signals from all possible classes.

4. Results

Accuracy and Loss While Training

Figure 9 shows the accuracy curve for training and validation, and loss of the model with respect to the number of epochs elapsed. The loss function is categorical cross-entropy. When the epoch reached 130, the training accuracy was found to be greater than 90%, providing a loss value of 0.2. The validation rate was 80% with a loss of 0.6. The model obtained the optimal parameters in 188 epochs.

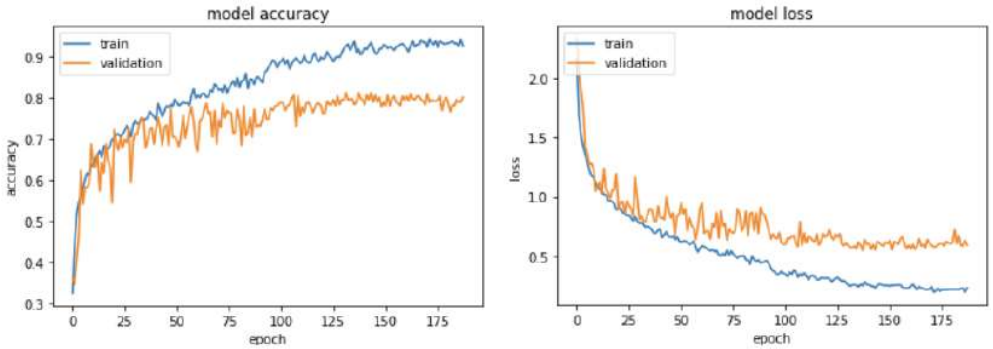
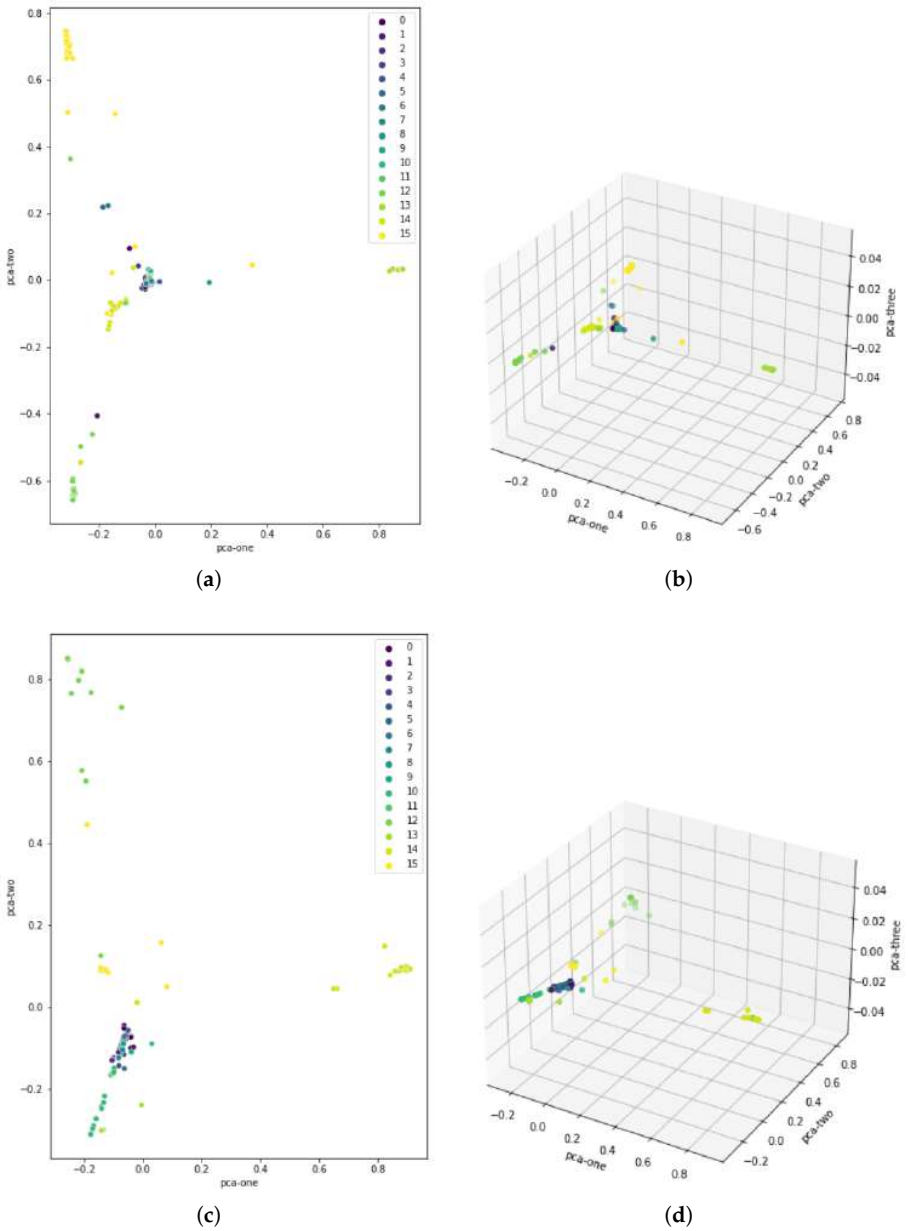


Figure 9. Accuracy and loss curve of the CNN model during the training and validation phases.

Figure 10 shows how well the classes were segregated after 188 epochs in dimensions 2 and 3. A dimensionality reduction method known as principal component analysis (PCA) was used for visualization purposes. The correlation between different dimensions is used, and the goal is to provide as few variables as possible while preserving as much variation or information about the distribution of the original data as possible.



(**a**) (**b**)

(**c**) (**d**)

Figure 10. Scatter plot of the training and testing sets according to predicted labels: (**a**) 2D scatter plot of training set labels; (**b**) 3D scatter plot of training set labels; (**c**) 2D scatter plot of testing set labels; (**d**) 3D scatter plot of testing set labels.

It can be seen that the distinction between primary and secondary driving activities is very apparent. The latter are also separated in such a way that they usually do not overlap. However, primary activities cover areas very close to each other, so the greatest misclassifications are anticipated.

The distinction between primary and secondary driving activities is readily apparent, as can be seen. The latter are divided in such a way that they do not primarily overlap. The greatest misclassifications were expected for groups of similar primary activities that covered areas that are relatively close to each other.

All activity predictions shown in Table 4 had a weighted average precision, recall, and F1 score of 0.83, 0.80, and 0.80, respectively. Drinking as a secondary activity is the category that has the best performance with all values equal to 1, while primary parallel

parking on the left and perpendicular parking on the right are the categories that are mostly misclassified with F1 scores 0.42 and 0.44, respectively. In general, secondary driving actions performed better, all receiving F1 scores greater than 0.9.

Table 4. Evaluation results (such as precision, recall, and F1 score) of driving activities.

Label	Activity	Precision	Recall	F1 Score
0	P_Crossroad_Left	1.00	0.67	0.80
1	P_Crossroad_Right	0.75	0.75	0.75
2	P_Crossroad_Straight	0.75	0.90	0.82
3	P_Parking_Diagonal_Left	0.67	0.75	0.71
4	P_Parking_Diagonal_Right	0.50	0.50	0.50
5	P_Parking_Parallel_Left	0.44	0.40	0.42
6	P_Parking_Parallel_Right	0.86	0.60	0.71
7	P_Parking_Perpendicular_Left	0.38	1.00	0.55
8	P_Parking_Perpendicular_Right	1.00	0.29	0.44
9	P_Roundabout_Left	1.00	0.88	0.93
10	P_Roundabout_Right	0.82	0.86	0.84
11	P_Roundabout_Straight	0.86	0.75	0.80
12	S_Bending	0.95	0.90	0.93
13	S_Drinking	1.00	1.00	1.00
14	S_Eating	0.90	0.95	0.93
15	S_Turning_Back	0.88	0.94	0.91

The accuracy of the prediction of 15 driving actions is shown in Figure 11, where the accuracy of the prediction of each class is shown on the diagonal and inaccurate classifications are shown outside the diagonal.

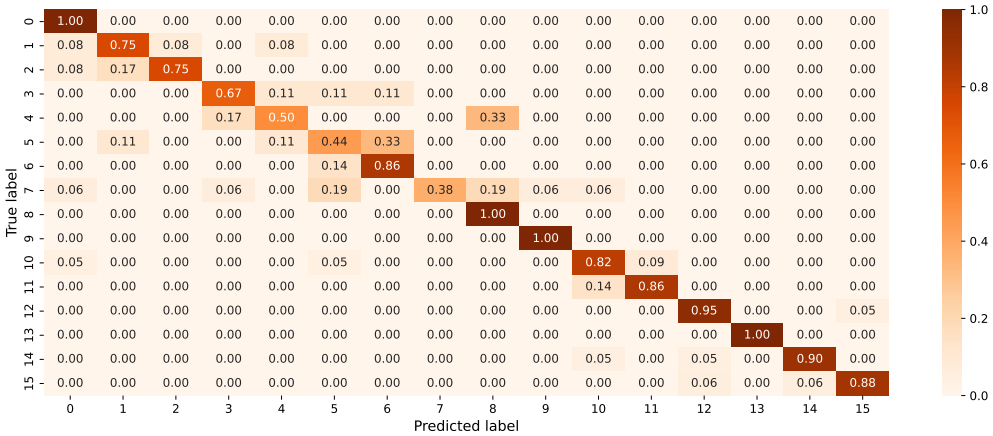


Figure 11. Confusion matrix of the driving activities classification.

Most misclassifications occurred in a group of activities that were related to each other. Parking activities show that the model had the most trouble detecting the difference between the same action being conducted on the left and right sides due to their similarity. The binary classification between secondary and primary activities has an accuracy rate of 99.5%. Although the latter was mistakenly classified as eating, the former was consistently assigned to the appropriate group.

An investigation of classifications for a particular collection of activities, including crossroad, parking, roundabout, and secondary activities, yielded accuracy ratings of 97.9%, 96.8%, 97.4%, and 99.5%, respectively. Table 5 displays these results together with the precision, recall, and F1 score values. Although the network received these actions

as individual activities, it was still able to indicate patterns that differentiate the different types of action.

Table 5. Evaluation scores such as accuracy, precision, recall, and F1 scores, of the type-based classification.

Activity	Accuracy [%]	Precision	Recall	F1 Score
Crossroad	97.9	0.97	0.91	0.94
Parking	96.8	0.92	0.96	0.94
Roundabout	97.4	0.94	0.92	0.93
Secondary	99.5	0.99	1.00	0.99

5. Discussion

Electrooculography (EOG) is a technique that is based on electrical features generated by the eye. By measuring the voltage difference between the cornea and the retina, it aims to capture the movements of the eyes [37]. JINS MEME ES_R Glasses (JINS Inc., Tokyo, Japan) are a smart glasses device that consists of a three-point electrooculography (EOG) and a six-axis inertial measurement unit (IMU) with a gyroscope and an accelerometer. They acquire ten channels: linear and angular acceleration on the X, Y, and Z axes, and four EOG channels: electric potentials on the electrodes on the right (EOG_R) and left (EOG_L), and the vertical (EOG_V) and horizontal (EOG_H) difference between them [61,69,70].

We have recognized road conditions based on electrooculograms acquired from drivers wearing JINS MEME ES_R smart glasses. The highest precision, recall, and F1 score for drinking (1.00 for each metric) were observed, whereas the lowest results were observed for parallel parking on the left side (precision of 0.44, recall of 0.4, and F1 score of 0.42).

Most misclassifications occurred in a group of activities that were related to each other, e.g., parking on the left and parking on the right side due to their similarity. The binary classification between secondary and primary activities has an accuracy rate of 99.5%. Although the latter was mistakenly classified as eating, the former was consistently assigned to the appropriate group.

In this study, the recognition of primary and secondary driver activities based on the processing of EOG signals with a convolutional network achieved excellent recognition performance, but there are still some limitations. The first limitation was to obtain the EOG signals in a simulated driving experiment. Although the experimental results showed that the turn or park condition was successfully induced and verified the effectiveness of the experimental scheme, it cannot be compared with the complexity of driving in real traffic. The second limitation was the limited number of experimental data segments. This setup could be used in future studies that do not expose volunteers to the dangers of real traffic. Classification models were trained on short signal samples. The third limitation was the use of only one time window width (5.6 s) to calculate the EOG characteristics without fully examining the impact of other time window divisions on the classification results.

6. Conclusions

In this paper, we introduced a CNN-based machine learning model to classify nine primary and four secondary car driver activities using physiological sensor data from JINS MEME ES_R (smart glasses):

1. We conducted a comparative analysis of wearable sensor data, including nine activities performed by the first driver and four activities performed by the second driver. Our proposed system achieves an impressive overall accuracy of 97% (±2) and an average F1 score of 95% (±2) in detecting these activities. Moreover, our model has the potential to prevent traffic accidents without requiring expensive safety equipment. To further validate our approach, future studies will involve acquiring additional data from real-world road conditions. Such an application would be beneficial for drivers, particularly older individuals or those with disabilities.

2. Research involves a comparative analysis of wearable sensor data obtained from different driving activities in various scenarios. By analyzing the signals collected from these sensors, researchers can assess the different activities performed by drivers, gaining insight into driver behavior and activity patterns in various driving scenarios. The developed system holds promise in preventing traffic accidents without the need for costly safety equipment.
3. Our investigation focuses on the utilization of sensor data from JINS MEME ES_R smart glasses and the development of an advanced machine learning model that can identify and classify primary and secondary activities of drivers. This state-of-the-art model learns the patterns associated with these activities and assigns them to their respective classes.
4. The use of JINS MEME ES_R sensor data involves analyzing and recognizing activities and scenarios associated with driving a vehicle. By integrating data from these wearable glasses, we created an efficient machine learning model that can learn activity patterns and accurately classify them into respective classes. This novel approach to the use of wearable sensor data offers valuable insights into driver behavior and activity recognition.
5. A notable contribution of this research is the realistic and noninvasive collection of data. The use of JINS MEME ES_R smart glasses provides a user-friendly and noninvasive method for gathering data during experiments. Unlike intrusive methods, these glasses capture data from the driver's perspective without causing discomfort or interfering with the driving experience. This noninvasive approach ensures that the collected data closely resemble real-world driving scenarios, allowing for more precise analysis and classification of driver activities. By addressing the challenge of obtaining realistic data while prioritizing participant safety and comfort, this research underscores the importance of using such technology.

In summary, the main contributions of this research involve the utilization of JINS MEME ES_R sensor data, development of a machine learning model for activity recognition, comparative analysis of wearable sensor data, and a review of related approaches. These contributions improve understanding of driver behavior and activity recognition, potentially leading to improved driver safety and accident prevention when the time comes when autonomous car traffic with the participation of human drivers will become commonplace on the roads.

Author Contributions: Conceptualization, R.D. and J.K.; methodology, R.D.; software, J.K. and R.D.; validation, R.D. and J.K.; formal analysis, R.D., J.K. and M.T.I.; investigation, R.D., J.K. and M.T.I.; resources, R.D.; data curation, J.K. and R.D.; writing—original draft preparation, R.D. and J.K.; writing—review and editing, R.D., S.S., M.T.I., A.P. and M.G.; visualization, R.D., J.K., N.P., M.T.I., M.A.H. and A.P.; supervision, R.D., S.S., F.L., M.A.N. and M.G.; project administration, R.D. and M.G.; funding acquisition, R.D. and M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received funding for car simulator from the pro-quality grant 57/2021 of the Rector of the Silesian University of Technology, Gliwice, Poland; decision number ZP/165980.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and the protocol was approved by the Bioethics Committee of the Medical University of Silesia on 16 October 2018 (KNW/0022/KB1/79/18).

Informed Consent Statement: All subjects gave their informed consent for inclusion before they participated in the study. The authors thank all participants in the experiment.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy concerns.

Conflicts of Interest: The authors declare no conflict of interest.

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Classification of Roads and Types of Public Roads Using EOG Smart Glasses and an Algorithm Based on Machine Learning While Driving a Car

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Abstract: Driving a car is an activity that became necessary for exploration, even when living in the present world. Research exploring the topic of safety on the roads has therefore become increasingly relevant. In this paper, we propose a recognition algorithm based on physiological signals acquired from JINS MEME ES_R smart glasses (electrooculography, acceleration and angular velocity) to classify four commonly encountered road types: city road, highway, housing estate and undeveloped area. Data from 30 drivers were acquired in real driving conditions. Hand-crafted statistical features were extracted from the physiological signals to train and evaluate a random forest classifier. We achieved an overall accuracy, precision, recall and F1 score of 87.64%, 86.30%, 88.12% and 87.08% on the test dataset, respectively.

Keywords: car driving; classification; electrooculography; machine learning; smart glasses; wearable devices

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Citation: Doniec, R.; Piaseczna, N.; Li, F.; Duraj, K.; Pour, H.H.; Grzegorzek, M.; Mocny-Pachońska, K.; Tkacz, E. Classification of Roads and Types of Public Roads Using EOG Smart Glasses and an Algorithm Based on Machine Learning While Driving a Car. *Electronics* **2022**, *11*, 2960. https://doi.org/10.3390/electronics11182960

Academic Editors: Juan M. Corchado, Stefanos Kollias and Javid Taheri

Received: 31 July 2022
Accepted: 13 September 2022
Published: 18 September 2022

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1. Introduction

The ability to move (mobility) is essential in our daily lives nowadays. One of the most widely used means of transportation is cars due to the increased convenience they provide compared with other means, such as public transport.

Statistics show that the estimated number of worldwide car sales has followed a constant increasing trend over the past 10 years, with the exception of the period between 2020 and 2021 that corresponded to the COVID-19 pandemic lockdown time [1]. Despite this, car sales started to raise again in 2021 after the end of most lockdown-related restrictions.

This increased usage of cars has led to a need for further exploration of car-related research areas, including driver behavior analysis [2] in relation to traffic, safety [3] and environmental issues [4–6].

Driving a car is an activity that involves many neural circuits in the brain that are related to visual-motor coordination, episodic and procedural memory, visual search and executive functions such as the ability to plan, change the strategy of conduct or initiate and inhibit reactions [7]. Most of the information that reaches the driver while driving a car takes place through the visual system, due to the need to perceive signs, objects, people or events [8]. Therefore, proper visual and motor coordination of the driver is necessary [9].

There are undeniable differences in road behavior between a driver who is just learning to drive and one who is already experienced [10]. An experienced driver performs the basic

driving activities (e.g., turning the steering wheel, shifting gears or pressing the pedals) automatically without paying special attention to them. Analyzing the driving styles and behaviors of both new and experienced drivers could lead to insightful findings for the future development of the automotive industry by taking advantage of the advances in driving, which could be made economical and safer [11,12]. Research on driving style analysis in particular has possible applications to logistics, the transport industry, car insurance companies, government regulatory organizations, the controlled development of infrastructure and public transport [13].

One specific field of interest of driving style analysis is accident detection. According to a WHO report in 9 February 2004, road accidents are a major but neglected public health challenge that requires a concerted effort toward effective and sustainable prevention. Of all the systems people deal with on a daily basis, road traffic systems are the most complex and dangerous. It is estimated that 1.2 million people worldwide are killed in road accidents and as many as 50 million are injured each year. These numbers are projected to increase by around 65% over the next 20 years unless a new prevention commitment is made [14].

Studies on the topic of accident detection can be divided into two main categories. The first category focuses on accident prevention based either on the recognition of cognitive activities using wearable sensors during driving [15], detection of the road type using either vision-based or car internal sensors [16] or the monitoring of specific dangerous events during driving (e.g., wrong-way driving or a drop in vigilance) using either wearable or vision-based sensors [17–19]. The second category investigates the topic of post-crash detection for either the dispatching of emergency services [20,21] or as an inspection tool for car-renting companies [22–24].

In this paper, we investigate the first category of work through the topic of road type detection. To the best of our knowledge, the number of past studies regarding this topic is very limited, and they exclusively use either vision-based or car internal sensors. Jo et al. for instance [25] proposed a vehicle-tracking and behavior-reasoning algorithm to provide advanced driver assistance using LIDAR, radar and RGB camera data to obtain insight on the surroundings of the vehicle. Ramanishka et al. [26] introduced the *Honda Research Institute Driving Dataset* , a dataset combining RGB and car modalities (GPS, LIDAR, CAN-Bus and IMU sensors) in suburban, urban and highway environments to help researchers investigate the topic of automated driving scene analysis. Finally, many other studies have been proposed in the past to automatically analyze the surroundings of a vehicle without necessarily directly classifying road types. Examples include the monitoring of cars in neighboring lanes in a highway environment [27] or of weather or traffic conditions in highway and urban environments [28]. It can be noted from the aforementioned work that the topic of road type detection using wearable devices is still unexplored.

We therefore propose a system for the automatic detection of road types based on applying state-of-the-art machine learning techniques on physiological data acquired from a pair of smartglasses. We use in our study the *JINS Meme* glasses (Jins Inc., Tokyo, Japan) that record electrooculography (EOG), characterizing eye movements, and the linear acceleration and angular velocity, characterizing head movements. The data acquired by such a device have been shown to be useful for recognizing cognitive activities in a driving context in past studies [15]. We try to verify if road type detection is possible on the basis of solely using wearable modalities in particular, without any assistance from other external sensors such as car internal sensors. To the best of our knowledge, this study is the first to tackle this specific classification problem exclusively using physiological sensor modalities.

To abstract the problem of road type detection from a machine learning point of view, we translate it into a classification problem and solve it using standard supervised learning techniques, following the standard pattern recognition chain that comprises the following steps [29]:

- **Data acquisition:** the choice and set-up of sensors and design of an experimental set-up;

- **Data processing:** operations to clean the data such as noise removal, filtering, synchronization and segmentation;
- **Feature extraction:** computations of specific values in the data that carry a specific relevance for the classification problem to be solved;
- **Classification:** training and evaluation of a classifier operating on vectors of the features previously extracted.

In particular, we focus on four types of areas to recognize: a city, a highway, a housing estate and an undeveloped area [30]. We manually extracted statistical features from the data following our past observations that more complex feature-learning methods using deep neural networks tend to not necessarily produce better results for problems where physiological time series data are involved and data are relatively scarce [22,31]. Using these features, we perform a comparative study of the most widely used state-of-the-art classifiers and a feature analysis based on the computation of feature importance scores using ANOVA.

To summarize, the main contributions of our paper are as follows:

- We perform a machine learning study for the classification of four different road types (city road, highway, housing estate and undeveloped area) using manually crafted features extracted from physiological signals (EOG, acceleration and angular velocity) acquired from smart glasses worn by the driver;
- We perform a comparative experiment involving several state-of-the-art classifiers to find the best configuration for the classification problem to be solved;
- We perform feature selection with ANOVA to determine what the top-performing features are for the classification problem at stake.

The rest of our paper is structured as follows. The materials and methods used in our study are first described in Section 2. The results of our experiments are presented in Section 3 and discussed in Section 4. Finally, a conclusion and comment about future outlooks are provided in Section 5.

2. Materials and Methods

2.1. Technology Used

For the data acquisition, we used JINS MEME smart glasses, a device furnished with three-point EOG and a six-axis inertial measurement unit (IMU) with an accelerometer and a gyroscope [15,32]. The sampling frequency of the acquired signals was 100 Hz. The data were transmitted to a computer via Bluetooth or USB and could be exported to a CSV file.

For the data preparation and classification, we used MATLAB R2022a. The models were trained using a PC with an Intel(R) Core(TM) i5-9300H CPU processor and 16 GB of RAM.

2.2. Data Acquisition

A dataset of physiological data obtained by the JINS Meme smart glasses (i.e., EOG, IMU linear acceleration and angular velocity), was acquired for this and previous related studies [8,33]. The study was conducted in accordance with Chapter 4 of the Act on Vehicle Drivers of the Republic of Poland and with the permit issued by the Provincial Police Department in Katowice. Before the study, the volunteers presented all the necessary documents confirming that they were allowed to participate in road traffic. The participants voluntarily gave their informed consent to participate in the study.

Data were acquired under real road conditions from 30 healthy subjects, including 20 experienced drivers and 10 students attending a driving school [34–36]. There were 16 males and 14 females with an average age of 38 ± 17 who participated in the study. The complete dataset is available at the IEEE *DataPort* [37].

Each participant performed a driving test on a route of 28.7 km, which took approximately 75 min. The route was localized in the Silesian Voivodeship (southern Poland) in the cities of Tarnowskie Góry, Radzionków, Bytom, and Piekary Śląskie. The course of

the route was determined in consultation with the driving instructor and on the basis of the rules of practical driving tests in Poland. While performing a test, the driver was wearing the smart glasses. The set-up of the experiment is presented in Figure 1.



Figure 1. Experiment set-up.

All data were labeled during the drive and then divided the into four groups regarding the type of the road (1: highway; 2: city road; 3: undeveloped area; 4: housing estate). The labeling process was performed manually by simply putting a marker when the particular type of road started and ended.

2.3. Data Preparation

The data acquired from smart glasses include signals from three axes of the accelerometer (ACC_X, ACC_Y and ACC_Z), signals from three axes of the gyroscope ($GYRO_X$, $GYRO_Y$ and $GYRO_Z$), and the four channels of the EOG signal (EOG_L, EOG_R, EOG_H and EOG_V). Table 1 contains general statistics for all the acquired signals.

Table 1. Dataset description: general statistics.

Signal	Minimum	Median	Maximum	Mean	Standard Deviation
ACC_X	–12,083	340	19,519	1070.2	1616.9
ACC_Y	–32,767	–453	19,199	–1342.9	1853.3
ACC_Z	–32,768	–2128	32,767	–8230.8	7017.4
$GYRO_X$	–10,575	12	2519	11.8098	141.3119
$GYRO_Y$	–3465	3	4427	3.1471	132.9203
$GYRO_Z$	–10,279	14	10,073	10.7835	345.0692
EOG_L	–2048	470	2047	379.7323	640.3718
EOG_R	–2048	–69	2047	41.6679	730.8121
EOG_H	–4080	189	4095	338.0645	825.8395
EOG_V	–2047	–61	2048	–210.6461	548.9904

The magnitude of the acceleration was computed using the Euclidean norm of the 3D acceleration, as shown in Equation (1) [38]:

$$ACC = \sqrt{ACC_X^2 + ACC_Y^2 + ACC_Z^2} \quad (1)$$

All signals were then filtered using the third-order median filter and rescaled to the range [0 1] using min-max normalization, as specified in Equation (2):

$$X_{\text{rescaled}} = \frac{X - \min_X}{\max_X - \min_X}, \tag{2}$$

where the min and max values were determined for each signal. All normalized sensor signals were then segmented with a sliding time window approach with a window length of 1 s (100 samples) and a 50% stride (50 samples). We applied the original label to each window. If the signal length was not divisible by 50, then the last samples were discarded.

2.4. Feature Extraction

For this problem, we decided to apply traditional feature engineering. For each window, the following features were calculated:

- μ and σ of a normal distribution fitted to the data [39];
- Skewness and kurtosis;
- Minimum and maximum value.

The feature extraction process resulted in 36,669 feature vectors of 48 dimensions (6 features for each of the 8 sensor channels) that were used to train, validate and test the classifiers.

Finally, feature selection was also performed using ANOVA on each feature separately to determine which ones maximized the distance between the four classes we used in our problem. Figures 2 and 3 present the F scores and associated *p*-values, respectively, for each feature on which ANOVA was applied.

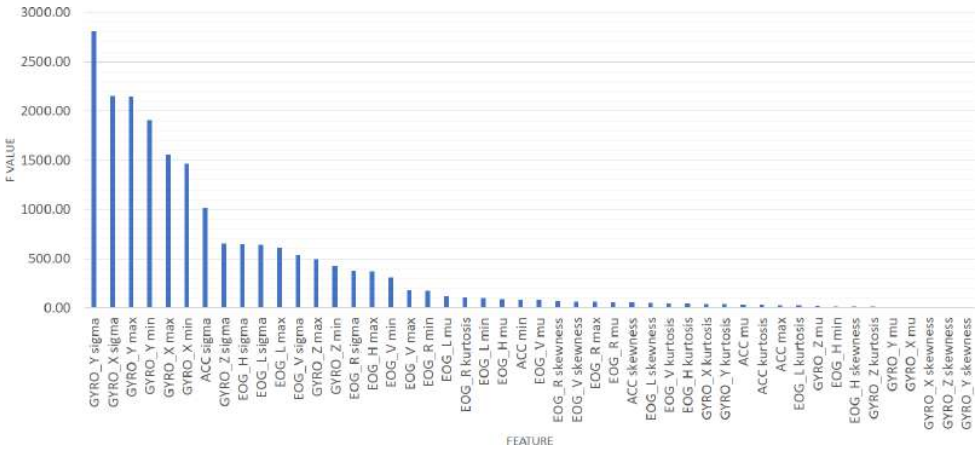


Figure 2. All features ranked by decreasing ANOVA F scores.

Through the trial-and-error method, it was decided to select the 30 features that maximized the ANOVA F score, as it was the configuration that produced the best results.

2.5. Classification

For this study, we used a tool available in MATLAB called Classification Learner [40]. It enabled quickly training, validating and testing many classifiers, tuning the parameters and comparing the results. The models available in this tool are different types of widely used supervised machine learning classifiers, whose list is provided below:

- Classification trees;
- Model with Gaussian, multinomial or kernel predictors (nearest neighbors);
- K-nearest neighbor;
- Support vector machine;

- Boosting, random forest, bagging, random subspace and ECOC ensembles for multi-class learning (generalized additive model).

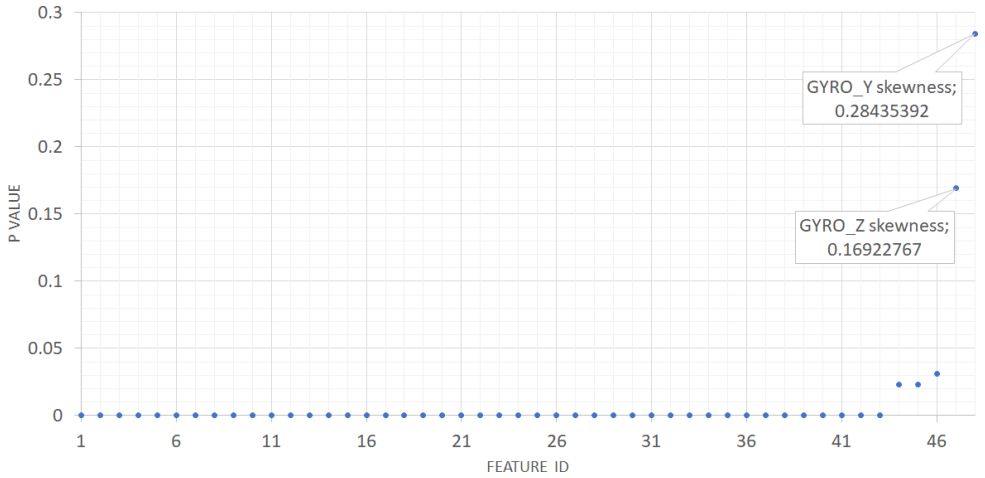


Figure 3. The *p*-Values associated to the ANOVA test for each feature. The features are ranked in order of decreasing F-score. It can be noted that with the exception of two features, all *p*-values were below 0.05, meaning that their associated F-scores were significant.

Data were randomly separated into training, validation and test datasets in proportions of 70%, 20% and 10%, respectively, and the validation scheme was holdout validation. We performed a series of tests on different classifiers and hyperparameters, compared them and chose the one that best handled the problem.

The preliminary experiments showed that most misclassifications were concerning examples from classes 1 and 2. To reduce their numbers and improve the performances of our models overall, we introduced classification penalty costs to make examples belonging to specific classes count more in the computation of the loss during the training of the models. The matrix of such costs is provided in Table 2.

Table 2. Misclassification costs.

		Predicted Class			
		1	2	3	4
True Class	1	0	2	1	1
	2	2	0	1	1
	3	1	1	0	1
	4	1	1	1	0

Table 3 presents the comparison of the overall performance parameters of the four best classifiers from the initial tests. A detailed comparison of results obtained with these classifiers can be found in Appendix A.

Table 3. Comparative evaluation metrics of state-of-the-art classifiers on the test dataset. Bold font indicates best result obtained for each metric.

Classifier	Accuracy	Precision	Recall	F1 Score
SVM	0.74	0.72	0.73	0.72
KNN	0.73	0.72	0.72	0.72
Neural networks	0.77	0.76	0.76	0.76
Ensemble classifiers	**0.84**	**0.82**	**0.85**	**0.83**

The initial tests showed that the problem was significantly better when solved by an ensemble classifier. For this reason, we decided to continue working on improving only this model.

In order to obtain the best possible classification accuracy, we decided to conduct a hyperparameter optimization process. The method was Bayesian optimization, and the acquisition function was expected in terms of improvement per second. Figure 4 shows the process of tuning the hyperparameters.

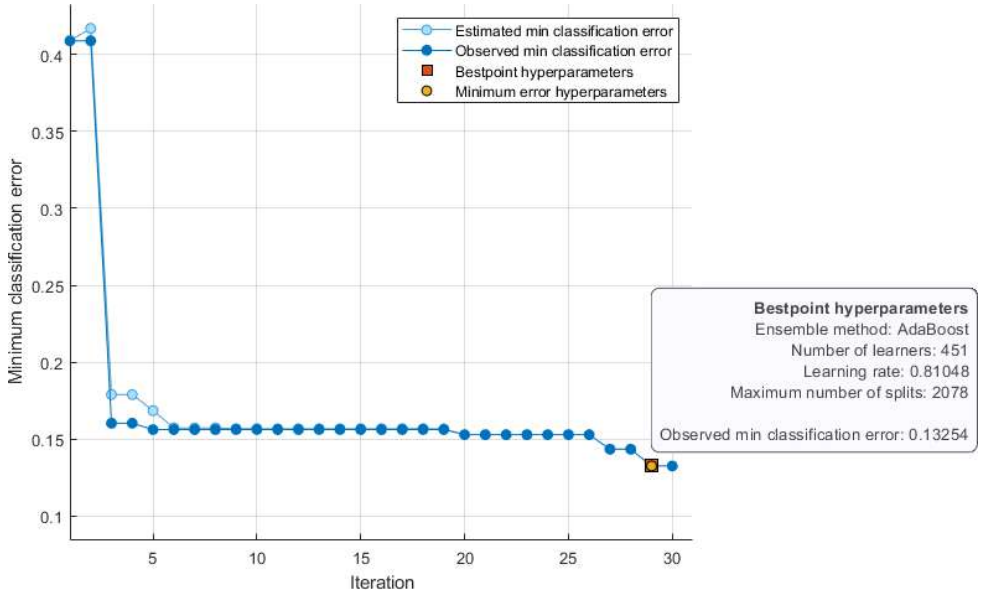


Figure 4. Hyperparameter optimizing process.

In this process, different sets of hyperparameters were tested, and the set with the smallest classification error was selected. The hyperparameters tested include the following:

- Preset: specifies the type of the classifier to be used. The types available were boosted trees, bagged trees, subspace discriminant, subspace KNNs and RUSBoost trees.
- Ensemble method: a method to meld the weak learners into a model with a high-quality. There was a different choice of ensemble methods for each preset.
- Number of learners: this parameter defines a number of weak learners to use in the ensemble;
- Learning rate: regulates the speed of the learning process. Using a smaller learning rate helped to make sure that the model was not overfitted;
- Maximum number of splits: this parameter controlled the depth of the tree learners (i.e., "branch points").

The best classification model that we found was ensemble classification with random undersampling boosted trees (RUSBoosted Trees) [41], a random forest classifier where each weak learner (e.g., decision tree) is trained on a random subset of the whole training set that is undersampled when it comes to the dominant class. More specifically, RUSBoosted Trees iteratively trains a chosen number of weak learners, with each learner being trained on a subset of the training set that underwent two modifications: a random subsampling of the dominant class and a normalized weighting of the examples of the training subset, which is taken into account when computing the loss of the learner. The weights are initialized to follow a uniform distribution for the first iteration and then iteratively updated using an update parameter computed using the loss at the previous iteration. The model hyperparameters that were determined to be optimal in the end were as follows:

- Preset: RUSBoosted Trees;
- Ensemble method: AdaBoost;

- Learner type: decision tree;
- Maximum number of splits: 2078;
- Number of learners: 451;
- Learning rate: 0.81048.

3. Results

To evaluate the relevance of our trained classifier, we calculated some standard evaluation metrics computed from the confusion matrix of the classifier (shown in Figure 5), which presented the number of examples from the test dataset classified into a specific group (predicted label) compared with their real class label (true label).

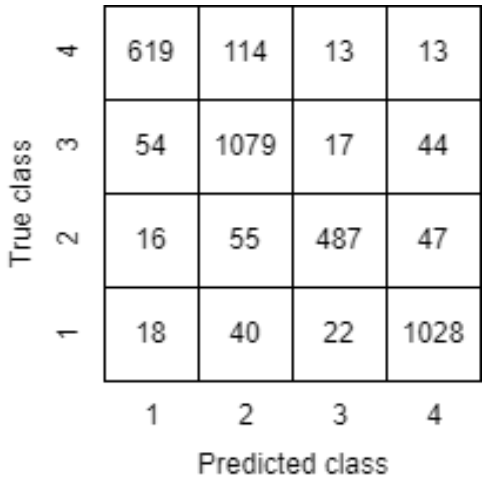


Figure 5. Confusion matrix for the test dataset.

We also compute the accuracy, precision, recall and average F1 score, whose expressions are provided in Equations (3)–(6):

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative}} \quad (3)$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (4)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (5)$$

$$\text{F}_{\text{1-Score}} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

Finally, we used the receiver operator characteristic (ROC) as a tool to assess the correctness of the classifier. It provided a joint description of the sensitivity and specificity; in other words, it can be described as a graph of dependency between the true positive rate and false positive rate [42,43]. In a multi-class model, we could plot the N number of the area under the curve (AUC) ROC curves for the N number of classes using the one vs. all methodology. In our case, we had a class 1 threshold, minimizing or maximizing the distributions overlapping when the AUC was around 0.9, which means that there was a 90% chance that the model would be able to distinguish a positive class from a negative class [44]. For comparison, the work related to driver drowsiness or anger evaluation with the ROC-AUC showed that the AUCs for the models were 0.904, 0.863 and 0.805, related to the threshold balancing classification between the AUC and ROC curves for drowsiness [45], and 0.7914–0.8635 for driver anger evaluation [46]. Figures 6–9 present the ROC curves for all four classes.

The values obtained for all the aforementioned evaluation metrics (accuracy, precision, recall, average F1 score and AUC) are provided in Table 4.

Table 4. Performance parameters for the test dataset.

Type of Road	Accuracy	Precision	Recall	F1 Score	AUC
Highway	0.8755	0.8155	0.8755	0.8445	0.98
City road	0.8377	0.9037	0.8377	0.8695	0.97
Undeveloped area	0.9035	0.8050	0.9035	0.8514	0.99
Housing estate	0.9081	0.9278	0.9081	0.9179	0.99
Overall	0.8764	0.8630	0.8812	0.8708	

The proposed approach yielded an overall accuracy of 87.64%. Among the four specific classes, housing estates were the best recognized. The highway was the least well-recognized class, although its recognition accuracy remained relatively high for a four-class classification problem at 83.77%.

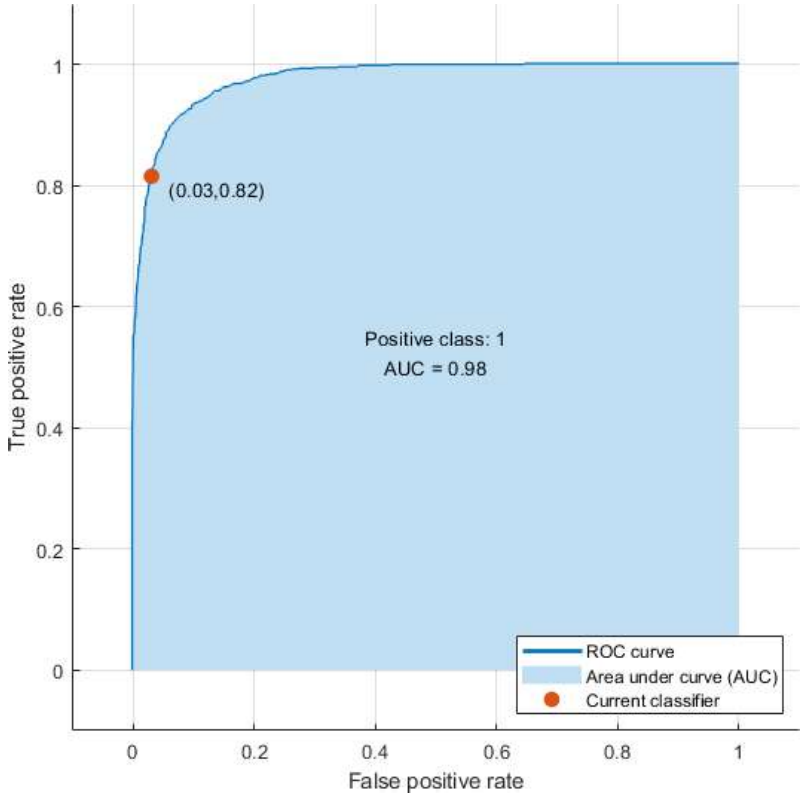


Figure 6. ROC: class 1 (positive).

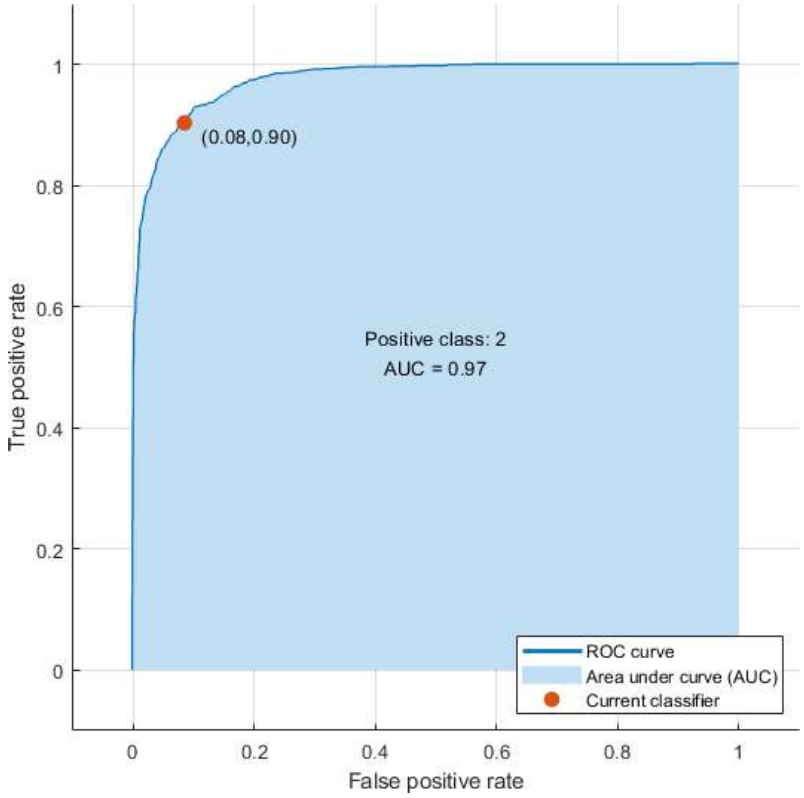


Figure 7. ROC: class 2 (positive).

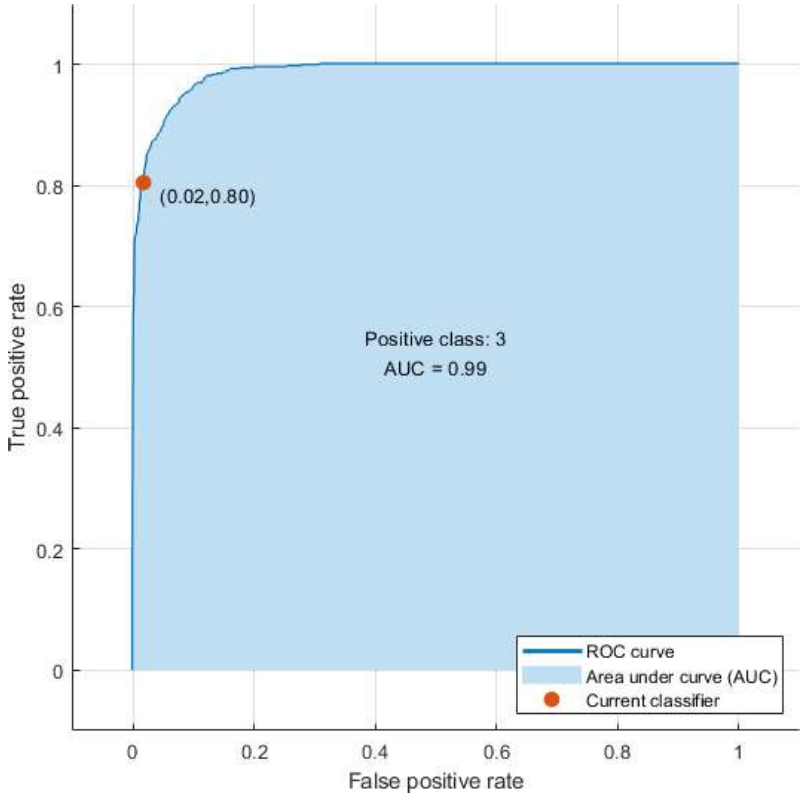


Figure 8. ROC: class 3 (positive).

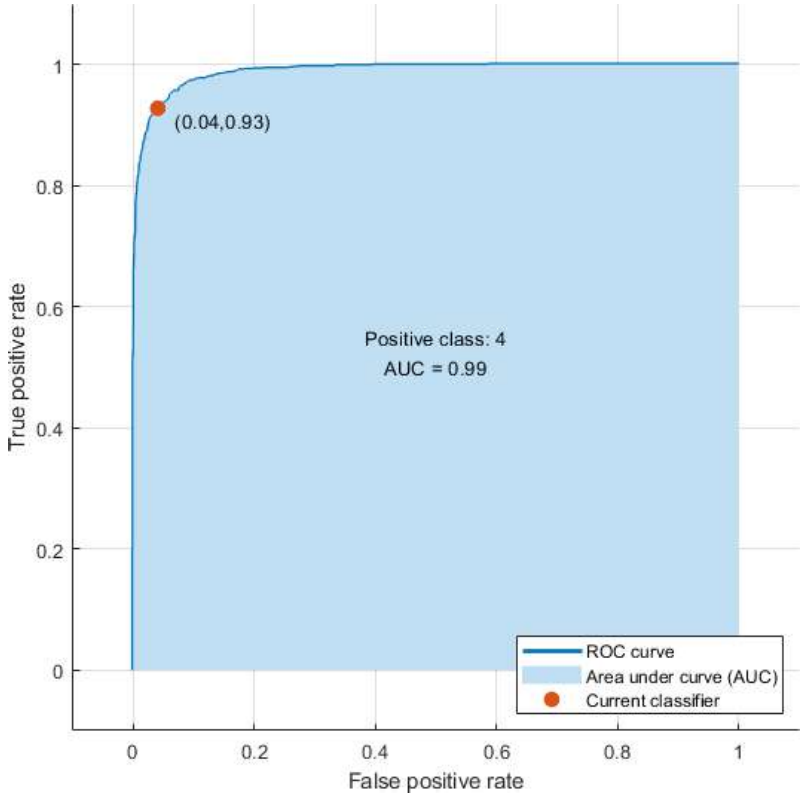


Figure 9. ROC: class 4 (positive).

4. Discussion

The topic of this paper was the development of a classification algorithm based on machine learning techniques for road type classification. The problem faced by this work was to determine whether physiological data acquired with smart glasses (EOG, ACC and GYRO signals) are suitable for classifying the type of road traveled by the person driving the car.

The best classifier that was found (RUSBoosted Trees) yielded a promising accuracy of 87.64% for a four-class classification problem. This relatively high accuracy indicates that physiological data acquired from JINS MEME smart glasses (EOG, acceleration and angular velocity) are sufficient to determine the type of road being traveled. It should be noted that the ANOVA analysis we performed on our features showed that the most relevant information to our classification problem resided in the IMU data, as shown in Figure 2, and more specifically the angular velocity measured by the gyroscope. This might indicate that head movements (rather than eye movements) are one of the main factor that could lead to the distinction of a road type.

A possible axis of development is the investigation of additional physiological modalities that could be set up in an unobtrusive way for the driver to provide insights regarding the environment they are driving in. For instance, Leicht et al. [47] investigated the monitoring of the heart rate (HR) and respiration rate (RR) of drivers in both urban and rural scenarios. More specifically, the efficiency of unobtrusive sensors for obtaining an estimation of both the HR and RR was evaluated in both real and simulated conditions by comparing the estimations derived from them to the readings of the reference HR and RR sensors. Under laboratory conditions, magnetic induction and photoplethysmography, both integrated into the seat belt, and hybrid imaging, combining visual and thermal imaging, were evaluated for respiration rate (RR) sensing. In real driving, the sensing of the RR by hybrid imaging and sensing of the heart rate (HR) by a seat-integrated capacitive electrocardiograph (ECG) were evaluated. Under laboratory conditions, reliable RR

detection was possible using all three sensor technologies. In real-world driving, reliable HR and RR detection was possible during the rural scenario only. In the urban scenario, only RR detection was feasible. Due to motion artifacts, the capacitive ECG was disturbed, and the HR detection was impaired. The evaluated unobtrusive measurement systems can monitor physiological parameters during, for example, driving for a long time on highways, but they could not reliably accomplish this during agile inner city driving situations due to motion artifacts.

The overview literature devoted to research on transport infrastructure cannot be separated from the aspects of artificial intelligence that support the management and organization of modern transport and logistics. The field of computer science that deals with the practical application of algorithms for data analysis, based mainly on machine learning, aims to create an automatic system that, based on accumulated experience and knowledge, will be able to detect driving style patterns in the processed data, predict future events and also react to them, such as during real travel [17]. Among the practical applications of machine learning systems, the following can be distinguished. First, research about recognizing elements in the image may also inspire analyzing single or multi-modal signals such as EOG [48,49], recognition of speech by detection using wearable devices around the head with all interference caused by such devices [50], written text, navigation in an unknown area, recommendation systems, guidance, forecasting financial and economic trends, and more pioneering research can open up new areas [51].

Finally, possible improvements regarding the machine learning aspects of the study could be tested. The investigation of several methods of signal analysis and their impact on the results might be advantageous [52,53]. More advanced feature extraction methods such as feature learning with deep neural networks (e.g. convolutional neural networks) [29] could be investigated once the dataset size is increased to a point where enough data are available to properly train such models. Time-series transfer learning techniques to refine the performances of these models could also be investigated [54].

5. Conclusions

In this paper, a machine learning method using physiological data acquired from smart glasses for the detection of road types while driving a car was presented. A pair of JINS Meme smart glasses collecting the EOG, linear acceleration and angular velocity was used by 30 subjects driving a car in real-life conditions. Statistical features were manually extracted from the data and used to train a classifier for the recognition of four different road types (city road, highway, housing estate and undeveloped area). A comparative study between various state-of-the-art classifiers was carried out and led to a best overall accuracy of 87.64% using boosted trees. Additionally, a feature importance calculation based on ANOVA showed that the most important features were coming from head movements.

Despite the very promising results obtained by our proposed approach, our study still has some major limitations. The most important one is that we used a single dataset for our analysis due to the lack of publicly available data that deal with a similar problem. Moreover, the dataset was limited in size because of sanitary restrictions caused by the COVID-19 pandemic, which might limit the generalization capacities of our method. Finally, it is currently not possible to compare our results to other studies due to the lack of past research working on a similar problem.

Future works will focus on increasing the amount of data used for such a study. This will first accomplished by resuming and extending the data acquisition campaign in real conditions that were interrupted by the COVID-19 pandemic. Alternative approaches based on acquiring synthetic data using simulators will also be tested, as they provide a relatively cost-effective way to acquire additional data that could be used to boost the generalization capacity of our trained classifiers [55–57]. Finally, additional unobtrusive sensor-monitoring physiological modalities such as the HR or RR [47] will be considered in future studies.

Author Contributions: Conceptualization, R.D., N.P. and F.L.; methodology, R.D. and N.P.; software, N.P.; validation, N.P., K.D. and F.L.; formal analysis, R.D. and N.P.; investigation, R.D. and F.L.; resources, R.D. and K.M.-P.; data curation, N.P.; writing—original draft preparation, R.D. and N.P.; writing—review and editing, R.D, N.P., K.D., H.H.P. and F.L.; visualization, N.P.; supervision, R.D., M.G. and E.T.; project administration, R.D.; funding acquisition, M.G. and E.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Bioethics Committee of the Medical University of Silesia on 16 October 2018 (KNW/0022/KB1/18).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are openly available in IEEE DataPort at https://doi.org/10.21227/4yte-5s06.

Acknowledgments: We would like to thank the volunteers who participated in the study and the driving school for providing the opportunity to acquire signals on learner drivers.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EOG	electrooculogram
RR	respiration rate
HR	heart rate
ECG	electrocardiogram
EMG	electromyograpram
ROC	receiver operator characteristic
AUC	area under the ROC curve
SVM	support vector machine
KNN	k-nearest neighbors
NN	neural network

Appendix A. Comparison of Classifiers

To justify the choice of the final classifier we ended up using, we present a comparison of the four best solutions from different groups in this appendix. For all the classifiers, we used the same validation scheme (holdout validation) and the same data partition scheme (70, 20, 10).

Appendix A.1. Support Vector Machine

From the group of SVM classifiers, the best results were achieved with the following hyperparameters:

- Preset: cubic SVM;
- Kernel function: cubic;
- Kernel scale: automatic;
- Box constraint level: 1;
- Multiclass method: one vs. one;
- Standardize data: true.

Figures A1 and A2 and Table A1 present the performance of aforementioned model.

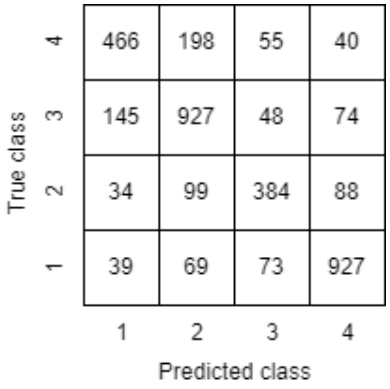


Figure A1. Confusion matrix of the SVM classifier.

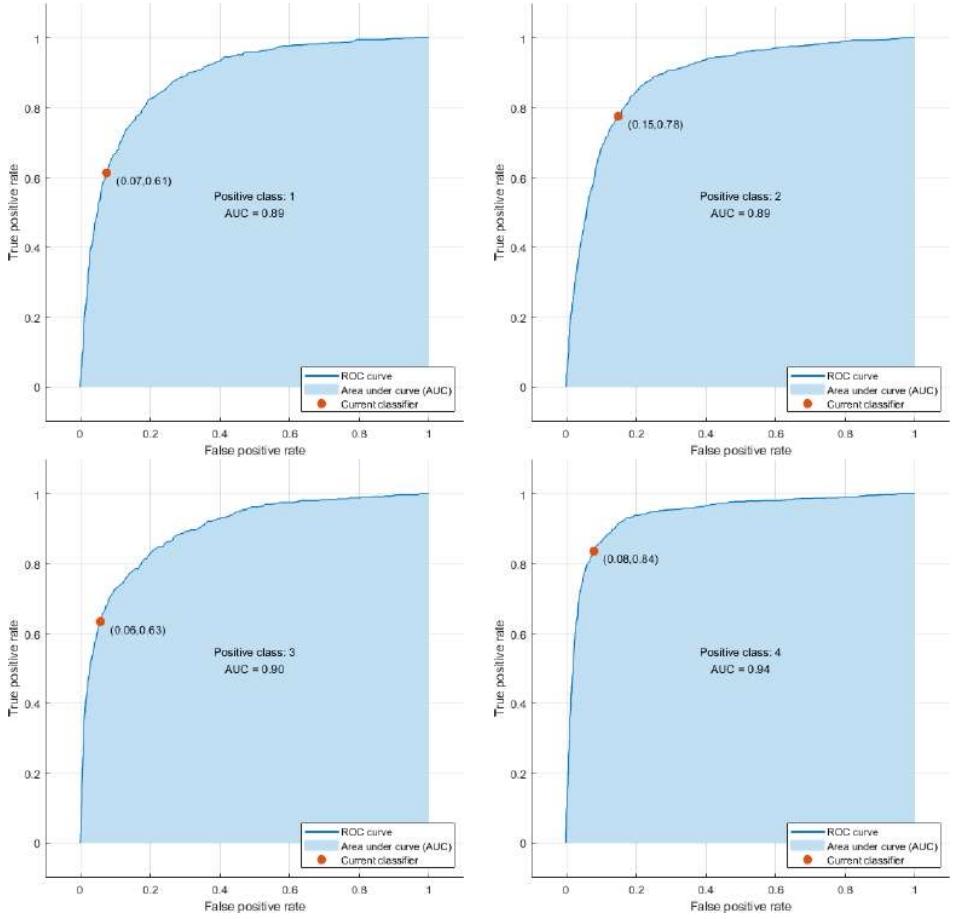


Figure A2. ROC curves of the SVM classifier.

Table A1. Evaluation metrics of the SVM classifier on the test dataset.

Type of Road	Accuracy	Precision	Recall	F1 Score	AUC
City road	0.68	0.61	0.68	0.65	0.89
Highway	0.72	0.78	0.72	0.75	0.89
Housing estate	0.69	0.63	0.69	0.66	0.90
Undeveloped area	0.82	0.84	0.82	0.83	0.94
Overall	0.74	0.72	0.73	0.72	

Appendix A.2. k-Nearest Neighbors

From the group of KNN classifiers, the best results were achieved with the following hyperparameters:

- Preset: Fine KNN;
- Number of neighbors: 1;
- Distance metric: Euclidean;
- Distance weight: equal;
- Standardize data: true.

Figures A3 and A4 and Table A2 present the performance of the model.

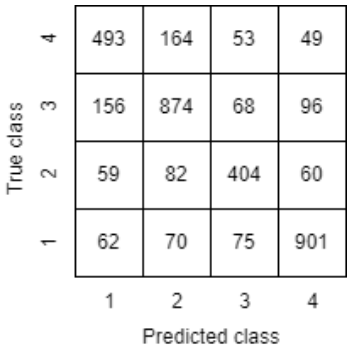


Figure A3. Confusion matrix of kNN.

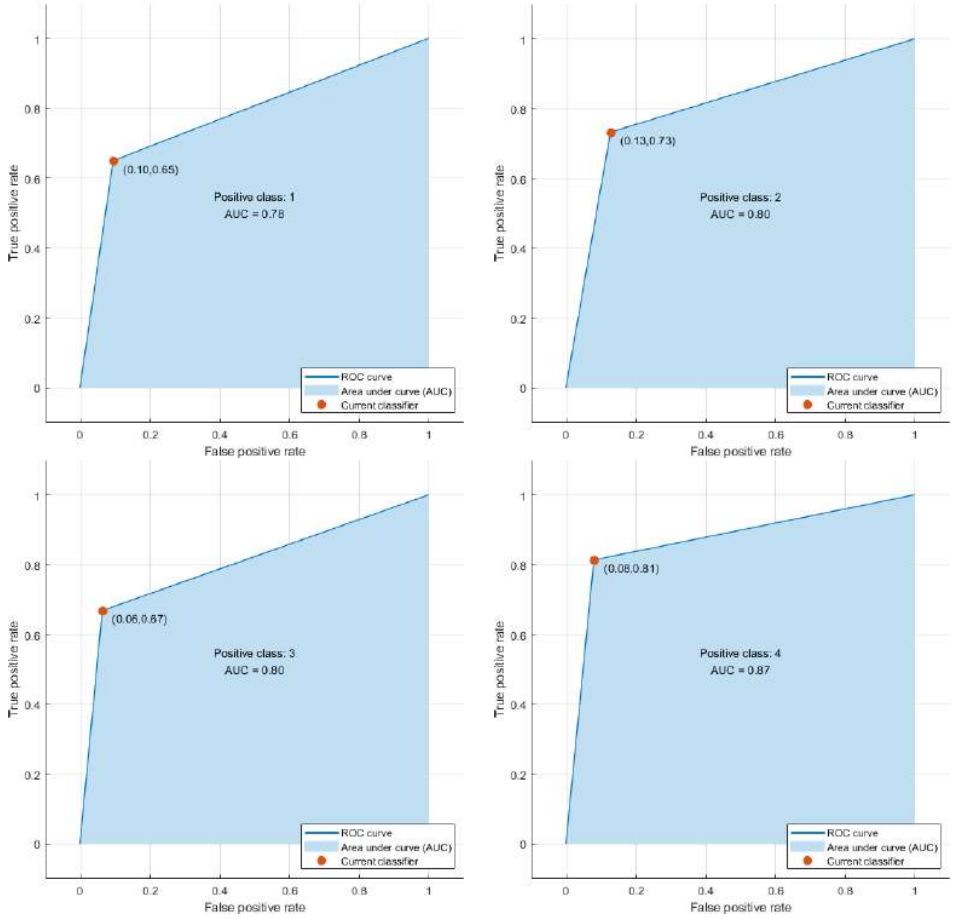


Figure A4. ROC curves of kNN.

Table A2. Evaluation metrics of the kNN classifier on the test dataset.

Type of Road	Accuracy	Precision	Recall	F1 Score	AUC
City road	0.64	0.65	0.64	0.65	0.78
Highway	0.73	0.73	0.73	0.73	0.80
Housing estate	0.67	0.67	0.67	0.67	0.80
Undeveloped area	0.81	0.81	0.81	0.81	0.87
Overall	0.73	0.72	0.72	0.72	

Appendix A.3. Neural Networks

From the group of NN classifiers, the best results were achieved with the following hyperparameters:

- Preset: wide neural networks;
- Number of fully connected layers: 2;
- First layer size: 100;
- Second layer size: 10;
- Activation: ReLU;
- Regularization strength (Lambda): 0;
- Standardize data: yes.

Figures A5 and A6 and Table A3 present the performance of the model.

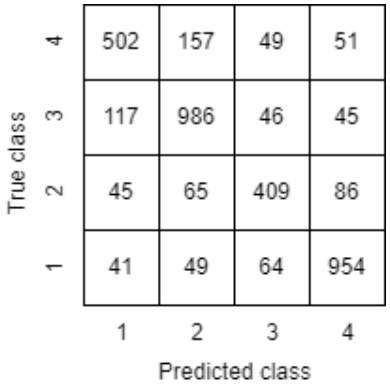


Figure A5. Confusion matrix of neural networks.

Table A3. Evaluation metrics of the neural network classifier on the test dataset.

Type of Road	Accuracy	Precision	Recall	F1 Score	AUC
City road	0.71	0.66	0.71	0.69	0.91
Highway	0.78	0.83	0.78	0.80	0.93
Housing estate	0.72	0.68	0.72	0.70	0.90
Undeveloped area	0.84	0.86	0.84	0.85	0.95
Overall	0.77	0.76	0.76	0.76	

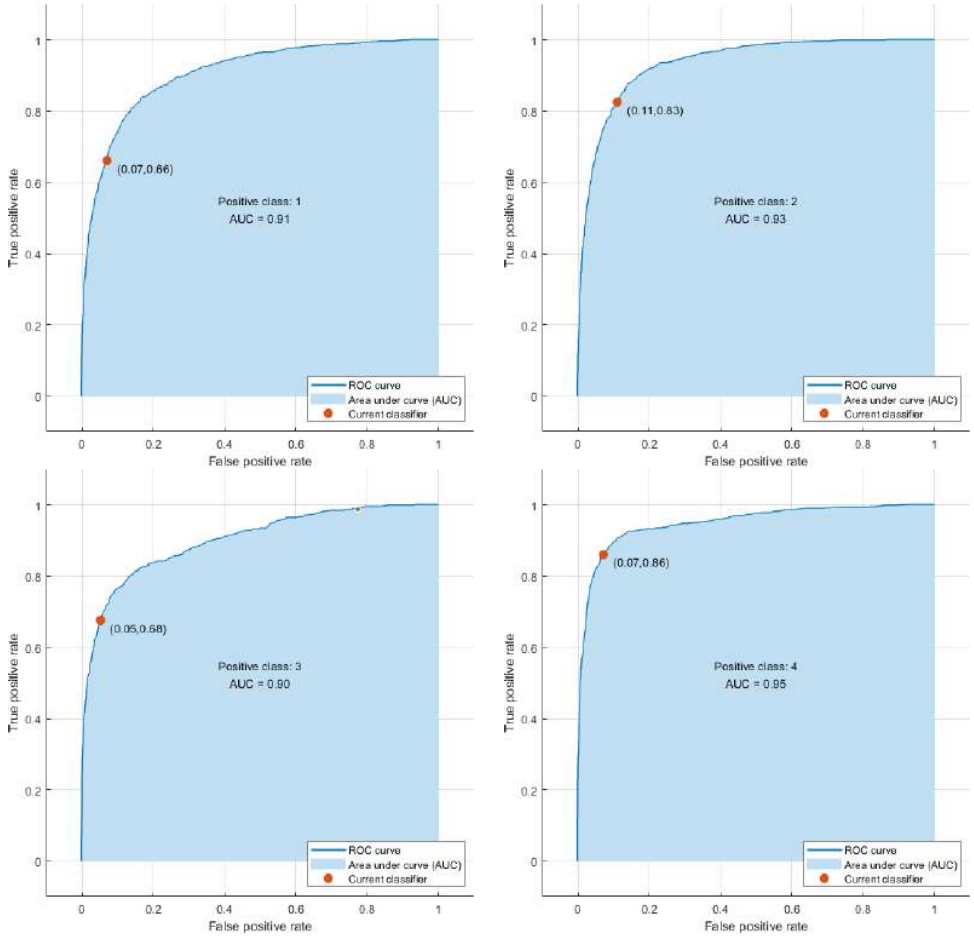


Figure A6. ROC curves of neural networks.

Appendix A.4. Ensemble Classifiers

From the group of ensemble classifiers, the best results were achieved with the following hyperparameters:

- Preset: bagged trees;
- Ensemble method: bag;
- Learner type: decision tree;
- Maximum number of splits: 33,002;
- Number of learners: 30.

Figures A7 and A8 and Table A4 present the performance of the model.

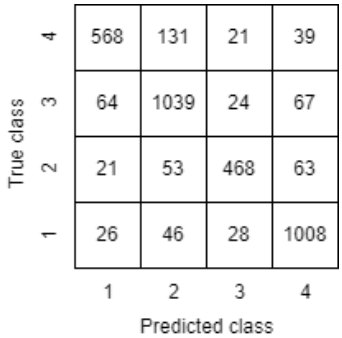


Figure A7. Confusion matrix of the ensemble classifier.

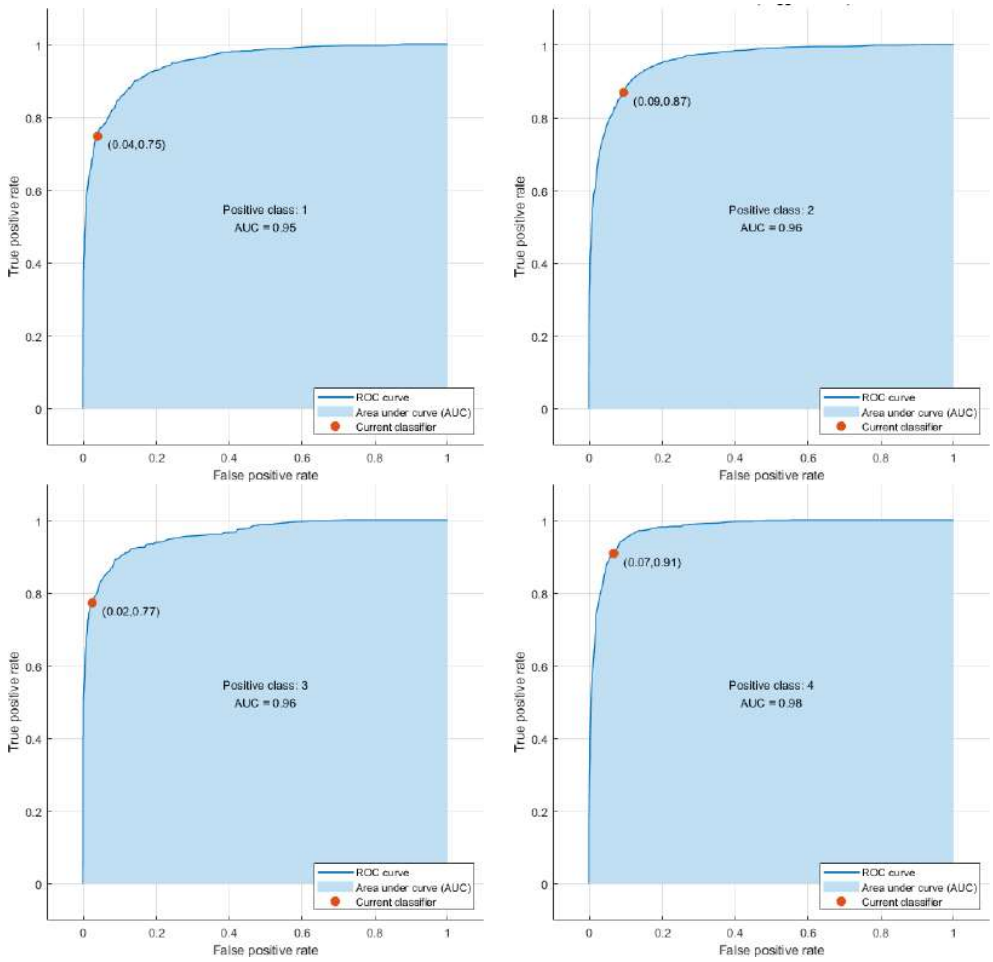


Figure A8. ROC curves of the ensemble classifier.

Table A4. Evaluation metrics of the ensemble classifier on the test dataset.

Type of Road	Accuracy	Precision	Recall	F1 Score	AUC
City road	0.84	0.75	0.84	0.79	0.95
Highway	0.82	0.87	0.82	0.84	0.96
Housing estate	0.87	0.77	0.87	0.82	0.96
Undeveloped area	0.86	0.91	0.86	0.88	0.98
Overall	0.84	0.82	0.85	0.83	

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A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars

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Abstract: Identifying accident patterns is one of the most vital research foci of driving analysis. Environmental or safety applications and the growing area of fleet management all benefit from accident detection contributions by minimizing the risk vehicles and drivers are subject to, improving their service and reducing overhead costs. Some solutions have been proposed in the past literature for automated accident detection that are mainly based on traffic data or external sensors. However, traffic data can be difficult to access, while external sensors can end up being difficult to set up and unreliable, depending on how they are used. Additionally, the scarcity of accident detection data has limited the type of approaches used in the past, leaving in particular, machine learning (ML) relatively unexplored. Thus, in this paper, we propose a ML framework for automated car accident detection based on mutimodal in-car sensors. Our work is a unique and innovative study on detecting real-world driving accidents by applying state-of-the-art feature extraction methods using basic sensors in cars . In total, five different feature extraction approaches, including techniques based on feature engineering and feature learning with deep learning are evaluated on the strategic highway research program (SHRP2) naturalistic driving study (NDS) crash data set. The main observations of this study are as follows: (1) CNN features with a SVM classifier obtain very promising results, outperforming all other tested approaches. (2) Feature engineering and feature learning approaches were finding different best performing features. Therefore, our fusion experiment indicates that these two feature sets can be efficiently combined. (3) Unsupervised feature extraction remarkably achieves a notable performance score.

Keywords: automated accident detection; feature extraction; feature learning; time series processing; deep neural networks

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Citation: Hozhabr Pour, H.; Li, F.; Wegmeth, L.; Trense, C.; Doniec, R.; Grzegorzek, M.; Wismüller, R. A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars. *Sensors* **2022**, *22*, 3634. https://doi.org/10.3390/s22103634

Academic Editor: Felipe Jiménez

Received: 14 March 2022
Accepted: 6 May 2022
Published: 10 May 2022

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1. Introduction

Identifying accident patterns is one of the most vital research foci of driving analysis. According to the global status report on road safety conducted by the World Health Organization (WHO) [1], the number of traffic-related fatalities continues to rise steadily.

Despite considerable improvements in road safety by programs such as "Driver Assistance", "Safety Awareness Services" and "Automatic Crash Notification (ACN)" systems, accident detection and prevention in driving studies are still of crucial significance. For this reason, accident detection studies have drawn the attention of insurance and fleet

management companies [2,3]. Environmental, road safety, and commercial applications such as insurance and loan qualifications are just a few fields where the contribution of accident analysis could be significant [4].

An important contribution of the accident detection studies is the post-crash applications concerning immediate dispatch of the emergency and roadside assistance services [5–8]. However, these studies do not analyze accident patterns but rather imply factors such as airbag deployment to detect an accident. A recent application of accident detection, which studies accident patterns, is automated boxes installed in cars that minimize the service and overhead inspection cost of fleet operators by detecting car damages due to minuscule accidents, bumps, accelerations and braking manoeuvres [9].

In this regard, there are very few studies concerning accident detection using machine learning (ML) [4]. The reasons for this are multifaceted. To begin with, in study cases such as accident detection, providing positive labeled data is nearly impossible. Moreover, preparing a large real-world data base containing accident events is not only expensive and time consuming, but also hindered by competitive automobile industry and data privacy issues. To the best of our knowledge, real-world accident data provided by the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) [10] is the only large-scale data base (including vehicles time series) that has been collected so far. Data scarcity in the field of accident detection is an obstacle to obtaining an automated accident detection system trained using ML, since the latter requires a large data set to train models that should be inclusive/unbiased and of good quality. There can also be times where one must wait for new data to be generated. Finally, the complex nature of accident events themselves present enormous challenges. Study cases like these require manually labeled training data, where the exact conditions characterizing the definition of an accident need to be predefined. According to Virginia Tech Transportation Institute (VTTI) [10], an accident is defined as "any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. This also includes non-premeditated departures of the road, as well as instances where the subject vehicle strikes another vehicle, roadside barrier, pedestrian, cyclist, animal, or object on or off the roadway". Based on the above definition, minor crashes where the tire is struck with little or no risk element (e.g., clipping a curb during a tight turn) could be considered as accidents. Such cases could only be noticed by reporting the incident or during an inchmeal inspection. These cases often pose a major challenge for automated accident detection as well.

Accident detection is usually translated into a binary classification problem, where input data are used to train models representing accident and non-accident classes. ML-based accident detection studies can be categorized depending on the type of data used to train their model. Two large categories can be identified, one relying on traffic data, the other on external sensors such as smartphones, acoustic sensors or cameras [4]. However, the performance of these kinds of prediction and detection systems is greatly confined by the availability of monitoring sensors, funds, weather, traffic flow, etc., while external sensors can end up being difficult to set up and unreliable, depending on how they are used [11]. For the aforementioned reasons, internal car data have been investigated as the third possibility for ML-based accident detection, which does not suffer from the abovementioned disadvantages. As a general remark, the term *car* in this paper refers to a *passenger vehicle*. Each modern car (manufactured starting from the mid-1990s), contains a variety of sensors that provide reliable time-series data for the most basic driving attributes such as speed, steering wheel angle and gas pedal position. This data can be of great advantage for accident detection and is readily available by monitoring the in-car network. For instance, the on-board diagnostics (OBD) adapter is the most available modality to capture driving patterns in network (e.g., CAN-Bus) protocols inside cars. More information about classifying and finding out the semantics of the most important signals transmitted on the in-car network can be found in our previous study in [12].

ML can be applied on in-car network data by following a standard framework usually referred to as the *pattern recognition chain* (PRC) that consists of four steps as illustrated in Figure 1. Firstly, during data acquisition, the chosen sensors based on the nature of the classes and their availability are to be considered. In the second step, data pre-processing includes operations such as sensor calibration, unit conversion, normalization and segmentation to make the data suitable for further analysis. Next, feature extraction is about deriving the most relevant information to the classes from each segment of data, thus leading to an abstracted and informative representation of each data segment. In the last step, classifiers are trained to separate different classes in the feature space, which in our case study would be distinguishing between accident and non-accident driving events.

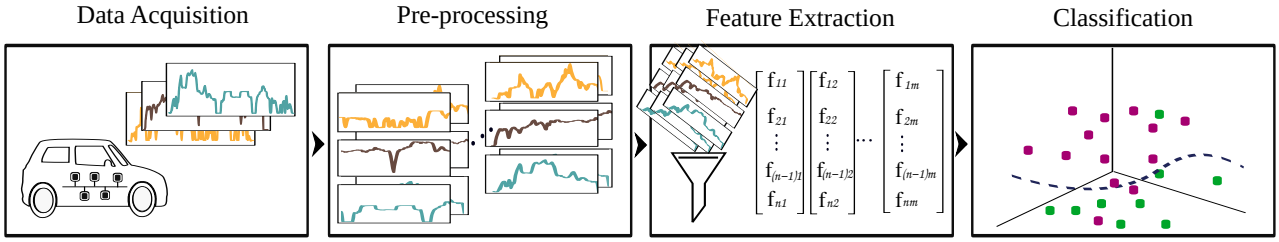


Figure 1. Machine learning framework for accident detection. First, time-series data is being acquired from in-car network signals. After pre-processing and segmentation, different feature extraction approaches are applied and compared. Finally, classifiers are trained and tested on the extracted features.

Experience has shown that each of these steps has a significant impact on accident detection performance [13]. However, data acquisition and pre-processing are mostly dependent on the data itself, while classification relies on well-known state-of-the-art approaches whose reliability was proven in past studies. For these reasons, feature extraction is the step where the margin of improvement is the largest and which has been the most investigated in past ML studies. Accordingly, to provide a ML framework for accident detection, a study on applicable feature extraction approaches is of great significance.

Past feature extraction research concentrates on two types of feature extraction techniques: feature engineering and feature learning. On the one hand, feature engineering is a traditional feature extraction approach relying on prior expert knowledge of the data to propose manually crafted features adapted to the problem to be solved. Feature engineering, for instance, includes the so-called *handcrafted* method that computes very simple statistical values as features on the input data and/or designed by experts to solve a specific problem [14–16]. However, feature engineering is not always an optimal way of extracting features when the expert knowledge is not available, and there is no guarantee that the chosen features would be optimal. On the other hand, feature learning is an automated feature extraction process using artificial neural networks (ANNs) that are ML models that were shown to be able to extract highly efficient features, provided decent pre-processing and segmentation steps on the data [17] have been carried out. Despite the popularity of ANNs in obtaining efficient features, finding the proper parameters and properly training the model can be complicated. Additionally, the features learned by ANNs are usually difficult to interpret, which can be a major obstacle to their use in many applications. Therefore, providing a comprehensive study on applying feature engineering and feature learning approaches and analyzing the optimal feature extraction approaches in spite of their respective drawbacks is of tremendous importance. To summarize, the contributions of our paper are as follows:

- This paper is the first study investigating ML-based accident detection on basic in-car network data. Our work is a unique and innovative study on detecting real driving accidents from the most accessible and affordable data sources inside cars.

- This paper presents a detailed ML framework based on the PRC introduced in Figure 1 to perform accident detection using basic in-car network data. In addition, it uses this framework to provide a comparison of state-of-the-art ML feature extraction techniques, applicable on in-car sensor data for accident detection based on SHRP2 NDS crash data set providing gas-pedal position, speed, steering angle and acceleration sensors. Using this framework, we obtain very promising results for automated accident detection based on a naturalistic data set.

This paper is organized in the following manner: In Section 2, we present the related work. Section 3 describes the proposed ML framework illustrated in Figure 1, with a brief explanation of materials and the chosen techniques. Section 4 is about the implementation details of all applied algorithms. Section 4 discusses the results. In Section 5, the interpretation of results is performed. We conclude the paper in Section 6 by describing our accomplishments, study limitations and future work.

2. Related Work

Due to the increased need for mobility, driving behavior analysis applications have become an important area of research. The result of driving behavior analysis has significant importance for the automotive and intelligent transportation industry, automobile insurance and the government organizations controlling infrastructure and public transportation. Numerous works address the importance of driving behavior analysis in relation to traffic, safety and ecological concerns [18–21], whereas many others concern the driver's behavior analysis [4,22]. Due to the diversity of research goals, applications, study contributions and data modalities, there is no specific study baseline or research categorization in the domain of driving behavior analysis specifically for accident detection. Therefore, to review the recent state-of-the-art on accident detection, an overview of the relevant works in the field of driving behavior analysis is needed. It can be noted that time-series feature extraction is a topic that is quite well explored [23,24]. However, the conclusions of such feature extraction studies do not seem to transfer from one application field to another, and this topic has remained relatively unexplored for accident detection. Two main categories of studies are presented in this section. The first category summarizes the state-of-the-art in "driving behavior analysis" in general. The second category is specific to "accident detection" literature.

2.1. Driving Behavior Analysis

Various past studies have surveyed the field of driving behavior analysis. Zinebi et al. [22] performed a literature review splitting driver behavior analysis work into three main sub-applications: (i) accident prevention, (ii) driving styles assessment and (iii) driver intent prediction. It also identifies three categories of methods used to solve the problem: 1. index systems, 2. image processing and 3. statistical methods and ML. The principle of index system methods is to define *indices*, i.e., metrics that can objectively quantify high-level concepts linked to driver behavior such as risk of accident, degree of consciousness, etc. An example is an index such as TTC (time to collision) defined by Mori et al. [25] to measure the time the vehicle spends before hitting an object in its environment. They used this index to calculate the environmental risk score at a given time. Based on the correlation between the two vectors of driver's attention and the environmental risk score, they observed that the degree of awareness is generally higher for expert drivers than for non-expert drivers.

Image processing is another popular method for driving behavior analysis due to how easily available vision sensors have become. Detecting driver's drowsiness using computer vision techniques from an iPhone and the GPS to track the position of the car is an example of an image processing application for driving analysis [2]. The last category of methods used in the reviewed literature in Zinebi et al. [22] is statistical and uses ML methods. Bachoo et al. [26] utilized multiple linear regression to explore the role of personality traits such as anger, impulsivity, etc., on reported actions of risky driving behavior using a cross-sectional questionnaire. A random forest (RF) classifier was used by Jahangiri et al. [27]

to classify driver behavior into two categories: violation and compliance at signalized intersections. They utilized the distance to the intersection, velocity, acceleration, time to the intersection, required deceleration parameter and velocity-based handcrafted (HC) features acquired from radar, video cameras and signal phase sniffers at intersections. In their work, they predict driving violations at the signalized intersection with accuracies of 97.9% and 93.6% for the SVM and RF models, respectively. Ohn et al. [28] adopted support vector machine (SVM) to classify the driver's activities based on his/her hand positions using cameras placed in the car. In their study, they used hand motions in terms of activity classification and prediction from naturalistic driving images. Image-based features were used to track hand motions and detect six classes of hand patterns among the four regions of wheel, instrument cluster, gear shift and side rest, and the SVM with a linear kernel achieved over 80% normalized accuracy.

All mentioned ML-based driving behavior analysis studies reviewed in [22] detect different types of driving behaviors or activities and driving styles, and none concern accident detection. Another comprehensive study provided by Meiring et al. [4], reviews driver style analysis systems, the application of these systems and the underlying artificial intelligence algorithms applied to these applications. In this review, two major categories of driving study researches (i.e., driving style and applications assessing driver behavior studies) are presented. In the papers reviewed in [4], the most popular AI, ML and statistical algorithms are used on different driving research topics such as driver assistance, drowsiness detection, driver distraction detection, Eco driving, road and vehicle condition monitoring, fleet management, accident detection and insurance applications. Most of the mentioned literature in [4] focuses on detecting various driving styles such as normal and safe, aggressive, inattentive and drunk driving utilizing various data modalities such as multiple sensors (e.g., car networks, smartphone, telematics, video, etc.), but very few exist on accident detection. For instance, Lee et al. [29] proposed a log–linear model to predict crashes based on crash precursors (i.e., traffic flow conditions prior to the crash) using traffic flow data extracted from traffic loop detectors.

Bagdadi et al. [30] proposed the recognition of critical jerk on the naturalistic Virginia Tech Transportation Institute (VTTI) near-crash data with a detection rate of 86% on identifying safety critical braking events during car driving. Critical jerks [31] are defined as sudden changes in acceleration magnitude. Events involving an abrupt braking response, which creates a critical jerk, are classified as safety critical braking events.

2.2. Accident Detection

To more easily compare our study to past ones, we divide the related works from the literature into two categories: rule-based and ML-based accident detection studies.

2.2.1. Rule-Based Accident Detection

Rule-based approaches are simple problem-solving techniques that are usually heuristic rules based on experts' knowledge. These approaches are chosen to fit the given problem, and they work well only on specific data modalities and problems for which they are intended. Many research studies are carried out in the domain of rule-based accident detection systems based on traffic-monitoring data [32–35].

Traditional traffic accident prediction uses annual average traffic volume. Real-time traffic accident detection, on the other hand, uses monitoring devices such as induction loops, infrared detectors and cameras. Nevertheless, the usability of these specific devices is greatly limited by important installation and maintenance costs and their poor road network coverage which is typically restricted to well-known congestion zones, e.g., on highways, tunnels or bridges [11]. Conventional built-in automatic accident detection systems utilize impact sensors or the car airbag sensors to detect an accident and GPS to locate the accident location [36]. Sheu et al. [37] proposed a new methodology for real-time detection and characterization of freeway incidents. In this system, incident symptoms are identified from raw traffic data (the segment-wide inter-lane, intra-lane traffic dynamics,

lane-changing fractions and queue lengths) utilizing the signal processing techniques, extended Kalman filtering and the modified sequential probability ratio test (MSPRT).

In addition to traffic data, smartphones are the next most used sensors in rule-based accident detection research. Zaldivar et al. [5] presented an application that ,automatically informs emergency services about an accident by SMS based on the vehicle diagnostics interface (OBD-II). In this study, an accident is detected with airbag triggers on the basis of the force overload experienced in the event of a frontal collision. A slightly different approach proposed in [38] measures the tilt angle change using an accelerometer sensor and speed using GPS to detect the moment of collision and send an alert on detection of an accident. Another method proposed in [39] focuses on the use of the smartphone accelerometer to monitor vehicle speed and report an accident if it falls below a certain threshold. It can be noted however that smartphones may be unreliable for accident detection. The main issue with these systems is that the smartphone may tilt or fall any time inside the vehicle without a real accident, and thus, the probability of a false positive will increase and a false alarm will be reported. Past literature ubiquitous computing has shown that there are also significant differences between smartphone brands: a machine learning model trained for a smartphone might see a strong degradation in its performances when used with another smartphone of a different brand, even if the latter contains the same sensors [40].

2.2.2. ML-Based Accident Detection

ML techniques notably differ from an algorithmic point of view depending on what type of input data is used to apply them. Due to the large data requirements of ML and relative scarcity of labeled car accident data sets, only a few related studies can be found. Among them, three main sensor modalities can mostly be seen combined with ML in the literature: traffic data, sensor data and car internal signals.

Studies that propose accident detection based on ML approaches are mostly based on traffic monitoring data. For instance, Ozbayoglu et al. [41] used Istanbul City traffic-flow data for the year 2015 from located RTMS (real-time monitoring system) sensors. Specific handcrafted features characterizing lane velocity, occupancy and capacity usage were manually crafted and computed for each sensor. The extracted features were then fed into a nearest neighbor model, a regression tree and a feed–forward neural network model to predict the possibility of an accident. The overall accuracy of their models are mostly over 99%, but with a considerable number of false alarms.

A review of the literature related to IoT (Internet of Things)-based accident detection, prevention and reporting systems is provided by Alvi et al. [13]. In this review various applications of IoT are introduced and referenced. Accident detection papers in the study are grouped into two categories: (1) conventional- and (2) ML/AI-based accident detection techniques. For the second category of the reviewed accident detection papers in [13], three key ML/AI-based accident detection approaches are discussed: (a) fuzzy logic, (b) SVM and (c) artificial neural network (ANN). Pan et al. [42] used vehicle speed, acceleration and lane changing factor from a microscopic traffic simulator and classified incident vs. non-incident with a SVM. With their proposed methodology, the SVM accuracy based on speed data was almost 100%. In their work, they imply the assumption that every vehicle collects its own traffic data and sends them through an OBU (on-board unit). Then the traffic data is collected via RSU (roadside units) and uploaded to the central service for processing. The simulated scenarios they tested only consider accidents on three-lane urban roads at traffic lights.

Harlow et al. [32] proposed a system that involves a method for processing and recognizing accidents from recorded vehicle acoustic signals at intersections and construction sites. A database of vehicle sounds, car braking sounds, construction sounds and traffic sounds was created. The mel-frequency cepstral coefficients were computed as a feature vector given as input in a neural network classifying between crash and non-crash events. In their study the classification testing results achieved 99% accuracy. Although their

proposed methodology is highly efficient, this system is bound to specific locations e.g., intersections and construction sites.

Other works have attempted to leverage data coming from external sensors (video, audio, movement) for accident detection. An accident detection approach based on a convolutional neural network (CNN) was proposed by Ghosh et al. [43] using video footage obtained from the CCTV cameras installed on highways. By placing CCTV cameras and a Raspberry Pi 3, using a pre-trained CNN model from 10,000 accident frames and 10,000 non-accident frames, their model can detect accidents to an accuracy of about 95%. The main disadvantage of such models is that accidents outside the area covered by cameras are overlooked. Monitoring all roads and highways with Pi cameras and Raspberry Pi is a costly approach for accident detection. Maintaining privacy and security is another disadvantage of the proposed system. Finally, weather can affect the cameras viewability.

The abovementioned works present approaches utilizing systems that are limited by challenges such as maintaining the privacy and security of users, huge expenses of a large-scale network, many manufacturers, industries, power consumption, architecture challenges, heterogeneity, mobility and interoperability problems. A similar solution to ours using internal car data to bypass the drawbacks of other monitoring devices was proposed by Osman et al. [44]. This study introduces a ML model to predict collisions on the SHRP2 NDS vehicle kinematic data (speed, longitudinal acceleration, lateral acceleration, yaw rate and pedal position). They hypothesize that vehicles experience micro-level turbulence in their kinematic patterns over a period of time known as the turbulence horizon prior to a crash. They use the input feature as the standard deviation of the vehicle kinematics parameters in the period starting at the beginning of the turbulence horizon and ending at the beginning of the prediction horizon (the time interval between the predicted hazard time and the impact time) as features in their study. To classify near crash data and normal driving data, several classification algorithms are trained and compared. Although this model achieved a substantially high 99% $F1$ score, the feature extraction approach used in this study was based on label re-computation, which might not guarantee features generic enough to be successfully re-applied on data other than SHRP2 NDS.

Two major points distinguish our study from [44]: First, our work focuses on accident detection rather than prevention. Therefore, we do not include near-crash scenarios in our data set. Second, and more importantly, our work is also testing feature-learning approaches based on deep neural networks that learn features in an automated way without the need of any prior knowledge.

3. Materials and Methods

This section introduces the proposed ML framework (Figure 1) and describes in details how to use it for car accident detection based on internal car data. Since the largest improvements in classification performances can usually be obtained at the feature extraction stage, we use our proposed framework to analyze and compare the respective performances of state-of-the-art feature extraction techniques. To do so, we fix the acquisition, pre-processing and classification steps as described in the following subsections.

3.1. Data Acquisition

Data acquisition is the process of defining an experimental protocol to properly set up sensors, defining a strategy to properly annotate the data with labels, sampling relevant sensor signals, converting the resulting samples into digital numeric values and acquiring and merging the data from appropriate sources. Access to a suitable data set and the quality of the data are the basic prerequisites for the successful establishment of ML-based studies. Since our study focuses on accident detection based on real data, finding a suitable labeled database was necessary in advance. In the frame of our experiments, it was decided to use the SHRP2 NDS [45] database acquired from Virginia Tech Transportation Institute (VTTI) [10]. In the following section, a brief description of the SHRP2 data set is presented.

SHRP2 Data Set

The SHRP2 research project in the study of naturalistic driving behavior, monitored around 3400 apprentice drivers from over 277 unique car makes/models from six locations across the United States. The participants' vehicles were equipped with a data acquisition system (DAS) that included a forward radar, four video cameras, a front-facing wide-angle camera, accelerometers, vehicle network information, a geographic positioning system, on-board computer lane tracking, various computer vision algorithms and additional data storage capabilities. An accident data set (mostly from cars, followed by SUV-crossovers, pickup trucks and van–minivans) was created from 5,512,900 trip log files extracted from the SHRP2 naturalistic driving study (NDS). To identify accidents, a team of data analysts and data quality coordinators manually validated and analyzed the log files to annotate the data. An accident was defined as any contact a vehicle has with an object, either moving or stationary, at any speed in which kinetic energy is measurably transferred or dissipated. The definition also includes non-premeditated departures from the road where at least one tire leaves the paved or intended route road surface. The acquired data set consists of 546 synchronized accident events containing the time-series data channels shown in Table 1.

Table 1. SHRP2 data set sensor channels.

Variable Name	Unit	Description
Time stamp	millisecond	Time since beginning of trip, in milliseconds
Gas pedal position	none	Position of the accelerator pedal collected from the vehicle network and normalized using manufacturer specs
Speed network	km/h	Vehicle speed indicated on speedometer collected from network
Steering wheel position	degree	Angular position and direction of the steering wheel from neutral position

3.2. Data Pre-Processing and Segmentation

Data pre-processing refers to operations applied to clean the data of flaws usually caused by data transmission errors or sensor failures. They include, in particular, operations such as eliminating any duplicates, irregularities in the data, normalizing the data to compare, filling out missing data values, which is a commonly encountered problem, and providing the ML model data that are consistent to improve the accuracy of the obtained result. Usually, original raw data records are too long and might not contain homogeneous information. Therefore, splitting the data into shorter segments is needed. Segmentation is the procedure of splitting the signal values (in our case time series) into separate time intervals called windows, depending on the attribute or the behavior of the desired classes. Figure 2 illustrates the pre-processing and segmentation steps applied on the SHRP2 data set in this study.

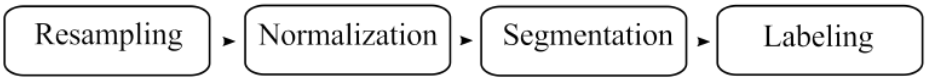


Figure 2. Pre-processing procedure applied on SHRP2 data set for accident detection.

First, to synchronize the sensor channels of the SHRP2 data set, we re-sampled data from different sensors at a frequency of 40 Hz. Afterwards, to bring the sensor values into the same range, min–max scaling normalization was applied. For the segmentation, a traditional sliding time window approach was employed. The labeling was performed

by using the information from event descriptions provided with the SHRP2 accident data set, which contains the event start and end time stamps. Based on this information, we decided to set the segment length to $T = 100$ which corresponds to approximately 2.5 s. This duration was chosen to be equal to the maximum event duration based on the SHRP2 data description. An overlapping factor of 50% was also chosen to segment the time series.

The labeling process adds a label of zero or one to each time window depending on whether the frame at a specific time stamp is part of the event. Windows containing more than half of the duration of the frame dedicated to an accident event are labeled as one and the rest of the windows as zero. After the aforementioned steps, our data consists of 34,339 time windows sized of shape $T \times S$ where $T = 100$ is the length of the time window, and $S = 4$ is the number of sensor channels. Among these 34,339 time windows, only 2281 are positive samples. Based on these numbers, as expected, we are dealing with a notably imbalanced data set in which the negative class represents 93% of the whole data set.

3.3. Feature Extraction

Feature extraction is the process of reducing the dimension of the raw data into an informative abstract representation of the classifier. Extracting features reduces the complexity of training a classifier by reducing the size of its input data and getting rid of information irrelevant for the classification problem to be solved.

In this section, the feature extraction techniques used in our study are briefly explained. We decided to work with the most common state-of-the-art feature extraction approaches in time-series analysis and apply them on four in-car signals, including gas pedal position, speed, steering wheel position and acceleration.

Feature extraction methods from both feature engineering and feature learning are presented in this paper. The most commonly used feature extraction approach is the traditional feature engineering method consisting of handcrafted features that we refer to as HC in the following sections. HC features have been implemented for decades and still serve as a powerful tool when combined with ML classifiers. Traditionally, HC features are engineered based on knowledge expertise of the data which is not always available. In this case, it is common to use simple statistical attributes computed on the time series, which have shown to perform well in practice despite their simplicity [46]. Feature engineering based on heuristic rules found in the past literature such as [15,16] was also adapted and tested in our experiments, though due to insufficient performance the method and results are not presented in this paper.

The second category of feature extraction approaches is deep feature learning. Deep feature learning refers to the automated learning of features using deep neural networks (DNNs). An ANN is a composition of L parametric functions represented by "layers". ANNs consist of 3 layers: input, hidden and output. A deep neural network (DNN) is an ANN with at least two hidden layers. Each layer consists of a group of multiple neurons. Neurons are simple non-linear computational units that output a single value given several inputs. In the general case, the layer l_i with $i \in 1 \ldots L$ takes as input the output of the previous layer l_{i-1} and applies a non-linearity to compute its own output. The last layer usually provides an estimation of class probabilities associated with the data given as input to the model. For this purpose, a softmax activation layer with a number of neurons equal to the number of classes is traditionally used. DNNs have shown to be extremely good feature learners, especially in image classification [17].

Since our evaluation framework fixes the classifier, an approach similar to what was done by Li et al. [14] and Girshick et al. [47] was employed to use DNNs as feature extractors. The DNNs were first trained in a supervised way using a softmax layer. The latter was then removed to let the DNN output feature vectors that were used train the classifier fixed in our framework. A brief explanation of the abovementioned feature extraction methods chosen for our study follows.

3.3.1. Feature Extraction Based on Handcrafted Features (HC)

Traditional HC feature extraction has been implemented for decades, and due to its simple set up, it still serves as a powerful baseline when combined with ML classifiers. The HC features extract information from simple statistical attributes such as minimum, maximum or a percentile or more elaborated descriptors such as features related to the frequency–domain based on the Fourier transform of signals. For HC features, we computed simple statistical features that are commonly used in many application domains using time-series data [14,46]. These features consist of 18 values computed either on the time series or their power spectrum as shown in Table 2. These features are computed on each sensor channel individually. The features from all channels are then concatenated together to form a feature vector of size $18 \times 4 = 72$.

Table 2. List of the handcrafted features used in our study. Each feature is computed on each sensor channel independently.

Handcrafted Features		
Maximum	Average	Auto-correlation
Minimum	Skewness	First-order mean
Percentile 20	Kurtosis	Second-order mean
Percentile 50	Interquartile	Standard-deviation
Percentile 80	Zero-crossing	Norm of the first-order mean
Spectral entropy	Spectral energy	Norm of the second-order mean

To improve the classification efficiency, prevent overfitting (less opportunity to make decision based on noise) and provide better insight into relevant features, in our paper HC feature extraction is followed by a feature selection approach. Three popular feature selection protocols, belonging either to the family of filter-based or wrapper-based methods, were tested in our study: ReliefF and Fisher score from filter-based and recursive feature elimination (RFE) from wrapper-based feature selection approaches [8,48–50]. Of these three methods, only RFE could yield proper improvements in performance. Therefore, only its results are reported in our paper.

RFE feature selection is a wrapper-based approach that aims at evaluating different sets of features by training and evaluating a classifier for each set and comparing their classification performances. Each wrapper approach proposes a strategy to select the sets of input features to test and avoid having to test all configurations, which would be too computationally expensive. RFE starts with using all features as a whole subset and training the classifier. Then it eliminates features by recursively considering smaller and smaller sets of features. In our study, features were eliminated based on feature importance scores returned by the classifier we chose (random forest and support vector machine). The $n =$ step size and number of features are based on the lowest score eliminated. The procedure is recursively repeated until the desired number of remaining features or level of performance is reached.

3.3.2. Feature Learning Based on Multi-Layer-Perceptron (MLP)

An MLP constitutes the simplest and most traditional architecture for deep learning models. This form of architecture is also known as a fully connected network since the neurons in layer l_i are connected to every neuron in layer l_{i-1} with $i \in [2, L]$, L being the number of layers. Parameters referred to as weights are attributed to each connection. Consequently, the connection between two consecutive layers of a MLP can be represented by the following equation:

$$\boldsymbol{x}_{l_i} = f(\boldsymbol{W}_{l_i} * \boldsymbol{x}_{l_{i-1}} + \boldsymbol{b}_{l_i}) \quad (1)$$

With $n^{(i)} \in \mathcal{N}^*$ number of neurons in layer l_i, $\boldsymbol{x}_{l_i} \in \mathcal{R}^{n^{(i)}}$, $\boldsymbol{W}_{l_i} \in \mathcal{R}^{n^{(i)} \times n^{(i-1)}}$, $\boldsymbol{b}_{l_i} \in \mathcal{R}^{n^{(i)}}$, $\boldsymbol{W}_{l_i}$ being the matrix of weights connecting the neurons of layer l_{i-1} to layer l_i, $\boldsymbol{b}_{l_i}$ the vector

of biases in layer l_i and $\boldsymbol{x}_{l_i}$ the output of layer l_i. Figure 3 illustrates the schematic of the MLP network used in our study.

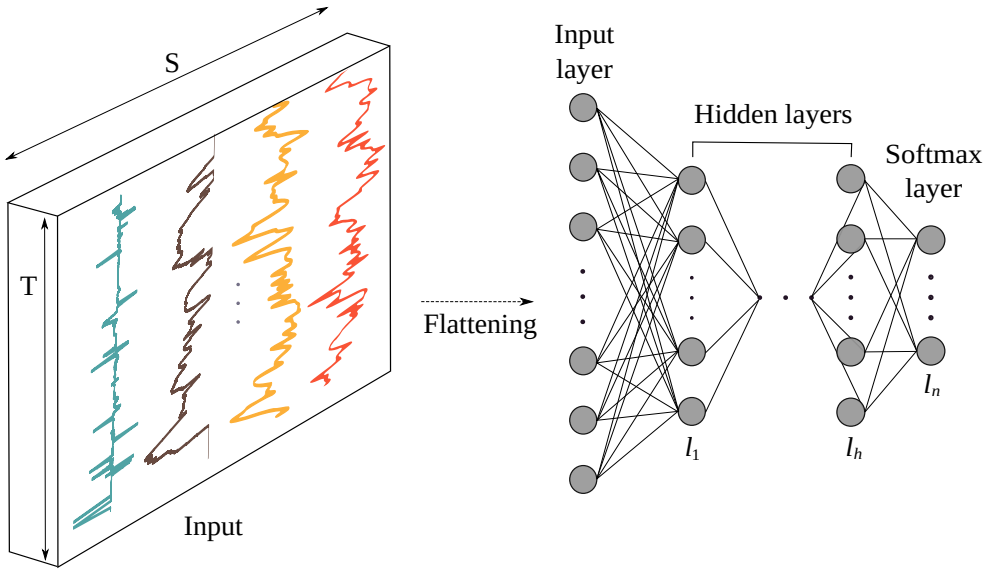


Figure 3. Architecture of a MLP model for accident detection with h hidden layers, n number of classes and S number of sensor channels. Input data are first flattened into a $(T \times S)$-dimensional vector and and then fed to the hidden layers. All layers are fully connected.

3.3.3. Feature Learning Based on Convolutional Neural Networks (CNN)

CNNs mainly contain convolution layers and pooling layers, and some deep learning architectures include batch normalization layers (see Figure 4). They have been successfully applied in image recognition [51,52], in various natural language processing tasks [53,54] and in timeseries analysis [55]. The general form of using a convolution for the centered time stamp t is given in the following equation:

$$\forall t \in [1, T], c_t = f(\boldsymbol{\omega} * \boldsymbol{x}_{t-l/2:t+l/2} + \boldsymbol{b}) \tag{2}$$

where $*$ designates the convolution product, c_t the result of the convolution at time t, f the activation function, $\boldsymbol{x}$ a 1D input, $\boldsymbol{\omega}$ the convolutional filter of length l and $\boldsymbol{b}$ a bias parameter. A convolution can be seen as applying and sliding a filter over a time series, or in other words as a generic non-linear transformation of an input vector $\boldsymbol{x}$. For instance, if convoluting a time series with a filter of length 3 with values equal to $[\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$ is the equivalent of applying a moving average with a sliding window of size 3.

The convolutional maps obtained after applying several convolutional kernels are usually given as input of a pooling layer, which can be either local or global. A local pooling operation, such as averaging or taking the maximum value in a sliding window is applied to downsample the input of the layer. For global pooling, the downsampling operation is applied across the entire input time dimension, resulting in a single output value. A normalization layer is sometimes added to the network to help the network converge quickly during training. A batch normalization [56] and instance normalization [57] are two popular normalization layers used in CNNs for time-series analysis. When used for classification, CNNs are usually connected to a classification MLP, whose last layer is a softmax layer, giving a distribution score over the class variables in the data set.

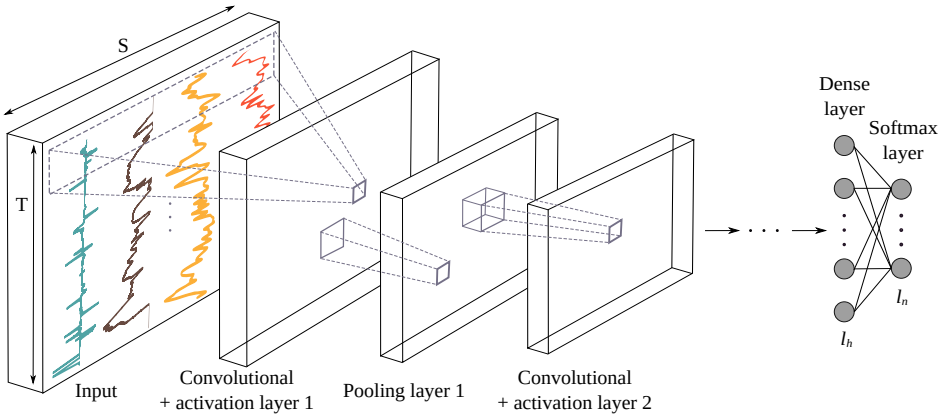


Figure 4. Architecture of a CNN model for accident detection. The designations n, h and S are the number of classes, layers and sensor channels, respectively. Convolutional layers apply convolution products on all convolution maps of the previous layer. Pooling layers then downsample the convolutional output and pass it to the next convolutional layer.

3.3.4. Feature Learning Based on Long Short-Term Memory (LSTM)

Long short-term memory networks are a type of recurrent neural network (RNN) being a special type of DNN that use loops and connections between nodes along the temporal sequences to save dynamic temporal information and carry it along the network. LSTM cells introduce internal mechanisms called gates that can regulate the flow of information over time by storing it in an internal memory and update output or erase this internal state depending on their input and the state at the previous time step [58]. Gate operations can be described as follows:

$$\boldsymbol{f}_t = \sigma(\boldsymbol{W}_f \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_f) \tag{3}$$

$$\boldsymbol{i}_t = \sigma(\boldsymbol{W}_i \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_i) \tag{4}$$

$$\boldsymbol{o}_t = \sigma(\boldsymbol{W}_o \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_o) \tag{5}$$

$$\boldsymbol{m}_t = \boldsymbol{f}_t \otimes \boldsymbol{m}_{t-1} + \boldsymbol{i}_t \otimes \sigma(\boldsymbol{W}_c \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_C) \tag{6}$$

where x_t is the input vector to the LSTM cell and h_{t-1} the hidden state vector also known as the output vector of the LSTM cell. $\boldsymbol{f}_t$, $\boldsymbol{i}_t$ and $\boldsymbol{o}_t$ represent forget, input and output gates, respectively. These gates have their own weights ($\boldsymbol{W}_*$), bias ($\boldsymbol{b}_*$) and activation functions (σ). The functionality of an input, output and forget gates are used to block the input of the cell , block its output, and erase its internal memory at time t. $\boldsymbol{m}_t$ is the memory state of the cell at time t, and $\otimes$ is the element-wise multiplication of two vectors. The architecture of the RNN with LSTM layers containing LSTM cells is shown in Figure 5. Like all DNNs, there are different architectural variations of LSTM layers, and the last layer is followed by dense and softmax layers.

3.3.5. Feature Learning Based on an Autoencoder (AE)

Autoencoders are special types of DNNs that are trained to reproduce input data on their output using a loss function such as mean squared errors in an unsupervised manner. An AE applies a dimensionality reduction by first projecting input data into an embedding space (of usually smaller dimensionality than the one of the input space) using an encoder to then decompress the embedding to match the original input as closely as possible using a decoder. By construction, an AE also always has the same number of inputs as outputs. Figure 6 shows a schematic view of the architecture of an AE. For feature extraction, an AE is first trained in an unsupervised way to reconstruct its inputs on its output layer. Then the decoder is removed, and the encoder is used to output feature vectors.

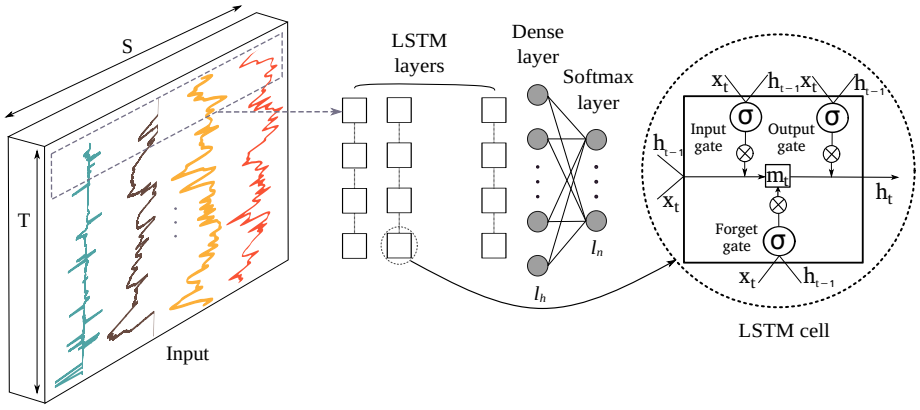


Figure 5. Architecture of a LSTM network for accident detection . The designations n, h and S are the number of classes, layers and sensor channels, respectively. The cells in the LSTM layers have one input, forget and output gates. $\boldsymbol{x}_t$, $\boldsymbol{m}_t$ and $\boldsymbol{h}_t$ refer to the cell input, memory, and output at time t, respectively, and σ designates the activation function.

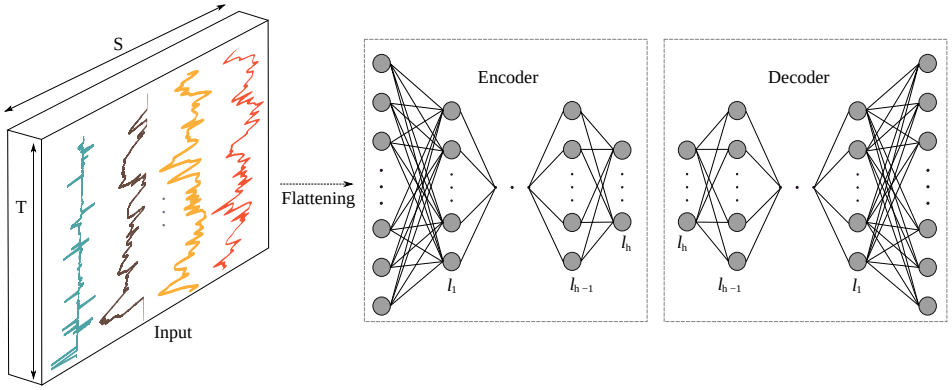


Figure 6. Autoencoder's architecture used for accident detection consists of encoder and decoder sections. The encoded layer is used as features for the feature learning purposes; S is the number of sensor channels and h denotes the number of hidden layers in both the encoder and decoder.

3.4. Classification

Classification is the final step of the ML framework which trains a model to predict class labels (categories) given an input feature vector associated with a specific data segment. The classifier constructs a separation between different classes in the feature space. Support vector machine (SVM) [59], random forest (RF) [60], k-nearest neighbors (KNN) [61], decision tree [62], etc., are among the most popular classifiers used in the past literature. In this paper, a soft-margin SVM (known as a C-SVM) with a radial basis function (RBF) kernel and a RF classifier are the two chosen classifiers due to their high performance and ability to overcome overfitting in the case of high dimensional data [14,63,64].

A SVM has been shown to be a very effective linear classifier that can also effectively be applied to non-linear cases with the kernel trick. C-SVM is a variation of a SVM that allows misclassifications during the training to reduce overfitting by regulating the soft-margin parameter C that controls how much misclassification is allowed. When training a SVM with the RBF kernel, two parameters must be considered: C and *gamma*. The parameter C trades off misclassification of training examples against simplicity of the decision surface. Proper choice of C and gamma is critical to the performance of the SVM. A grid search was performed to find the optimal C and *gamma* values for each feature set extracted by the abovementioned methods. The RF is a popular classifier that uses bagging mechanisms

with decision trees to reduce their propensity to overfit. The main hyper-parameter of RF is T, the number of trees. Similar to SVM parameters, the number of RF trees T was optimized by a 1-D grid search for each feature set separately.

It should be noted that DNNs are trained directly with a classification layer. To apply the aforementioned classifiers on the DNNs features, the following procedure needed to be done. At first the model was trained as usual, and then the classification layer (softmax) was removed to assign the output of the penultimate layer as an input feature to the classifier. In feature extraction based on AE, the output of the encoder is the assigned feature after training the full AE model.

4. Experiments and Results

This section is about the implementation details of all applied algorithms, the evaluation setting and the results. All the implementations in this study were coded in Python Feature learning approaches using DNNs were implemented using the *Keras 2.1.0* framework with a *Tensorflow 1.14.0* [65] backend, *scikit-learn 0.21.3* [66] and trained using the ADADELTA optimizer [67] with default parameters (initial learning rate of one) for 50 epochs with a batch size ranging from 100 to 1000.

To have a comprehensive measure of our model's performance, throughout the whole data set, a K-fold cross-validation [68] was applied to the data set. The number of folds in this case was set to $K = 5$ and for each training run, we selected a single partition from our five folds to be the test set and used the rest for training. The details of the experiments for each feature extraction algorithm are described as follows:

HC: The HC features consisted of 15 statistical values directly computed on the time series, and 3 frequency-related on their power spectrum were computed on each sensor individually and concatenated together. Then RFE feature selection with an elimination size of three was applied.

MLP: The MLP architecture used in this study contained three dense layers and REctified Linear Units (RELU) activation. MLP usually takes 1D inputs only, therefore a flattened layer was used to convert the 2D input to 1D. According to the recommendations of [14,56], a batch normalization layer was placed directly after the network input to improve results. Three fully connected dense layers with RELU activation function, containing 2000 neurons each, and a final softmax layer built up the MLP network used for our study (see Table 3). In Table 3, the values for the hyper-parameters used for feature learning approaches in this study are shown. Optimizing the hyper-parameters of DNNs is an important and difficult topic. Optimal parameters for our models were chosen after testing several manually selected configurations. Manual hyper-parameter selection is the default approach in the literature due to the absence of other more elaborated high performing approaches.

CNN: As listed in Table 3, the CNN layout consisted of three blocks of batch normalization and a convolutional layer with RELU activation followed by dense and pooling layers. The CNN design was based on [14] with some modifications, including a reduction in the size of the convolutional kernels and an increase pooling window size, while keeping the amount of kernels the same for each block.

LSTM: The values of all hyper-parameters for the LSTM architecture are provided in Table 3. Like other ANNs used in this paper, a batch normalization layer was added at the beginning and a dense and softmax layers at the end of the network. The gate activation used in the LSTM cells is a sigmond function, and in the dense layers, a tangent activation function was used.

AE: The AE architecture consisted of simple dense layers (three dense layers for the Encoder and then three for the Decoder designed as a mirror), with ReLU for the activation function. Different numbers of dense layers were tested, and the one achieving the best performance is presented in Table 3.

Table 3. Hyper-parameters of the ANN models on the SHRP2 data set.

Model	Parameter	Value/ Type
MLP	. # Dense layers	3
	. # Neurons in each layer	2000
	. Activation function	ReLU
CNN	. # Conv. blocks	3
	. Conv. kernel size for blocks 1, 2 and 3	(5, 1), (4, 1), (3, 1)
	. # Conv.kernels in each block	50
	. Pool size for blocks 1, 2 and 3	(2, 1), (3, 1), (4, 1)
	. # Neurons in the dense layer	1000
	. Activation function for the Conv. blocks	Tanh
	. Activation function for the dense layer	ReLU
LSTM	. # LSTM layers	2
	. # Output dimensions for each LSTM cell	600
	. # Neurons in the dense layer	512
	. Activation function for the dense layer	ReLU
AE	. # Encoder dense layers	3
	. # Neurons in layers 1, 2 and 3	5000, 3000, 1000
	. Activation function	ReLU

The evaluation of our feature extraction framework is based on three different metrics, average $F1$ score, overall accuracy and weighted $F1$ score. $F1$ score is the harmonic mean of precision and recall, and average $F1$ score is the mean value of each class $F1$ scores. As mentioned in Section 3.1, our data set was strongly imbalanced with only 6.65% positive samples, and both accuracy and weighted $F1$ score are very biased in case of an unbalanced data set. For this reason, the average $F1$ score, which is the mean value of each class $F1$ score, is considered as our main evaluation metric due to its ability to take class imbalance into account [69].

The results of the aforementioned feature extraction approaches with both SVM and RF classification methods are provided in Tables 4 and 5, respectively.

Table 4. SVM classification evaluation metrics (in percent) of different tested feature extraction models on the SHRP2 data set.

Methods	Accuracy	Weighted $F1$ Score	Average $F1$ Score
HC	94.34	92.99	66.56
MLP	83.60	82.30	75.00
CNN	85.72	84.9	79.10
LSTM	76.81	72.01	57.90
AE	83.40	82.40	75.50

Three main observations can be drawn from Tables 4 and 5. First, the choice of the classifier impacts the final classification performance. RF improved the average $F1$ score of HC feature extraction to 71.78%, and a notable improvement of the RF with almost 10% more for average $F1$ score is for LSTM feature learning. Second, deep feature learning outperforms feature engineering. In particular, CNN surpasses other methods by a remarkable average $F1$ score of 79.10% and 78.39% for SVM and RF, respectively. Finally, the quite decent performances with unsupervised deep feature learning (AE) when compared to supervised feature learning, is a remarkable observation of this study.

Table 5. RF classification performance metrics (in percent) of different feature extraction models of five cross on the SHRP2 data set.

Methods	Accuracy	Weighted *F*1 Score	Average *F*1 Score
HC	94.97	93.95	71.78
MLP	84.06	83.57	77.47
CNN	85.72	84.19	78.39
LSTM	78.00	76.61	67.22
AE	84.22	83.74	77.67

5. Analysis

The experiment on applying feature extraction approaches on a SHRP2 crash data set reveals the following points: First, all feature learning approaches except LSTM with both classifiers outperform the feature engineering. LSTMs are usually prone to high computation time and are difficult to tune. Another reason for the poor performances of LSTM is the length of the time horizon ($T = 100$) of the input samples being too long. This happens quite often when dealing with time series and is one of the reasons CNNs are preferred over RNNs for time-series processing in the literature.

CNN feature learning obtains a stable top performance with both classifiers. Obtained results are consistent with the literature, which seems to indicate that CNNs are the most reliable architecture for time-series classification [70,71]. To understand the difference between HC features and features created by deep feature learning, the best features extracted by both approaches were analyzed in our paper. For HC, it is possible to use the ranking of the RFE algorithm which was applied for feature selection.

Figure 7 shows the RFE on HC features for the five cross-validation folds. In these figures, the x-axis is the RFE eliminating steps, and the y-axis shows eighteen HC features of each sensor channel. The RFE method removes features iteratively, starting with the ones with the least impact on the final classification performance. As can be seen in all five figures, the HC features extracted by gas and acceleration sensors are the ones that are eliminated last, meaning that features from these two sensor channels are the most important HC features selected by RFE.

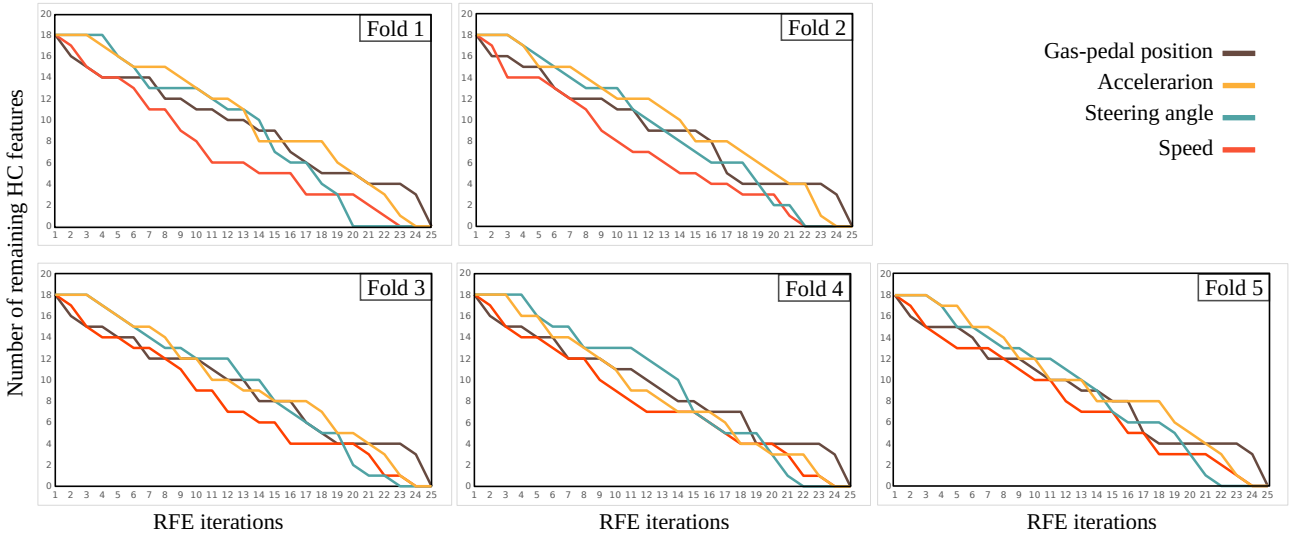


Figure 7. RFE results per sensor channel for five cross-validation folds. The y-axis shows the number of remaining features from each sensor, and the x-axis shows the step by step removal of features from each sensor.

For DNNs, finding the best features is more challenging since features learned by DNNs are hard to interpret. Instead, we decided to use an approach based on the Jacobian matrix of the model to determine which sensor channels are the most important and whether this matches the observation of the HC results. In case of considering a trained DNN as an approximation of a multi-input/multi-output function $f : \mathcal{R}^{L \times S} \rightarrow R^{C}$, where L is the length of a multichannel segment $\boldsymbol{X}$ belonging to the target data set $\mathcal{X}_T$, S is the number of channels, and C_T is the number of classes, it is possible to compute the Jacobian matrix of function $\boldsymbol{f}$. Each Jacobian value $J_{c,l,s}(\boldsymbol{X})$ in the Jacobian Matrix, represents the importance of x_{ls}—the value at the lth time point $(1 \leq l \leq L)$ of the sth sensor—on the predictive function for the cth class. It can therefore be used to indicate which parts of the input have the most impact on the output classification score. With this, it is possible to propose a 'Jacobian score' similar to [72] that would indicate how important to the final classification score a specific sensor channel is.

A channel-wise Jacobian score for $\omega_s(\boldsymbol{X})$ as the average of absolute $J_{c,l,s}(\boldsymbol{X})$ over all the L time points and all the C_T classes is,

$$\omega_s(\boldsymbol{X}) = \frac{1}{C_T} \frac{1}{L} \sum_{c=1}^{C_T} \sum_{l=1}^{L} \mid J_{c,l,s}(\boldsymbol{X}) \mid \tag{7}$$

In addition, as described in [72], the global channel-wise Jacobian score Ω_s is averaging $\omega_s(\boldsymbol{X})$ over all examples $\boldsymbol{X}_T$ in the data set, where $|(\mathcal{X}_T)|$ refers to the cardinality of $\mathcal{X}_T$:

$$\Omega_s = \frac{1}{|(\mathcal{X}_T)|} \sum_{\boldsymbol{X} \in \mathcal{X}_T} \omega_s(\boldsymbol{X}) \tag{8}$$

A high Ω_s indicates a high importance of the sensor channel for the classification problem. Figure 8 shows the Jacobian scores for the four input sensor channels (speed, gas position, steering angle, acceleration) and for each of the five CNNs trained on each cross-validation fold. According to the Jacobian scores of these sensors, steering-angle has the highest impact on the result. Speed and acceleration are the second most important input signals. Finally, this study shows that gas-position was consistently found to be considered as the least useful channel by CNN, which is opposite to feature extraction with HC that obtained its best features from this channel. This would indicate that the features learned by HC and CNN are different in nature and might be complementary. Additionally, we present a hypothesis regarding why steering-angle information was regarded as useful for the classification problem by CNNs and not by HC. The steering-angle signal, compared to the other sensor channels, is characterized by strong and rapid fluctuations that might contain valuable frequency-based information for the considered classification problem. Contrary to CNN, this information might not have been captured well enough by the HC features that were extracted.

Analysis of the feature importance results led us to combine CNN features with the optimal ranked HC features to improve the results. The same steps were used to calculate the features as described in Section 3.3.1. Then the RFE was used to rank all features and keep only the three best ones. These features were then appended to the 1000 features of CNN in Section 3.3.3. Combined CNN features improved the average $F1$ score from 79.10% to 80.12% for a SVM and from 78.39% to 79.10% for RF classifier which seems to confirm our hypothesis that both features contain complementary information.

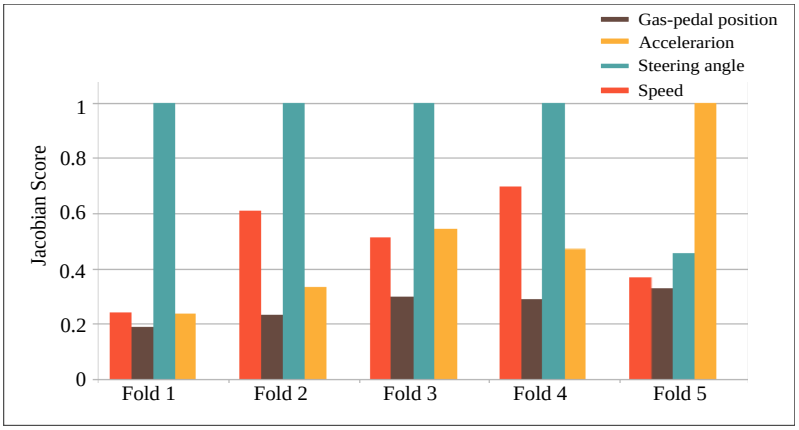


Figure 8. Jacobian score for CNN of five cross-validation folds of four signals. A higher Jacobian score indicates that the sensor channel contributed to the learning of more discriminative features. The y axis represents the normalized magnitude of the Jacobian score for each sensor channel.

6. Conclusions

In this paper, we presented a framework for accident detection from the most basic sensors in cars in the SHRP2 naturalistic data set using machine learning approaches. This framework was used to perform a study testing various feature extraction and classification approaches. The state-of-the-art feature extraction methods, including traditional manual feature extraction and feature learning, were combined with two classifiers. CNN features with a SVM classifier outperformed all other tested approaches including HC with an accuracy of 85.72%, an 84.9% weighted *F*1 score and an 79.10% average *F*1 score. This result is very promising, considering that the data used in this study are based on naturalistic accidents, and very few samples are severe accidents, recognizable by only four basic in-car sensors. Additionally, interpretability studies showed that the HC and DNN approaches were extracting their optimal features from different sensor channels and could therefore effectively be combined because of their complementarity.

The first major limitation of our study is that we use a single data set due to the extreme scarcity of data for this application, which limits the generalization capacity of our findings. Second, it is difficult to compare our findings to other studies due to different accident definitions and different types of input sensor channels.

Based on our observations and study conclusion, the *lessons learned* are listed briefly as follows:

- It is possible to obtain promising results with ML for the detection of accidents using basic in-car sensor data.
- A deep learning feature extraction method performs better in comparison with HC, and unsupervised feature extraction remarkably achieves the second best performance score.

Therefore, our future work will include four main points: First, the number of sensor channels tested in this work is limited. We would like to explore other combination of channels as well as other learning algorithms to further improve our classification performance. Including more sensor modalities such as lateral acceleration and yaw rate to the data set which are still counting as initial sensors and are available in all cars and analyzing their influences on the detection performance is a potential study investigation. The second possible way to improve the accident detection results is to employ more advanced feature selection algorithms such as embedded feature selection methods for unbalanced data sets (e.g., [73]) as future work. Third, following the promising performances of unsupervised deep feature learning (AE), further investigation of unsupervised feature learning techniques for future work is recommended. Finally, to bypass the struggle of insufficient labeled data, one possible solution would be to investigate transfer learning [74].

Author Contributions: Conceptualization, H.H.P. and F.L.; methodology, H.H.P. and F.L.; software, H.H.P., L.W. and C.T.; validation, H.H.P.; formal analysis, H.H.P., F.L. and L.W.; investigation, H.H.P. and R.D.; resources, H.H.P.; data curation, H.H.P.; writing–original draft preparation, H.H.P.; writing–review and editing, H.H.P., F.L. and L.W.; visualization, H.H.P.; supervision, M.G. and R.W.; project administration, M.G. and R.W.; funding acquisition, M.G. and R.W. All authors have read and agreed to the published version of the manuscript.

Funding: Research and development activities leading to this article have been supported by the German Federal Ministry of Education and Research (BMBF) within the project LEICAR (grant number: 01IS15048B) and German Federal Ministry for Economic Affairs and Climate Action (BMWK) within the project GEMIMEG-II (grant number: 01MT20001L).

Acknowledgments: The authors would like to thank Virginia Tech Transportation Institute (VTTI) for providing access to their data base. The findings and conclusions of this paper are those of the authors and do not necessarily represent the views of the VTTI, SHRP2, the Transportation Research Board, or the National Academy of Sciences.

Conflicts of Interest: The authors declare no conflict of interest.

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International Journal of
Environmental Research and Public Health

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Evaluation of the Most Stressful Dental Treatment Procedures of Conservative Dentistry among Polish Dental Students

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Abstract: Background: Dental schools are considered to be a very stressful environment; the stress levels of dental students are higher than those of the general population. The aim of this study was to assess the level of stress among dental students while performing specific dental procedures. Methods: A survey was conducted among 257 participants. We used an original questionnaire, which consisted of 14 questions assigned to three categories: I—Diagnosis, II—Caries Treatment, and III—Endodontic Treatment. Each participant marked their perceived level of stress during the performed dental treatment procedures. The scale included values of 0–6, where 0 indicates no stress, while 6 indicates high stress. Results: Third- ($p = 0.006$) and fourth-year ($p = 0.009$) women were characterized by a higher level of perceived stress during dental procedures related to caries treatment. Caries treatment procedures were the most stressful for 18.3% of third-year students, 4.3% of fourth-year students, and 3.2% of fifth-year s tudents. Furthermore, 63.4% of third-year students, 47.3% of fourth-year students, and 17.2% of fifth-year students indicated that they felt a high level of stress when performing endodontic procedures. Conclusion: Third- and fourth-year female students are characterized by a higher level of stress during caries and endodontic treatment procedures. The most stressful treatments for participants were endodontic treatment procedures.

Keywords: caries; dental education; endodontic treatment; stress

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Citation: Mocny-Pachońska, K.; Doniec, R.J.; Wójcik, S.; Sieciński, S.; Piaseczna, N.J.; Duraj, K.M.; Tkacz, E.J. Evaluation of the Most Stressful Dental Treatment Procedures of Conservative Dentistry among Polish Dental Students. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4448. https://doi.org/10.3390/ijerph18094448

Academic Editor: Gianrico Spagnuolo

Received: 11 March 2021
Accepted: 20 April 2021
Published: 22 April 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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1. Introduction

Stress is defined as the body's reaction to a change that causes a physical, mental, or emotional response and can be positive and stimulating and motivate individuals to act. In some situations, however, stress may negatively affect and limit the activity of individuals [1]. Individual perceptions of stress vary widely and can be influenced by beliefs, attitudes, and occupation, among other factors. Health sciences curricula have been related to a high level of stress in students. Dental schools are considered to be a very stressful environment, and the stress levels of dental students are higher than those of the general population [2–5].

Dental studies are characterized by an extensive program that requires significant effort and a predisposition to clinical work with patients. Many factors play a role in the mental development of a dental student, one of the most important being the ability to deal with stress. Stress factors include competition, comparisons between students, teacher/student relationships, patient/student relationships, clinical application of the the-

ory of knowledge, and individual skills. These factors can significantly influence a student's confidence and influence the way that they perceive and experience their education [1,6].

In pre-clinical or clinical dental education, stress is ubiquitous. To reduce these feelings, especially during the transition period between pre-clinical and clinical activities, teaching assistants and lecturers need to know how to support students. Clinical training can particularly affect the performance of students due to their exposure to a variety of patient-related stressors that are similar to those experienced by dentists [7,8].

This stress also depends on the type of procedures that students perform during their training. The number of procedures performed by students during the entire three-year clinical course necessary to pass the final exam for the Conservative Dentistry with Endodontics program at the Medical University of Silesia consists of 35 restorations, 6 root canal treatments ending with obturation, and 10 examinations (including diagnosis and treatment plan). Restorations include the treatment of dental cavities, described in Black Caries Classification (i.e., classes I, II, III, IV, and V) [9,10], using composite materials.

Endodontic treatment involves the preparation of root canals using the step-back method and filling them with the lateral condensation technique [11]. The number of required root canals to be filled does not meet the requirements of the European Society of Endodontology of 2001, which recommends that the student should feel confident in their subsequent work after filling in 20 root canals. The guidelines published in 2013 were changed to emphasize the quality of endodontic treatment [12]. Nevertheless, Honey et al. showed that 81% of students from 48 dental schools in the European Union had completed 8–30 root canals (17 on average) [13].

The anatomical variety of root canals, the need to provide adequate patient care, and the lack of self-confidence among students have prompted many of them to consider endodontics to be an extremely difficult and stressful discipline. In this area, it is extremely difficult for students to translate the outcome of pre-clinical training into successful clinical treatment in a real patient. The difficulties in the initial stage of endodontic treatment often lead to frustration and dissatisfaction with pre-clinical training [8,14,15].

The aim of this study was to assess the level of stress while performing specific dental procedures among dental students in three different years of study. The second aim of the study was to confirm the hypothesis that the level of perceived stress decreases with experience, while the third aim of the study was to identify the most stressful dental procedures for students, depending on their year of study and gender.

2. Material and Methods

2.1. Experiment Setup

A total of 360 dental students of the Faculty of Medical Sciences of the Medical University of Silesia (Zabrze, Poland) were invited to take part in the study. The choice of students, which represented the third, fourth, and fifth years, was based on the program curriculum. The study was conducted between 7 and 31 January, 2020. In total, 257 students completed the study.

Table 1 presents the demographic description of the study group. The χ^2 non-parametric test of independence showed no statistically significant differences between the age groups, regardless of the respondents' gender ($\chi^2 = 3.703$, $p = 0.157$).

Each participant filled out a questionnaire, which consisted of 14 questions. The questions were assigned to three categories: I—Diagnosis, II—Caries Treatment, and III—Endodontic Treatment.

Category I (Diagnosis) included three questions on making a diagnosis, performing a dental examination, and taking a complete medical history. Category II (Caries Treatment) included five questions on infiltration and conductive anesthesia, placement of a matrix, and the preparation and adjustment of the filling to the occlusion. Category III (Endodontic Treatment) included six questions about cleaning of a deep cavity, endodontic access (trepanation, amputation), finding the canal orifices, measuring the working length, filling the canal, and radiological assessment of the filled canal. Each of the participants in the

study marked the level of stress they felt during the performed dental treatment procedures. The blank questionnaire is provided in the Supplementary Materials.

Table 1. Demographic data of the participants (dental students at the Medical University of Silesia).

Year of Study	Number of Students	Median Age [Years]
Third	71 (53 women, 18 men)	23
Fourth	93 (58 women, 35 men)	24
Fifth	93 (68 women, 25 men)	24

The scale of levels of stress was based on a 7-point Likert scale (0, no stress; 6, high stress) [16]. The scale included values from 0 to 6, where 0 indicated stress free, 1 and 2—low stress, 3 and 4—medium stress, and 5 and 6—high stress. The questionnaire was filled in during seminar classes in accordance with the schedule of the given student group. All participants were provided with the same conditions: no more than 10 people in the room, a room insulated from noise, adequately lighting and ventilation, sufficient space to complete the survey, and comfortable sitting.

The study was approved by the Ethical Commission of Medical University of Silesia, under the resolution number KNW/0022/KB1/79/18 taken on 16 October 2018. All participants gave informed consent before inclusion in the study group.

2.2. Statistical Analysis

Statistical analysis was performed using the Statistica Version 9.0 (StatSoft, Inc., Tulsa, OK, USA) and Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) software. Due to the significant differences between the students representing different consecutive years of study and gender, we used the non-parametric χ^2 test of independence. The Mann–Whitney test was used to assess the significance of differences in the scale values between genders for the subsequent years of study. The significance of gender differences in the subsequent years of study was assessed by the Kruskal–Wallis test. The statistical analysis was supported by post hoc tests in two variants: Dunn's test (Dunn–Bonferroni test) and Conover test. The level of statistical significance (p) was set to 0.05.

3. Results

3.1. Reliability of the Scale

To examine the reliability of proposed stress scales, we calculated the Cronbach's alpha coefficients; for which an a value over 0.7 suggests high reliability [17]. Table 2 presents the Cronbach's alpha coefficients.

The values presented in Table 2 prove the high reliability of the proposed stress scale. The elimination of Question 3 (on making a diagnosis) slightly improved the reliability of the stress scale, similarly to the removal of Question 6. The question on the treatment of deep cavity group slightly improved the Cronbach's alpha coefficient.

Table 2. Analysis of scale reliability.

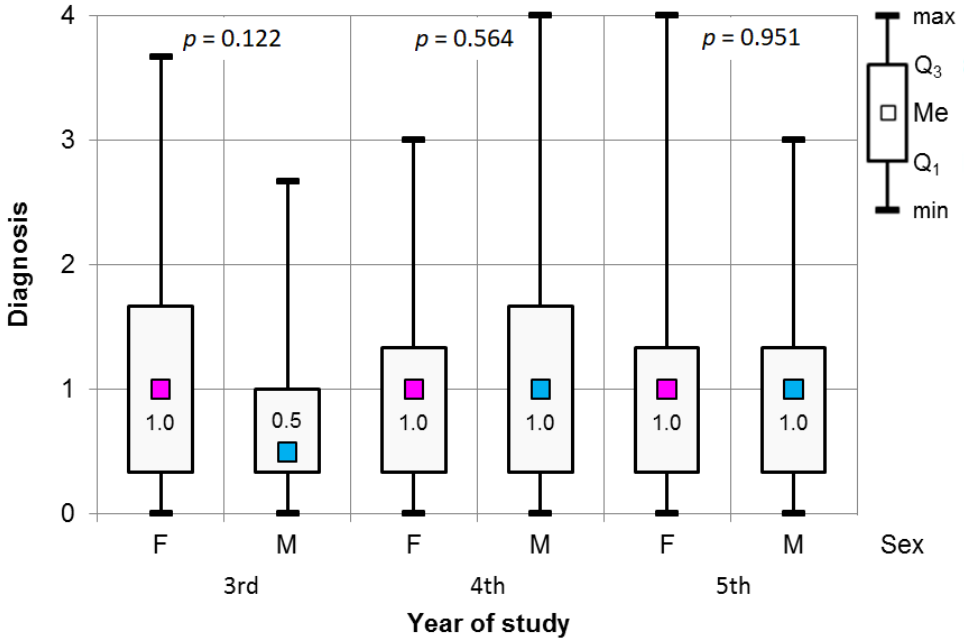
Survey Group					Item Elimination	
		α	α_{st}	$r_a v$	Item	α
I (Diagnosis)	Total	0.75	0.80	0.56	3	0.76
	Female	0.73	0.77	0.53	3	0.74
	Male	0.80	0.84	0.64	3	0.81
II (Caries Treatment)	Total	0.82	0.81	0.47	-	-
	Female	0.81	0.80	0.45	-	-
	Male	0.82	0.82	0.45	-	-
III (Endodontic Treatment)	Total	0.89	0.89	0.59	6	0.91
	Female	0.89	0.90	0.60	6	0.91
	All	0.88	0.89	0.57	6	0.90

α—Cronbach's alpha, α_{st}—standardized alpha, r_{av}—average correlation coefficient.

3.2. Category I (Diagnosis)

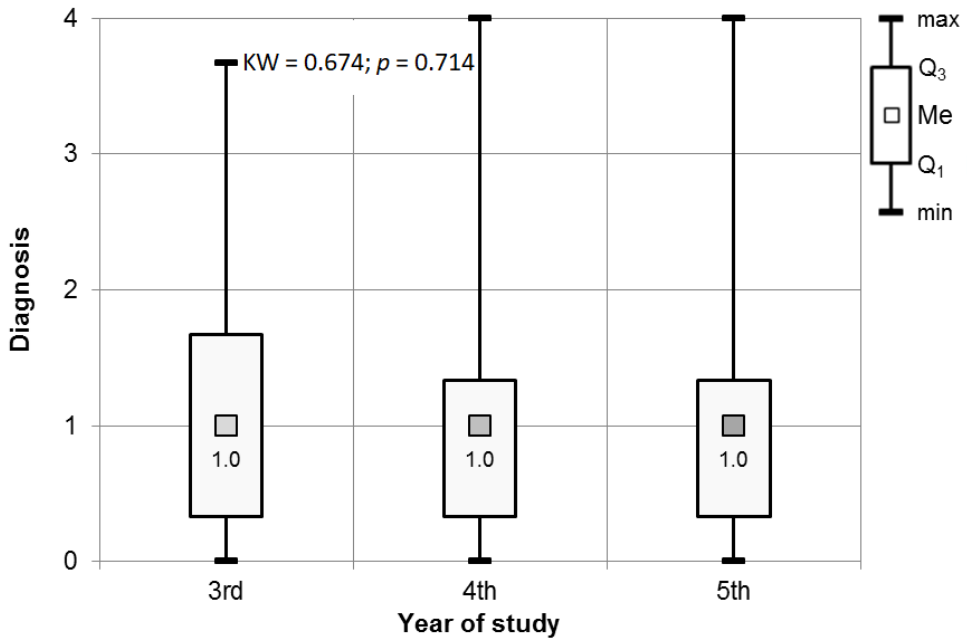
The results of the Mann–Whitney test showed insignificant differences between genders (see Figure 1) for Diagnosis procedures. We did not observe any significant differences in the stress level related to Diagnosis procedures between the participants as related to the year of study (see Figure 2).

No participant reported a high level of perceived stress when answering the questions relating to diagnosis. The responses indicated that 45.1% of the third-year students, 41.9% of the fourth-year students, and 46.2% of the fifth-year students felt no stress during the dental examination, interview, and diagnosis procedures (see Figure 3).



Q_1—first quartile, Q_3—third quartile.

Figure 1. Results of the Mann–Whitney test used to assess the significance of differences in the Diagnosis procedures in relation to gender and year of study.



Q_1—first quartile, Q_3—third quartile

Figure 2. Results of the Kruskal–Wallis test used to assess the significance of differences in the Diagnosis procedures in relation to gender and year of study.

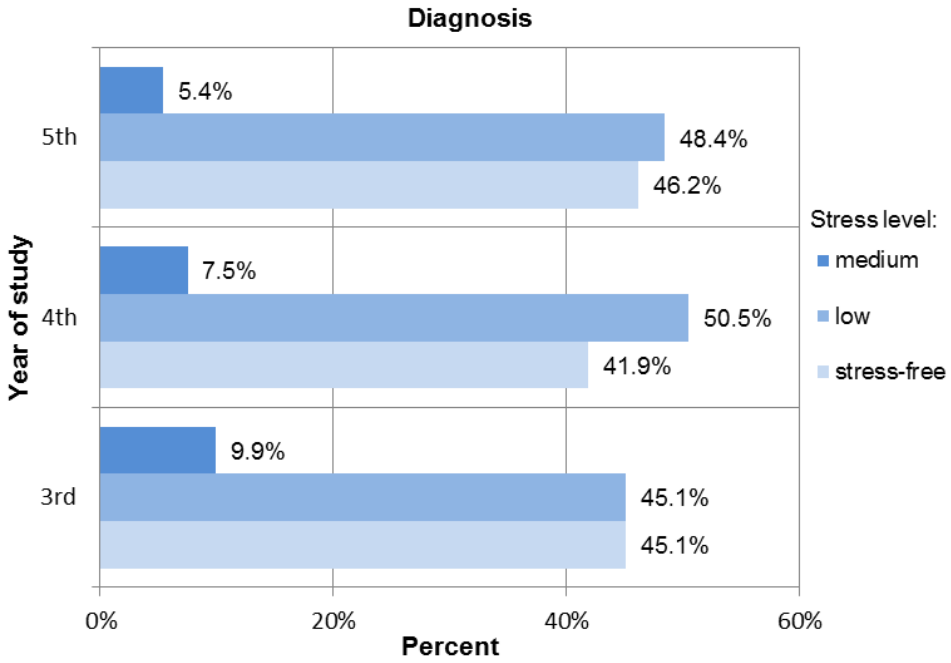


Figure 3. Distribution of the stress levels among students for Diagnosis procedures.

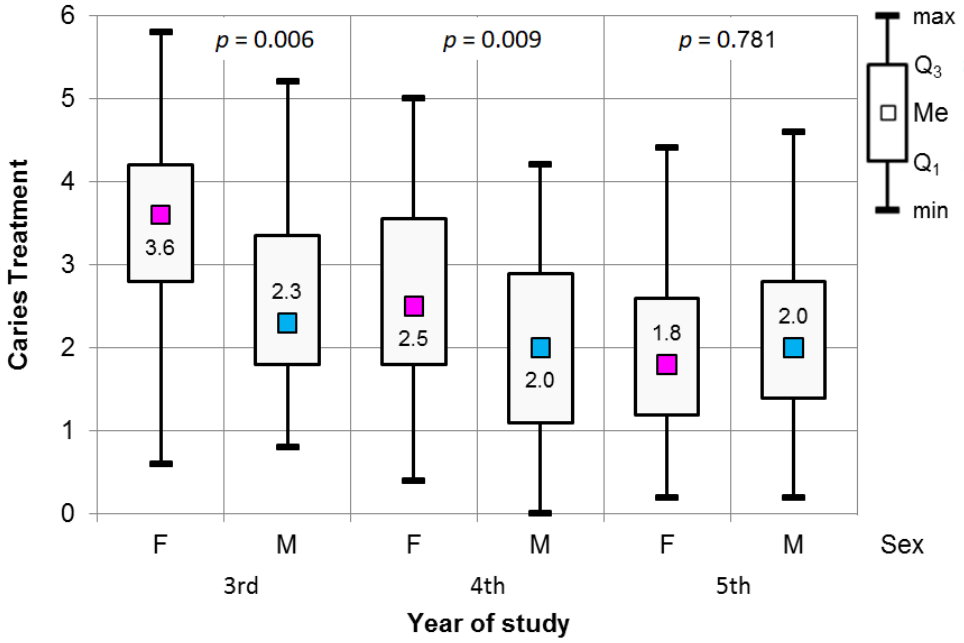
3.3. Category II (Caries Treatment)

The results of the Mann–Whitney test used to assess the significance of the differences in the values for the stress scale in Caries Treatment are presented in Figure 4. The differences between men and women in their third ($p = 0.006$) and fourth years of study were statistically significant ($p = 0.009$).

In both years of study, women were characterized by a higher level of perceived stress during dental procedures related to caries treatment. The median for women in their third year was 3.60, while that for men was 2.30. In the case of fourth-year students, these values were 2.50 for women and 2.0 for men (see Figure 4).

The most prominent differences in perceived stress were observed for the questions covering the caries treatment, which were proved by the Kruskal–Wallis test ($p < 0.001$) performed on participants representing each analyzed year of study. Complementary post hoc tests confirmed the significant differences in the level of perceived stress between the participants of each analyzed year (Dunn's test, $p < 0.001$), third and fifth year (Dunn's test, $p < 0.001$), and fourth and fifth year (Dunn's test, $p = 0.03$). In all cases, lower-year students were characterized by a higher level of perceived stress (see Figure 5, Table 3).

A total of 18.3% of third-year students, 4.3% of fourth-year students, and 3.2% of fifth-year students experienced high levels of stress related to caries treatment procedures; 54.8% of students in their fifth year experienced low levels of stress. In the case of third-year students, the dominant level of perceived stress was moderate (52.1%). Fourth-year participants experienced low stress in 47.3% of cases (see Figure 6).



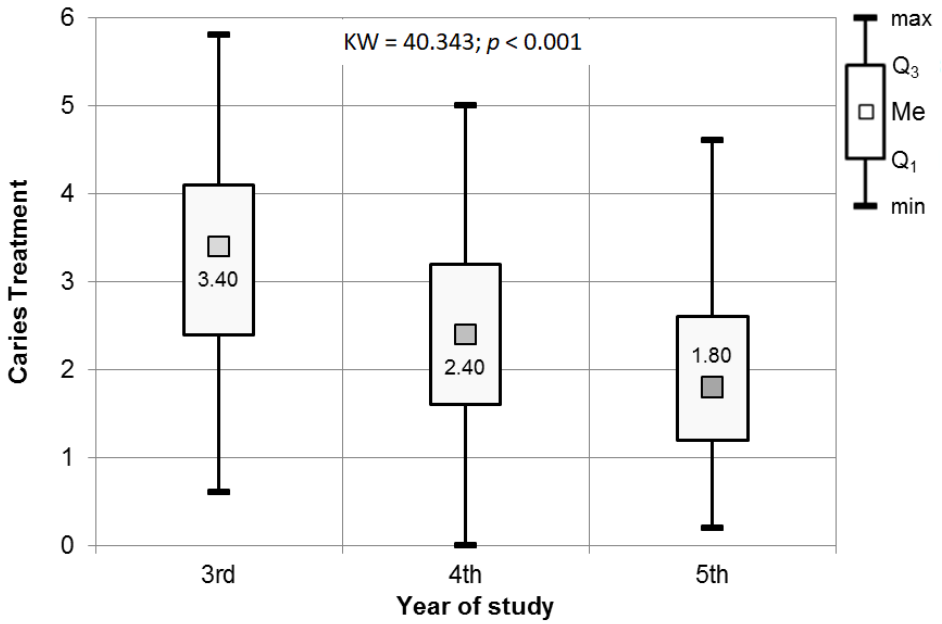
Q_1—first quartile, Q_3—third quartile.

Figure 4. Results of the Mann–Whitney test used to assess the significance of differences in the Caries treatment procedures in relation to gender and year of study.

Table 3. Results of post hoc tests—Caries treatment procedures.

		Dunn–Bonferroni		
Conover	Year of study	Third	Fourth	Fifth
	Third		<0.001	<0.001
	Fourth	0.05		0.03
	Fifth	0.02	NS	

NS: Not significant.



Q_1—first quartile, Q_3—third quartile.

Figure 5. Results of the Kruskal–Wallis test used to assess the significance of differences in the Caries treatment procedures in relation to the year of study.

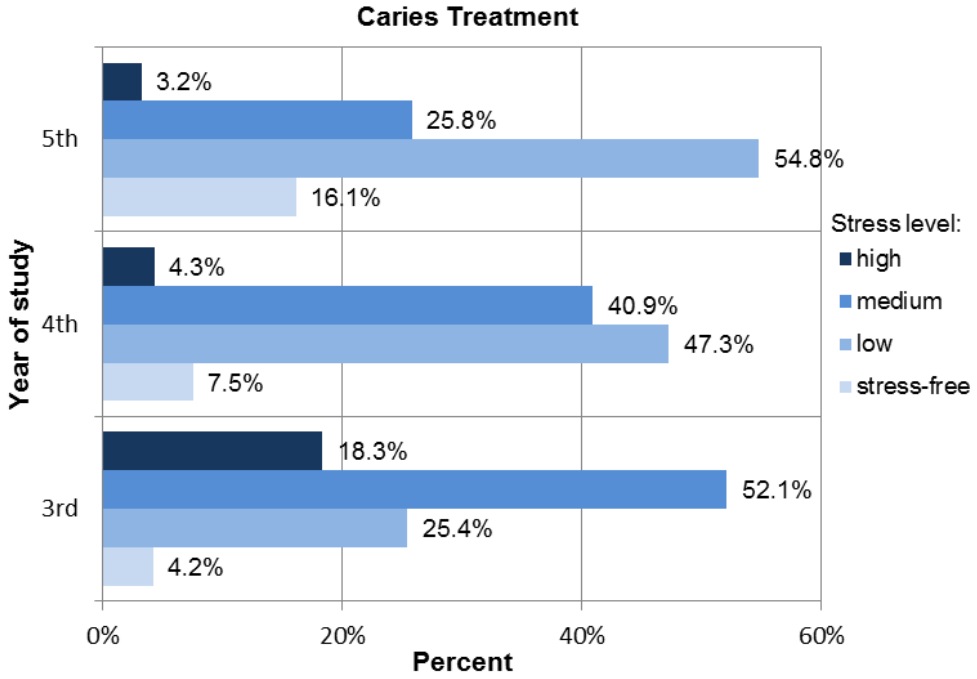
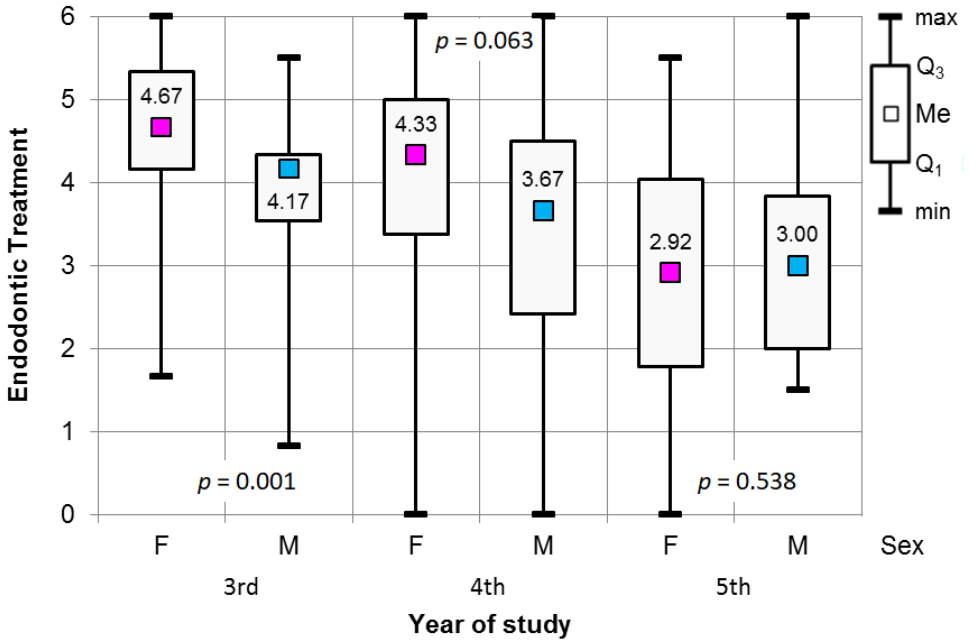


Figure 6. Distribution of stress levels among students for Caries treatment procedures.

3.4. Category III (Endodontic Treatment)

Endodontic treatment procedures were the most stressful for third-year participants. Women in their third year of study perceived a higher level of stress (median of 4.6) than men in the same year of study (median of 4.17), with a significance of $p = 0.001$. The results of the Mann–Whitney test, used to assess the significance of the differences in the values for the stress scale in Endodontic treatment, are presented in Figure 7. The difference

in perceived stress level between men (median of 3.67) and women (median of 4.33) representing the fourth year of study was statistically significant ($p = 0.063$), as shown in Figure 7.



Q_1—first quartile, Q_3—third quartile.

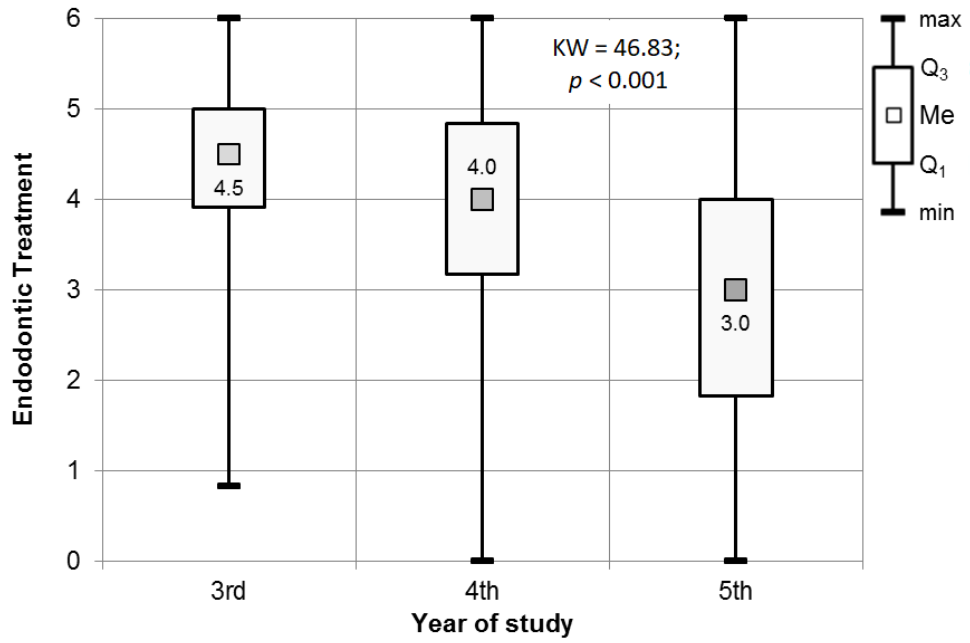
Figure 7. Results of the Mann–Whitney test used to assess the significance of differences in the Endodontic treatment procedures in relation to gender and year of study.

The results of the Kruskal–Wallis test ($p < 0.001$), supplemented with post hoc tests, demonstrated significant differences in the perceived level of stress during endodontic procedures between third- and fourth-year students (Dunn's test, $p = 0.04$), third- and fifth-year students (Dunn's test, $p < 0.001$), and between fourth- and fifth-year students (Dunn's test, $p < 0.001$). The fifth-year students (median of 3) were stressed the least when performing endodontic procedures (see Figure 8, Table 4).

Table 4. Results of post hoc tests—Endodontic treatment procedures.

		Dunn-Bonferroni		
Conover	Year of study	Third	Fourth	Fifth
	Third		0.04	<0.001
	Fourth	NS		<0.001
	Fifth	0.02	0.04	

NS: Not Significant.



Q_1—first quartile, Q_3—third quartile.

Figure 8. Results of the Kruskal–Wallis test used to assess the significance of differences in the Endodontic treatment procedures in relation to the year of study.

Endodontic treatment procedures turned out to be the most stressful treatment procedures for students: 63.4% of third-year students, 47.3% of fourth-year students, and 17.2% of fifth-year students indicated that they felt a high level of stress when performing endodontic procedures. Moreover, moderate stress was experienced by 31% of third-year students, 35.5% of fourth-year students, and 36.6% of fifth-year students (see Figure 9).

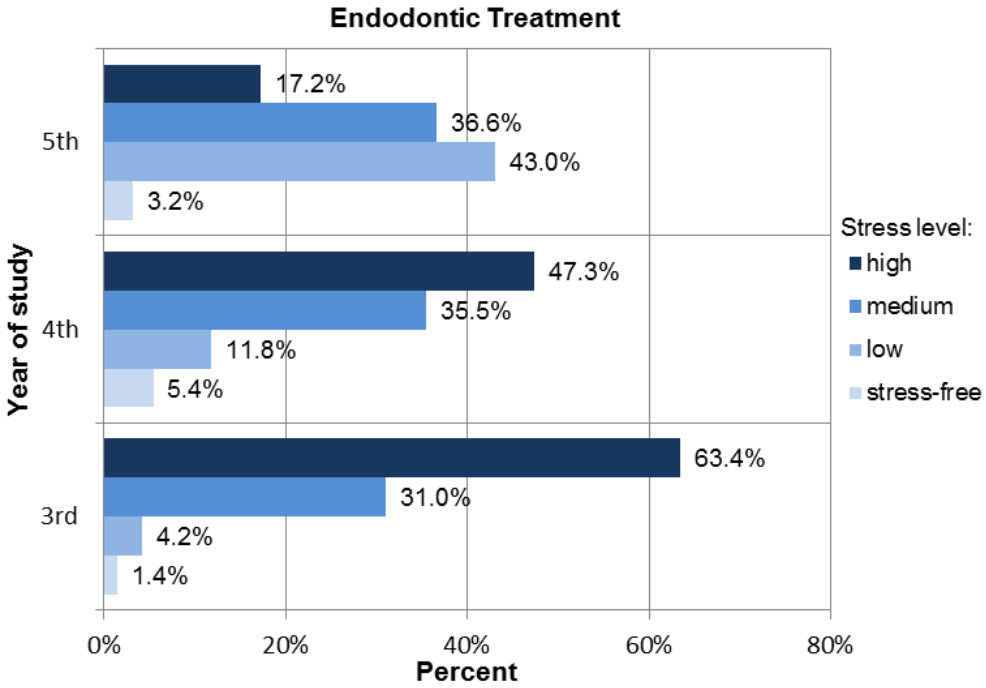


Figure 9. Distribution of the stress levels among students for Endodontic treatment procedures.

4. Discussion

Dental studies programs require students to master theoretical knowledge and to attend practical training sessions [18]. For many of them, the significant amount of theoretical knowledge and practical skills to master increases the level of perceived stress, especially for those with a lower level of manual skills. Many procedures performed during dental treatment are very demanding, such as endodontic treatment.

Tanalp et al., when assessing a group of 48 fifth-year students, discovered that 11.9% found endodontic procedures to be very difficult. The students felt the least confident in inserting a rubber dam, in whitening endodontically treated teeth, in the treatment of resorption, and with endo-perio cases, as well as in endodontic apexification and retreatment processes [12]. In our findings, 17.2% of the 93 fifth-year students who completed the questionnaire experienced high levels of stress related to endodontic treatment.

Meanwhile, 36.6% of the fifth-year students experienced an average level of stress. The questions did not mention complicated procedures, such as endodontic retreatment or resorption treatment—these procedures are not performed by students, according to the program curriculum at the Medical University of Silesia. The questions were related to the basic methods of treatment, including endodontic access, finding the root canal orifices, measuring the working length and filling the canal, and radiological evaluation after the end of treatment. Despite this fact, 53.8% of fifth-year students experienced moderate to high levels of stress. In the case of fourth-year students, 47.3% of them experienced a high level of stress during these procedures, while 63.4% of third-year students experienced high stress levels.

Tavares et al. observed that over 60% of 102 students who took pre-clinical or clinical classes in endodontics did not report any difficulties with proper endodontic access. On the other hand, approximately 44% of students in the pre-clinical endodontics phase reported difficulties with the correct performance of the crown-down technique, although the number of students reporting difficulties with this method decreased to 4% during the clinical course. A low percentage of students reported problems with determining the working length and choosing the correct instrumentation. Most problems were experienced by the stutters when the appropriate medication was prescribed during multi-session root canal treatment. Most students, however, confirmed that they were able to overcome the aforementioned difficulties, thanks to further education and experience [19].

According to the study of Alrahabi, the differences in the level of self-confidence between students in their fourth and fifth years of study were statistically significant, in favor of fifth-year students, with regard to the following procedures: the determination of the working length, the interpretation of radiographic imagery, the assessment of canal fillings, and setting follow-up visits [20]. In our study, the differences in the level of perceived stress related to the performance of endodontic procedures between students in their fourth and fifth year of study were statistically significant, where fifth-year students reported less stress. Female fourth-year students perceived a higher level of stress than their male counterparts.

Difficulties in performing endodontic procedures have also been noted in [7,20–23]. Another important aspect considered in the study was the transition of the theoretical knowledge and practical skills from the pre-clinical phase to the clinical environment, which requires contact with real patients. This was also confirmed in our study, where the highest level of stress was observed in third-year students in comparison with fourth- and fifth-year students [3].

Among the results, it can also be noted that female third-year students felt higher levels of stress than their male counterparts. This is probably due to the fact that the third year is when students start working in a clinical setting. In their study, Frese et al. showed that the level of perceived stress is clearly higher among students starting clinical classes, especially in the first weeks of these classes. According to Frese et al. [8], the most stressful procedures are endodontic treatment followed by restorative and periodontal treatment. Reported stress has also been associated with a negative impact on psychosocial interactions.

The main purpose of the course is to provide the relevant knowledge and skills to work efficiently as a dentist. Hattar et al. showed that fifth-year students felt most confident while performing direct restorations and simple endodontic treatment. However, they experienced difficulties while performing complex endodontic treatment and indirect restorations [24].

In our study, Polish fifth-year students perceived significantly lower levels of stress when performing procedures related to diagnosis, caries treatment, and endodontic treatment than third- and fourth-year students. In the case of caries treatment, over 50% of them experienced a low level of stress, while 16.1% did not find the procedures stressful. Similar results on caries treatment have been obtained by Rajan et al., where high confidence was experienced by undergraduate students for caries management and preventive care, while the lowest confidence was reported for the management of oral medicine, pathologies, and dental emergencies [25].

The levels of perceived stress and confidence among fourth- and fifth-year students during the preparation of cavities from deep caries and possible pulp exposure depend on the performed procedure, academic education, clinical training, the equipment and organization of the clinical room, vital pulp material, and the patient. In order to reduce stress, students have indicated the need to implement modern teaching methods (e.g., the use of 3D printers) and to develop the same algorithms of conduct among teachers [14].

5. Limitation of the Study

This study raises very important issues related to the dental education and the transfer of skills attained at university to the professional career. Nevertheless, it does come with some limitations. The study was conducted among students of only one university (Medical University of Silesia). Such a comparison between students of several Polish universities could give a broader perspective. Including more students in the study would certainly also strengthen the statistical analyses. These factors could affect any changes to the curriculum more significantly.

6. Conclusions

Women in their third year of study were characterized by a higher level of perceived stress compared to men in the same year of study. Third-year participants experienced the greatest stress in the case of caries treatment and endodntic treatment procedures. The obtained results confirmed the hypothesis that the level of perceived stress decreases with the experience acquired. We confirmed that endodontic treatment procedures are the most stressful procedures for students, regardless of their year of study. Emphasis on increased education in this direction should be included in the curriculum.

7. Practical Application

The information about the most stressful procedures for students should lead to underlining the importance of preparing the students for performing them in clinical practice. Our study showed that the the transfer of skills from the pre-clinical to the clinical phase is an important part of the dental studies curriculum. The highest level of stress was experienced by the third-year students, who had just begun classes in a clinical setting. Using medical simulation techniques could improve the outcomes of the pre-clinical phase by preparing the students to perform conservative dentistry procedures on patients in clinical conditions.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph18094448/s1, Questionnaire S1: What level of stress do you feel when performing the following procedures.

Author Contributions: Conceptualization, K.M.-P.; methodology, K.M.-P. and S.W.; validation, K.M.-P. and S.W.; formal analysis, K.M.-P. and S.W.; investigation, K.M.-P.; resources, K.M.-P.; writing–original draft preparation, K.M.-P. and S.W.; writing–review and editing, K.M.-P., R.J.D., S.S., N.J.P., K.M.D. and E.J.T.; visualization, K.M.-P. and S.W.; project administration, K.M.-P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Medical University of Silesia under the resolution number KNW/0022/KB1/79/18 taken on 16 October 2018.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on a reasonable request from the corresponding author.

Acknowledgments: We would like to thank the students who agreed to participate in the study.

Conflicts of Interest: The authors declare no conflict of interest.

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The Relationship between Stress Levels Measured by a Questionnaire and the Data Obtained by Smart Glasses and Finger Pulse Oximeters among Polish Dental Students

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Abstract: Stress is a physical, mental, or emotional response to a change and is a significant problem in modern society. In addition to questionnaires, levels of stress may be assessed by monitoring physiological signals, such as via photoplethysmogram (PPG), electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), facial expressions, and head and body movements. In our study, we attempted to find the relationship between the perceived stress level and physiological signals, such as heart rate (HR), head movements, and electrooculographic (EOG) signals. The perceived stress level was acquired by self-assessment questionnaires in which the participants marked their stress level before, during, and after performing a task. The heart rate was acquired with a finger pulse oximeter and the head movements (linear acceleration and angular velocity) and electrooculographic signals were recorded with JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan). We observed significant differences between the perceived stress level, heart rate, the power of linear acceleration, angular velocity, and EOG signals before performing the task and during the task. However, except for HR, these signals were poorly correlated with the perceived stress level acquired during the task.

Keywords: stress level; dental education; wearable devices; heart rate; electrooculography; smart glasses; JINS MEME ES_R; linear acceleration; angular velocity

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Citation: Mocny-Pachońska, K.; Doniec, R.J.; Sieciński, S.; Piaseczna, N.J.; Pachoński, M.; Tkacz, E.J. The Relationship between Stress Levels Measured by a Questionnaire and the Data Obtained by Smart Glasses and Finger Pulse Oximeters among Polish Dental Students. *Appl. Sci.* **2021**, *11*, 8648. https://doi.org/10.3390/app11188648

Academic Editor: Gaspare Palaia

Received: 2 August 2021
Accepted: 15 September 2021
Published: 17 September 2021

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1. Introduction

Stress is the physical, mental, or emotional response to a change that is caused by an imbalance between the demands of an individual and the individual's ability to cope with them [1]. Despite the knowledge of the significant role of stress in the etiology of certain diseases (cardiac, mental, and many others) it is not classified as a separate ICD-10 or DSM V unit, but only considered a risk factor [2].

Stress has become a significant problem in modern societies and can lead to cognitive impairment, depression, and even cardiovascular diseases [3]. Stress affects not only mental health but also involvement in work and general attitude in everyday life [4–6].

The response to stress is related to the initiation of changes in its functioning. When a threat occurs, the autonomic nervous system (ANS) is stimulated and inhibits the activity of the parasympathetic system and activates the sympathetic nervous system. This reaction results in increased secretion of stress-related hormones, causing vasoconstriction, increased blood pressure, increased respiratory rate, increased muscle tone, heart rate (HR), and decreased heart rate variability (HRV). Among many different physiological stress

indicators, such as blood pressure, cortisol level, increased skin conductivity, and head and body movements, HRV is considered one of the reliable methods for assessing the physiological response of the body in response to stress. HRV is caused by the interaction of the sympathetic and parasympathetic parts of the autonomic nervous system and can be analyzed in time and frequency domains [6–11].

Head movement behavior is considered a part of non-verbal communication that expresses itself in various aspects of everyday life. There are several actions, such as lowering, lifting, tilting, nodding, or shaking, which have specific meanings and are recognizable in intercultural communication. Head movement features have been used in a few studies assessing whether a patient is under stress–they are usually more frequent, faster, and more significant [10]. The application of electrooculography (EOG) in the design of brain-computer interfaces and activity recognition has been described in several studies [12–16]. Electrooculography (EOG) is a technique for measuring the resting electrical potential between the cornea and retina of the human eye by registering the electrical signal via electrodes placed around the eyes [12,17]. Based on the fact that electrooculography is often used to detect eye blinks [12,13], we can assess the level of stress using EOG and analyzing the dynamics of eye blinks [18].

There are indications that EOG-measured eye movements are consistent with brain activation in both the parietal and frontal cortex during attention-shifting tasks. As a consequence, stress can cause visual distractions which have a negative influence on task performance [19]. Much research has focused on cognitive and perceptual processing based on eye movements and fixations [20]. In [21] Rayner showed that the duration of eye fixation depends on cognitive processes; these data on eye movement may provide important and interesting knowledge about human information processing.

Many studies have shown that dental students are at higher risk of stress than students of other faculties and study programs because of unique stressors, such as the need to acquire an extensive body of theoretical knowledge combined with manual training, practiced in preclinical simulation centers and then in clinical practice [22–31]. These circumstances are related to high levels of stress in dental students worldwide in comparison with the general population [27,29,30,32,33].

2. Related Works

A popular approach to the assessment of stress level is using questionnaires due to their simple setup. A widely used instrument to measure stress is the PSS-10 scale. The PSS-10 assesses the extent to which a person perceived life as unpredictable, uncontrollable, and overloaded in the previous month [34]. One common tool used in stress studies in academia is the Dental Environment Stress (DES) questionnaire [35]. In addition to demographics, the questionnaire contains 41 items grouped into seven stress-inducing domains as follows: self-efficacy beliefs, faculty and administration, workload, patient treatment, clinical training, performance pressure, and social stressors.

While DES is useful for investigating the source of stress, it was not designed to measure stress levels among students. Another well-proven and reliable tool for measuring experiences related to depression, anxiety, and stress is the DASS-21 scale. In this context, depression is characterized by the absence of positive feelings, a sense of hopelessness, and loss of self-esteem, while anxiety is characterized by autonomic agitation and fearfulness [36–38].

The DASS scale was initially developed to measure the signs of depression and anxiety. The development of DASS scale resulted in developing the third part of the scale which measures the physiological stress. The basic version of the DASS scale is a 42-point scale (also known as DASS-42), which consists of three 14-point sub-scales which measure the level of depression, anxiety, and physiological stress [37]. This structure is in line with the tripartite model of anxiety and depression proposed by Clark and Watson [39–41]. The shorter version of DASS-42, known as DASS-21, has slightly better psychometric properties compared to the full DASS scale (DASS-42) [42].

Another tool frequently used for assessing anxiety is the Immediate Anxiety Measures Scale, which is used for assessing anxiety associated with a task [43,44]. It evaluates the cognitive and somatic symptoms of anxiety.

In addition to questionnaires [2,45–48], the level of stress may be assessed by monitoring physiological signals, such as photoplethysmogram (PPG), electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), facial expressions, and head and body movements. The most common set of physiological signals involves heart rate variability (HRV) in combination with electrodermal activity [10,11,49–52].

Thanks to the technological improvements, monitoring of stress level could be performed with various wearable devices, such as smart watches and smart glasses, e.g., Google Glass or JINS MEME ES_R (JINS Holdings, Inc., Tokyo, Japan) [53–61], or smartphones [62]. These devices may be used to estimate the level of one's concentration; for instance, Ishimaru et al., conducted a study [63] which involved the use of JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan), further described in [61], to estimate the user's concentration level by processing the EOG signal and head position.

The development of wearable smart sensors for measuring basic physiological parameters enables data collection in everyday activities and opens new research areas in signal processing and data classification [64].

3. Study Objective

The purpose of the study was to find the relationship of the perceived stress level reported in the questionnaires and the changes of heart rate, electrooculographic signals, and the linear acceleration and angular velocity of the head measured by a finger pulse oximeter and JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan).

The study was based on the hypothesis that the level of stress experienced by participants of the study is reflected in physiological signals (such as HR, EOG, and head movements). If the hypothesis was confirmed, it would be possible to use the aforementioned signals as markers of stress.

4. Materials and Methods

4.1. Experiment Setup

The study was conducted on twenty 3rd year students (18 females and 2 males, aged 22.19 $\pm$ 1.50 years) of the Medical University of Silesia, Faculty of Medical Sciences in Zabrze (Zabrze, Poland) during seminar classes between 1 October 2020 and 15 October 2020. At that time, seminar classes could be conducted because of the state and university regulations on teaching during the COVID-19 pandemic in Poland [65]. The imbalance between male and female participants, expressed as the percentage of women in the examined population (90%) was higher than the gender distribution at the university (73.51%) ([66], p. 45), academic programs in medical sciences (78.48%) ([66], p. 24) and medical universities (72.4%) in Poland ([66], p. 15).

The experiment consisted of two phases: The first phase was the relaxation phase in which the subjects watched a 4 min video of landscapes with relaxing music. After one minute of the video, we started acquiring the data via JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan). After another minute, the video was interrupted by a sound signal ("Space" timer ringtone in iPhone 7 set with the maximum volume 40–50 dB and frequency 0–296 Hz). For each subject, the exact moment of the sound signal occurrence was documented in the experiment sheet. The setup for the first phase was similar to the example shown in Figure 1.



Figure 1. An example of subject setup for the experiment.

The second phase of the experiment was to complete a task which served as a stress-inducing factor: to match the endodontic instruments and dental burs with their names. The endodontic instruments are shown in Figure 2 and the dental burs are presented in Figure 3.



Figure 2. Endodontic instruments.

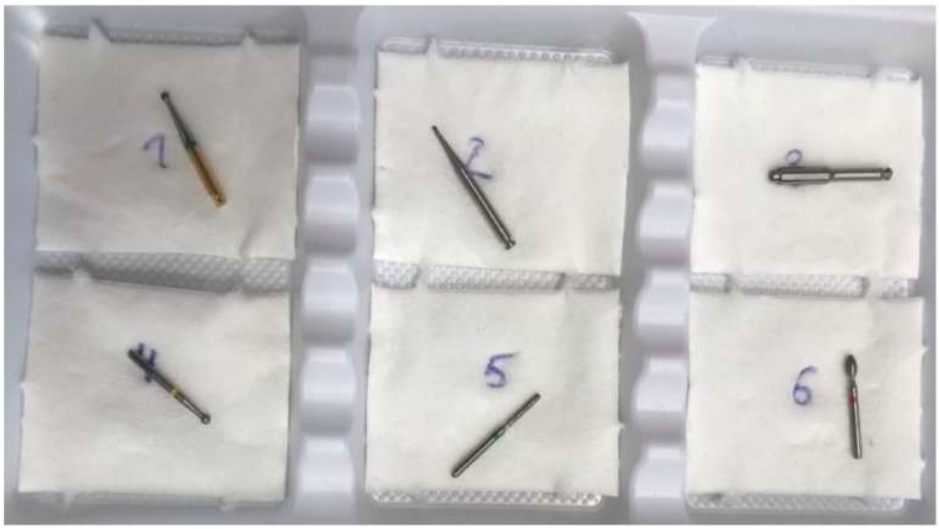


Figure 3. Dental burs.

There was not a strict time limit to finish the task; however, the EOG signal, linear acceleration, and angular velocity of the subject's head were acquired for approximately one minute. The heart rate was recorded during the entire experiment.

The participants (students) were informed about the experiment outline but they did not know when the signal would occur and how long the data acquisition would last. All participants were provided with the same conditions: a noise-insulated room, adequately lit and ventilated, with sufficient space to complete the answers, and a comfortable seat.

The students were also asked to complete the questionnaire after completing the task. The questionnaire consisted of the following questions in which the participants marked their perceived stress level during each phase (before, during, and after performing the task):

1. How performing a task affects your perceived stress level:
    a. While watching the film (before the sound signal)?
    b. During the performed task (after the sound signal)?
    c. After completing the task?
2. How stressful was waiting for the signal to occur and to start performing the task?

The questionnaire design was based on a seven-point Likert scale (0, no stress; 6, high stress) [67]. The scale included values from 0 to 6, where 0 means no stress, 1 and 2—low level of stress, 3 and 4—medium level of stress, and 5 and 6—high level of stress. The answers to the last question were not considered in further analyses.

The study design was approved by the Ethical Commission of Medical University of Silesia under the resolution number KNW/0022/KB1/79/18 taken on 16 October 2018. All participants gave informed consent before the experiment.

4.2. Technology Used

Electrooculographic (EOG) signals and head movement (linear acceleration—ACC, and angular velocity—GYRO) signals were acquired with JINS MEME ES_R (JINS Holdings, Inc., Tokyo, Japan) smart glasses. The glasses are equipped with three-point EOG sensors and a six-axis inertial measurement unit (IMU) with a three-axis accelerometer and a three-axis gyroscope. The six-axis sensor detects speed, motion, and rotation and may be used to measure movements of the head and whole body. The EOG sensor registers the electrical potential of an eye and can be used to detect eye blinks and eyeball movements [61,63,68]. We chose such smart glasses because of their minimal impact on the

subject's physical and psychological comfort, and the access to raw signal data [61]. The examples of registered raw signals are shown in Figures 4–6.

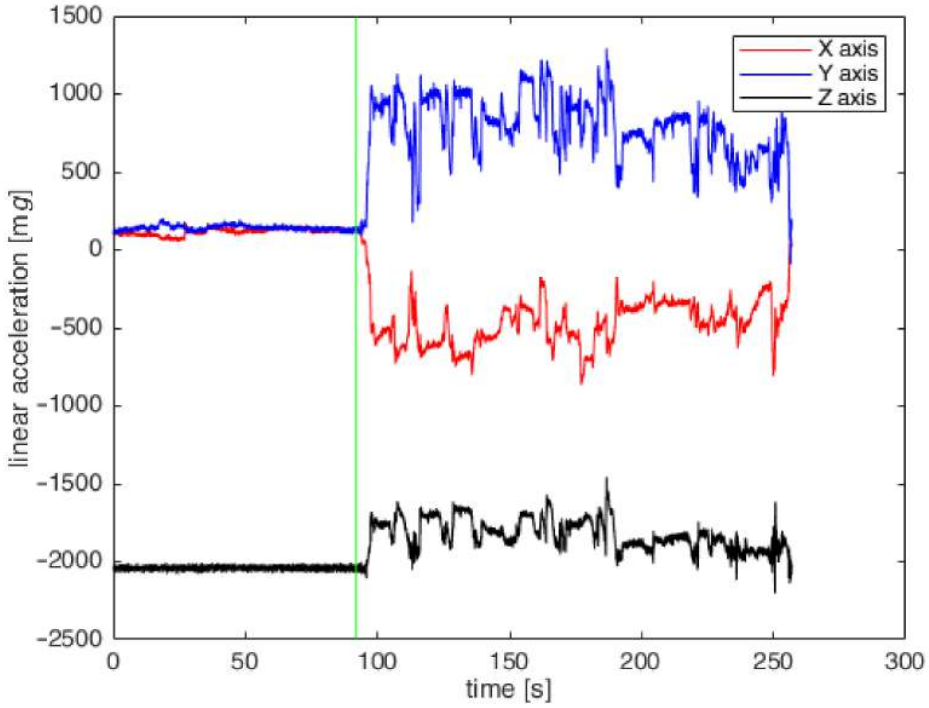


Figure 4. Linear acceleration of head during the experiment. Green vertical line denotes the occurrence of the sound signal.

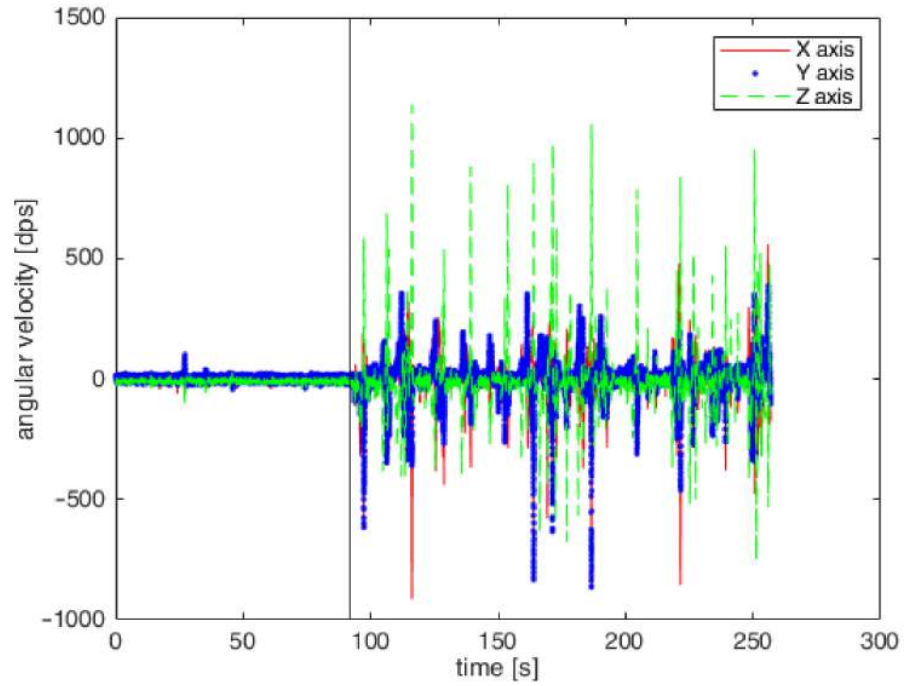


Figure 5. Angular velocity of head during the experiment. Black vertical line denotes the occurrence of the sound signal.

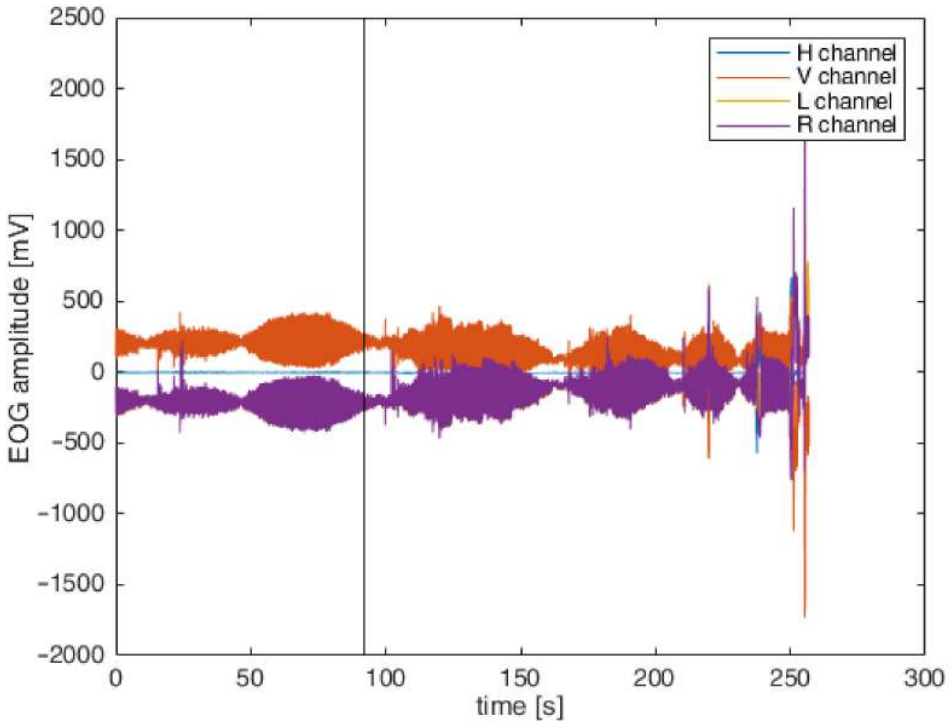


Figure 6. EOG signal during the experiment. Black vertical line denotes the occurrence of the sound signal.

Figure 4 shows linear acceleration (signals from accelerometer) of the subject's head during the experiment in X (red), Y (blue), and Z (black) axes.

Figure 5 presents the angular velocity (signals from the gyroscope) of the subject's head during the experiment in X (red line), Y (blue dots), and Z (green dashed line) axes.

Figure 6 shows sample signals from the EOG sensor (electric potentials) acquired during the experiment on the left electrode (orange) and right electrode (violet), as well as horizontal (blue) and vertical (red) differences between them.

To measure the heart rate, we used a TM-PX30 finger pulse oximeter (Tech-Med, Warsaw, Poland), which was placed on the index finger of the non-dominant hand. The subjects did not have their nails polished during the study to provide the optimal conditions for measurement. The heart rate was registered during each phase of the experiment (before, during, and after the task) for each subject, but only one measurement was considered in the analyses.

4.3. Signal Processing

The EOG and linear acceleration and angular velocity of the subject's head registered by smart glasses were divided into two parts, before the task and during the task, because the data had not been acquired after the task. The linear acceleration in each axis (X, Y, and Z) was combined into the total linear acceleration (ACC) as:

$$ACC = \sqrt{ACC_x^2 + ACC_y^2 + ACC_z^2} \quad (1)$$

The ACC signal is shown in Figure 7.

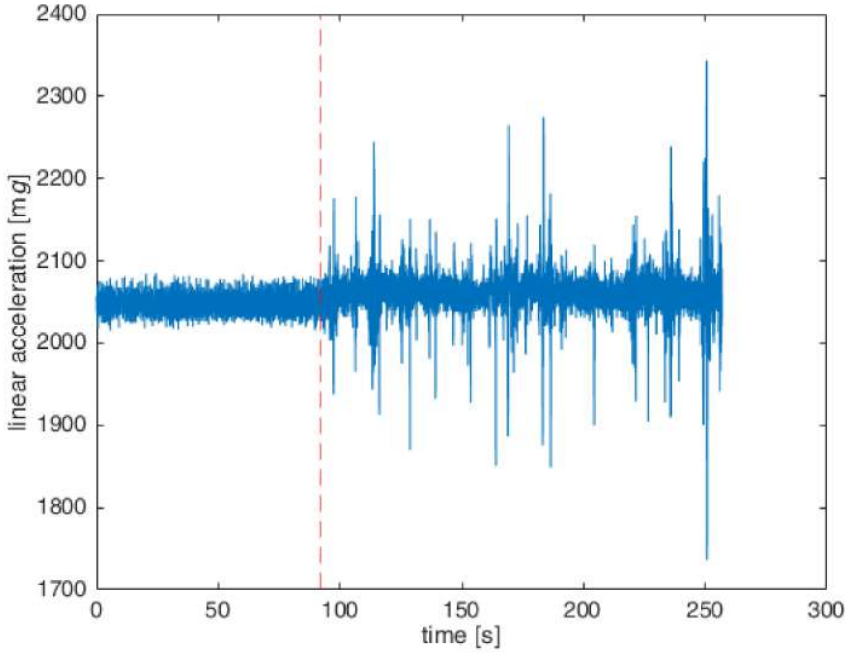


Figure 7. Total linear acceleration of head during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.

The angular velocity in each axis (X, Y, and Z) was also combined into the total angular velocity ($GYRO$) as:

$$GYRO = \sqrt{GYRO_x^2 + GYRO_y^2 + GYRO_z^2} \tag{2}$$

and the result is shown in Figure 8.

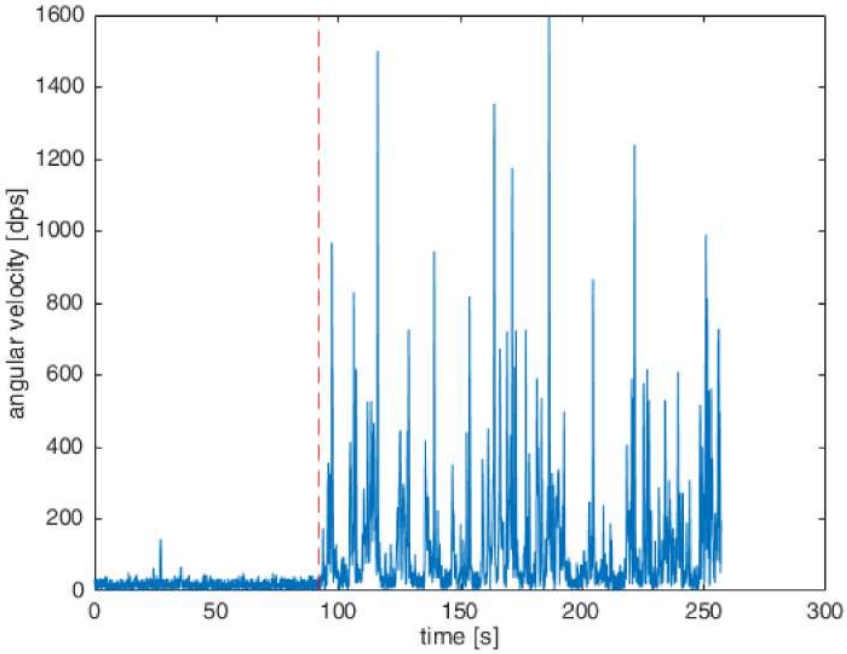


Figure 8. Total angular velocity of head during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.

Based on the approach presented in [69], the electrooculographic signals in four channels (H, V, L, and R) were combined into the total EOG signal as:

$$EOG = \sqrt{EOG_H^2 + EOG_V^2 + EOG_L^2 + EOG_R^2} \tag{3}$$

and the result is shown in Figure 9.

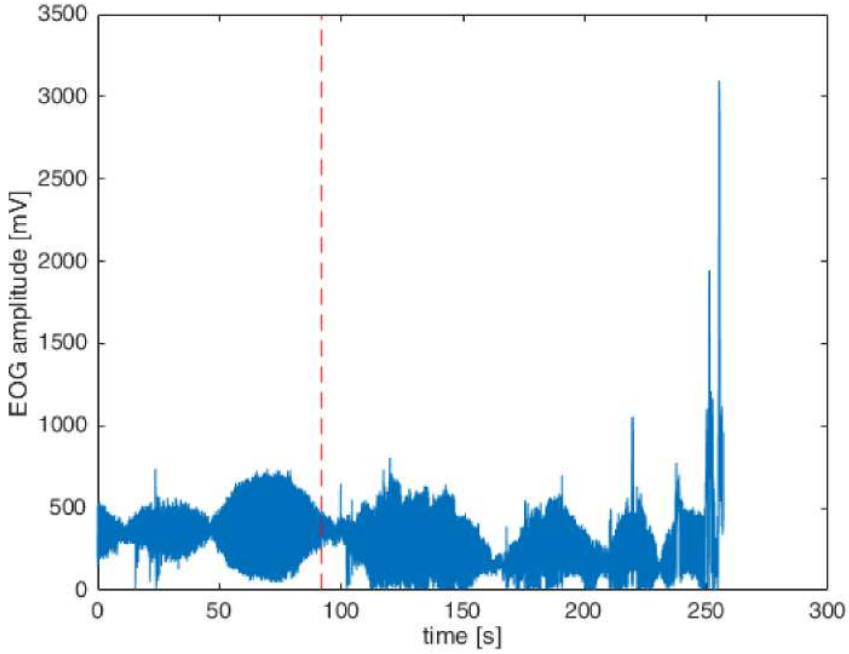


Figure 9. Total EOG signal during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.

The next step was calculating the power of the combined signal as:

$$\frac{1}{N}\sum_{n=1}^{N}|x_n|^2 \tag{4}$$

where x_n is the n-th sample of the signal x and N is the signal length.

Figures 7–9 show that it is possible to determine the difference in the envelope of the ACC, GYRO, and EOG signals.

4.4. Statistical Analysis

The perceived stress level between the three related samples (before, during, and after the task) is expressed in an ordinal scale (0–6), so we chose Friedman's test described in [70–72] to evaluate the differences between the analyzed phases of the experiment.

The heart rate in the three analyzed phases is expressed in the interval scale. In this case, we performed an all-sample normality test (Shapiro-Wilk test defined in [73]), and then we checked the compound symmetry of the data by performing the sphericity test further described in [74], and finally, we chose the Friedman's test. The statistical significance of differences between analyzed phases was evaluated by Conover and Dunn-Bonferroni post-hoc tests which are typically used after performing Friedman's test.

To analyze EOG, linear acceleration, and angular velocity, we chose the χ^2 test. The relationship between the measured heart rate, EOG signal, head movement signals, and the reported level of perceived stress was evaluated with the Spearman's rank correlation because of the use of the ordinal scale [75]. The level of statistical significance α was set to 0.05.

5. Results

Before selecting the parametric test for the HR data, we performed the Shapiro-Wilk normality of distribution test for all phases (before, during, and after the task). The obtained results (before—$p = 0.0036$, during—$p = 0.7600$, and after—$p = 0.7530$) led to the rejection of the normality hypothesis in the before case. Thus, the statistical analysis was completed by performing the Mauchly's and JNS sphericity test performed to evaluate the differences of variances between the phases. The results (JNS = 44.06, $p < 0.001$) indicated that the use of parametric tests was not applicable. Therefore, we decided to use Friedman's test in further analyses.

The Friedman's test results shown in Figure 10 confirm significant differences between the three phases of the experiment (Fr = 23.68; $p < 0.001$). The results of Friedman's test were supported with Dunn-Bonferroni and Conover post-hoc tests (see Table 1) which proved that the heart rate before performing the task was significantly lower than the heart rate during the task ($p < 0.001$) and after the task ($p < 0.001$).

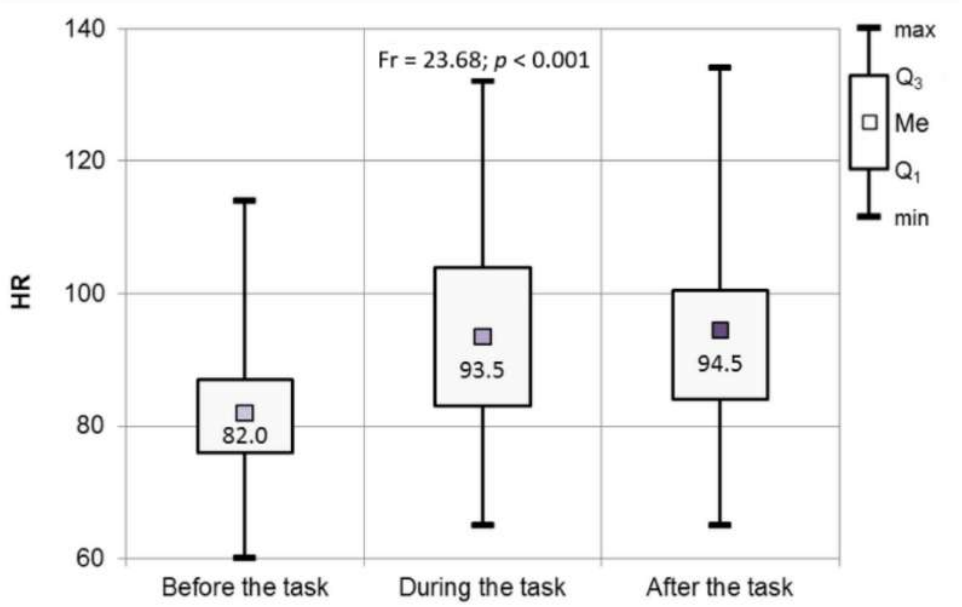


Figure 10. Results of Friedman Two-Way Analysis of Variance by Ranks of the differences between the heart rate measured in subsequent phases of the experiment. Q_1-first quartile, Q_3-third quartile.

Table 1. Results of post-hoc tests of the differences between the heart rate measured in subsequent phases of the experiment.

		Dunn-Bonferroni		
Conover	*p*	Before the task	During the task	After the task
	Before the task		<0.001	<0.001
	During the task	<0.001		0.953
	After the task	<0.001	0.030	

Figure 11 shows differences between the perceived stress levels in the subsequent phases of the task. The median of perceived stress level before the task was 2, during the task was 4, and after the task was 1.5. The highest perceived level of stress was 6 for participants in the "during the task" phase.

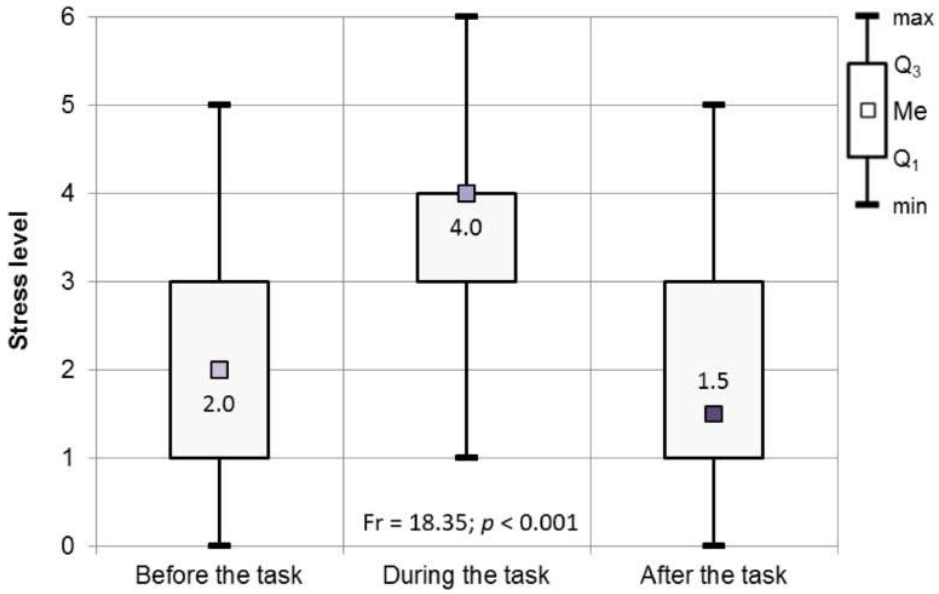


Figure 11. Results of Friedman Two-Way Analysis of Variance by Ranks of the differences between the perceived stress level in subsequent phases of the task. Q1-first quartile, Q3-third quartile.

The Friedman's test results shown in Figure 11 confirm significant differences between the three analyzed phases (Fr = 18.35, $p < 0.001$) and they were supported by Dunn-Bonferroni and Conover post-hoc tests (see Table 2) which proved that the perceived stress level during performing the task was significantly higher than the stress level before the task ($p < 0.001$) and after the task ($p < 0.001$).

Table 2. Results of post-hoc tests of the differences between the heart rate measured in subsequent phases of the experiment.

		Dunn-Bonferroni		
Conover	*p*	Before the task	During the task	After the task
	Before the task		<0.001	1.000
	During the task	<0.001		<0.001
	After the task	0.134	<0.001	

The results of Spearman's rank correlation analysis presented in Table 3 proved that the relationship between the heart rate and perceived stress level during the task was statistically significant ($p = 0.005$).

Table 3. The Spearman's rank correlation between HR and perceived stress level in subsequent phases of the experiment.

HR-Stress Level	Before the Task	During the Task	After the Task
r	0.070	0.561	0.317
p	0.385	0.005	0.087

The median power of total linear acceleration, angular velocity, and EOG signal before the task was $5.362 \times 105\ s^2$, $4.260 \times 106\ s^2$, and $7.533 \times 103\ s^2$, and the median power of total linear acceleration during the task was $5.483 \times 105\ s^2$, $4.330 \times 106\ s^2$, and $1.644 \times 105\ s^2$ (see Figures 12–14).

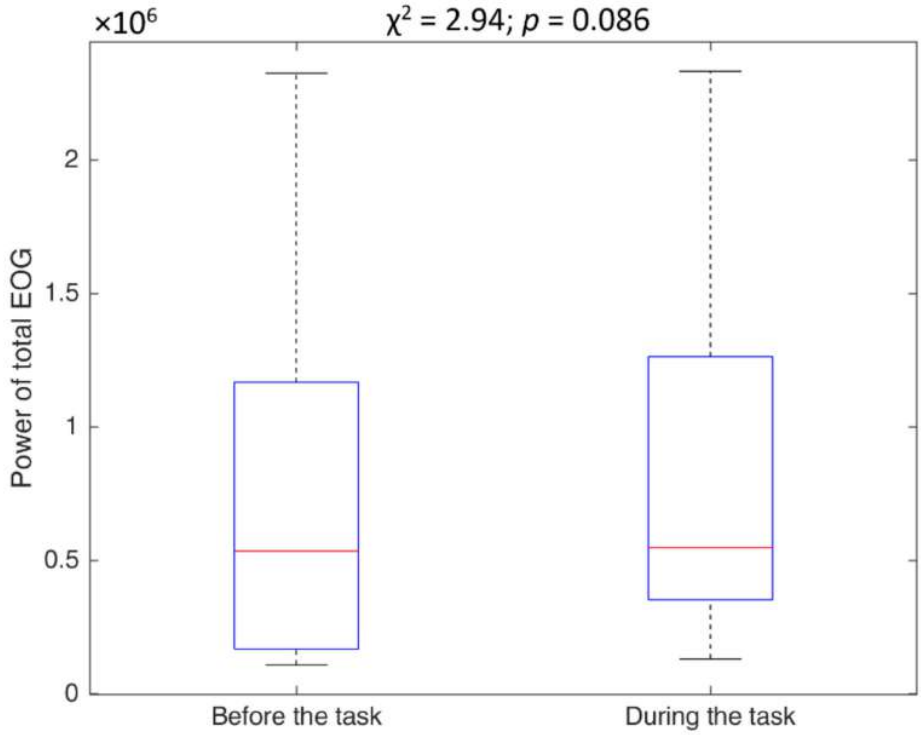


Figure 12. The differences between the power of EOG before the task and during the task.

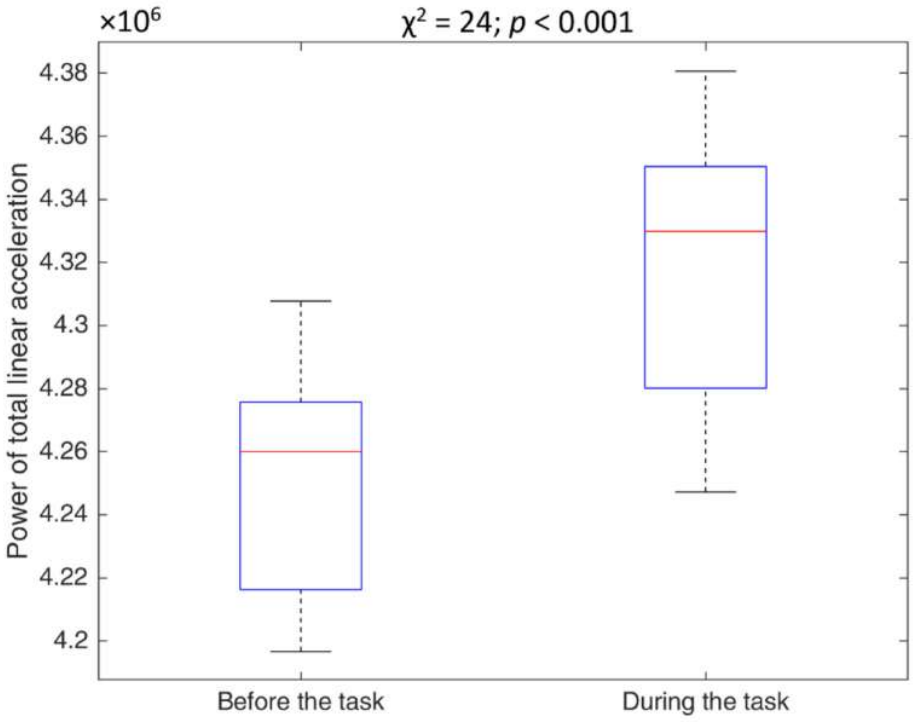


Figure 13. The differences between the power of linear acceleration before the task and during the task.

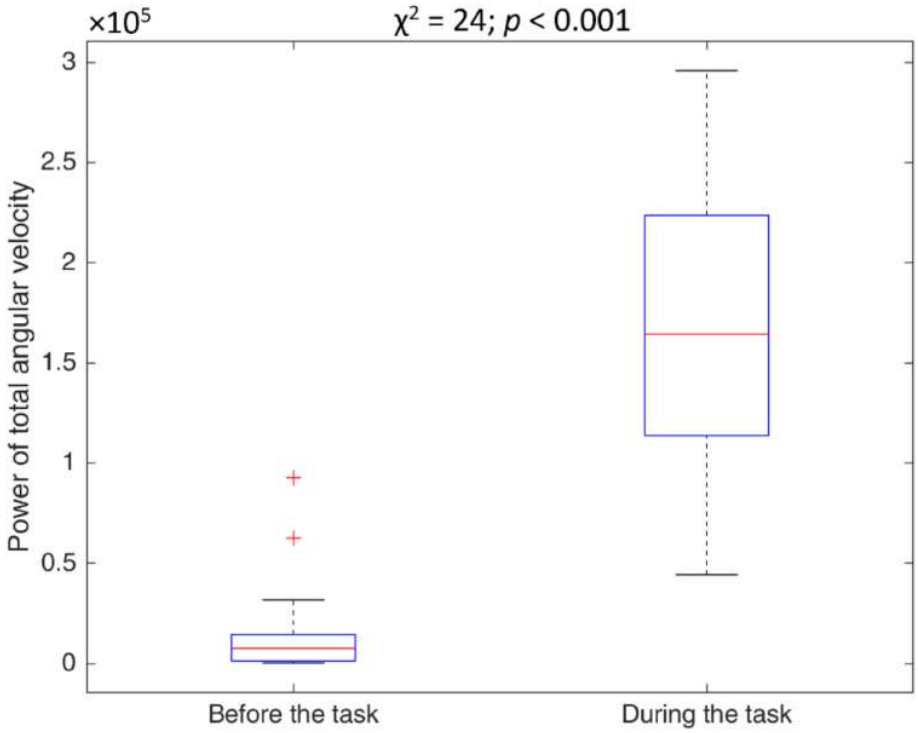


Figure 14. The differences between the power of angular velocity before the task and during the task.

The test χ^2 showed differences between all signals in the phases before and during the task, but only for linear acceleration and angular velocity were the differences statistically significant ($p < 0.001$). To check the correlation between signals and perceived stress level, we conducted Spearman's test.

The results of the Spearman's rank correlation analysis presented in Tables 4–6 proved that this correlation was not statistically significant.

Table 4. The Spearman's rank correlation between the power of total linear acceleration (ACC) and perceived stress level.

ACC-Stress Level	Before the Task	During the Task
r	−0.047	0.179
p	0.844	0.450

Table 5. The Spearman's rank correlation between the power of angular velocity (GYRO) and perceived stress level.

GYRO-Stress Level	Before the Task	During the Task
r	−0.170	0.312
p	0.475	0.181

Table 6. The Spearman's rank correlation between the power of EOG and perceived stress level.

EOG-Stress Level	Before the Task	During the Task
r	−0.301	0.300
p	0.197	0.199

6. Discussion

In this study, we attempted to find the relationship between the perceived stress level declared in the questionnaires and the linear acceleration, angular velocity of head, electrooculographic signals, and heart rate registered by smart glasses and a finger pulse oximeter. The role of the finger pulse oximeter was providing the heart rate, and the smart glasses were used to acquire the linear acceleration and angular velocity of the subject's head and EOG signals, which may be used to capture eyeball movements and other activities [63].

The acquisition of heart rate and other signals to enhance the stress recognition accuracy was described by Ahn et al. in [3] and Meina et al., in [6]. Ahn et al. in [3] achieved the stress level measurement accuracy of 87.5% by processing the EEG and ECG signals registered simultaneously. Meina et al. in [6] presented an approach to recognize the stress in firefighters based on 24 h registrations of ECG and acceleration in combination with the results of self-assessment of stress level in questionnaires. The performance of their approach expressed by the area under the curve (AUC) index was between 0.57 and 0.7.

Heart rate is the frequency of cardiac contractions and is susceptible to changes of the physical and mental condition. Therefore, heart rate is considered as one of the most important health indicators [58]. Many studies confirm the relationship between the HR and stress or anxiety level; Trotman et al. in [8] proved that the perceived heart rate is more significantly related to the level of anxiety than the measured heart rate. These findings play an important role in stress and anxiety coping strategies.

In [9] Szyjkowska et al. confirmed that work-related stress is strongly correlated with the heart rate and blood pressure; work-related stress in men was usually in association with higher blood pressure, whereas more prominent heart rate variability was usually observed in women. Moreover, stress also affects cognitive abilities; people suffering from stress make more mistakes and perform tasks less accurately [1].

In our study, the results of the Friedman's test and post-hoc tests prove that the heart rate before and during the task was significantly higher than after the task ($p < 0.001$), whereas the perceived stress level during performing the task was significantly higher than the stress level before and after the task ($p < 0.001$). The Spearman's rank correlation between the perceived stress level and heart rate was 0.561 ($p = 0.005$), which could be considered as a significant correlation. These results prove the hypothesis that the stress level and heart rate are correlated.

The differences between the power of total linear acceleration and total angular velocity before the task and during the task were statistically significant; however, we did not observe such differences for the power of the total EOG signal. This finding proves that the eyeball movements may not be correlated with the fact of performing the task, contrary to the findings of studies conducted by Doniec et al. [14,76], Li et al. [77], Shirahama et al. [78], and Deng et al. [79].

The study conducted by Dumitrescu et al. on a group of 50 students of physiology showed, as in our study, no statistically significant differences in the horizontal and vertical EOG values between the control group and the study group, classified in terms of visual dispersion. The authors emphasize that the visual distraction used in this study may not have been significant enough to deteriorate student performance in exams [19].

The literature presents a wide range of developed approaches to the selection of analyses for multidimensional data and various application purposes. Many existing methods, such as mean and variance values in sequence or first-order derivatives, are based on prior knowledge and manual examination, causing difficulties in providing detailed information and problems with statistical validation. There are also several methods of EOG data based on a heuristic approach using information on the basic types of eye movement, such vibrations, fixations, or batting [80–83]. The problem of extraction and selection of appropriate features from EOG signals in terms of the recognition of actions has not been thoroughly investigated. EOG signals acquired with smart glasses contain

lots of data, but the recognition of several cognitive activities (e.g., learning, relaxing, or stress) is challenging [14,76,78].

Meina et al., in [6] proved that the perceived stress level and physiological signals are strongly correlated based on the results of Welch's t-test. In our study, the Spearman's rank correlation between the power of total linear acceleration, angular velocity, and EOG signals show that the head movements and electrooculographic signals (electrooculograms) are poorly correlated with the perceived stress level.

The use of physiological observations for stress recognition began much earlier than the attempts to construct a polygraph–in ancient China, the testimony of an interrogated person was verified by testing for dry mouth with rice. Galvanometric methods use the fact of increased activity of sweat glands under stress resulting in changes of the resistance between the skin and the electrode [84]. In our study, we confirmed the relationship between increased HR and stress perception. Therefore, we recognize the necessity of using mixed methods to objectify the stress measurement.

6.1. Limitations of the Study

The limitations of the study are the lack of EOG and head movement data acquired after the performed task, a small study group from one university (20 dental students at the Medical University of Silesia, Zabrze, Poland), gender bias (the vast majority of the study group consisted of female dental students), and the fact that the heart rate was registered only once during each phase of the experiment. The number of subjects was limited due to the involvement of students of medical programs in combating the COVID-19 pandemic and the access to the university's facilities for students.

To address them, we consider including more subjects in the study group with more diverse characteristics, acquiring signals with smart glasses in all three phases of the experiment and including more signal features in future studies. Another part of this study worth further research is the fact of no statistically significant correlations between the perceived stress level were reported for questionnaires, head movements, and EOG signals.

6.2. Practical Application

This study shows some important problems in categorizing stress. First, sensors are highly dependent on the level of motion and conductivity of the electrodes. The glasses, although non-invasive, do not completely adapt to the patient. Due to the individual characteristics, the glasses can slip off and the nasal electrodes can stick out. For this reason, a better method for detecting and removing artifacts and conduction errors should be implemented.

Session data captured with glasses during activities performed in real conditions are a valuable carrier of information, but also errors and noises caused by reflex gestures (e.g., fixing glasses that fall off). They are definitely different from data collected under laboratory conditions and as such require special algorithms and techniques for signal processing. This issue should be addressed in further research.

7. Conclusions

A positive and statistically significant correlation between HR and the level of stress perceived in the "during the task" phase confirms the possibility of using HR as a stress marker. The HR signal can be used to objectify the stress level measurement.

No statistically significant correlation was found between the EOG, ACC, or GYRO signals and the level of stress perceived in the study group. Although the aforementioned signals acquired with JINS MEME_R smart glasses failed to indicate stress level in our study, further research needs to be done.

However, based on the test results of the head movement signals and the perceived stress level for the analyzed phases (before, during the task), we can distinguish the phases of the experiment.

Author Contributions: Conceptualization, K.M.-P., M.P., R.J.D., and S.S.; methodology, K.M.-P., R.J.D., S.S.; validation, K.M.-P., R.J.D., S.S.; formal analysis, K.M.-P., and R.J.D.; investigation, K.M.-P.; resources, K.M.-P., M.P., R.J.D.; writing–original draft preparation, K.M.-P., N.J.P., S.S., and M.P.; writing–review and editing, K.M.-P., R.J.D., S.S., N.J.P., E.J.T.; visualization, K.M.-P., S.S., and N.J.P.; project administration, K.M.-P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Medical University of Silesia under the resolution number KNW/0022/KB1/79/18 taken on 16 October 2018.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available in http://www.mdpi.com/1424-8220/xx/1/5/s2 (accessed on 13 September 2021).

Acknowledgments: We would like to thank the students who agreed to participate in the study.

Conflicts of Interest: The authors declare no conflict of interest.

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Extreme Situation Experienced by Dental Students of the Medical University of Silesia Due to the SARS-CoV-2 Epidemic during the First Lockdown

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Abstract: The pandemic declared in many countries in 2020 due to COVID-19 led to the freezing of economies and the introduction of distance learning in both schools and universities. This unusual situation has affected the mental state of citizens, which has the potential to lead to the development of post-traumatic stress and depression. This study aimed to assess the level of stress in dental students in the context of the outbreak of the SARS-CoV-2 virus pandemic. A survey on the PSS-10 scale was prepared to measure the level of perceived stress. The study included 164 dental students at the Faculty of Medical Sciences of the Medical University of Silesia in Katowice, Poland. The results showed the impact of COVID-19 on the stress of students, with 67.7% reporting high levels of stress. The study also revealed that stress was higher among older female students. This paper recommends that the university provide more intensive psychological care as psychological first aid strategies in epidemics or natural disasters and to consider telemedicine in order to deliver services due to the limitations of the pandemic.

Keywords: COVID-19; stress level; university students; education

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Citation: Doniec, R.; Wójcik, S.; Valverde, R.; Piaseczna, N.; Sieciński, S.; Duraj, K.; Tkacz, E. Extreme Situation Experienced by Dental Students of the Medical University of Silesia Due to the SARS-CoV-2 Epidemic during the First Lockdown. *Healthcare* **2021**, *9*, 1513. https://doi.org/10.3390/healthcare9111513

Academic Editor: Mariyana Schoultz

Received: 6 September 2021
Accepted: 3 November 2021
Published: 5 November 2021

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1. Introduction

On 12 December 2019, the first cases of the SARS-CoV-2 virus appeared in Wuhan, China. This virus is responsible for the development of severe respiratory distress syndrome (SARS) [1–3]. Human-to-human transmission of the virus occurs through direct or indirect routes. The direct route is associated with droplet transmission, while the indirect route is associated with contact with contaminated surfaces. The entry sites are the nose, mouth, and eyes [4–7]. Therefore, the SARS-CoV2 virus is a biological risk factor to which dental practice staff are inherently exposed: from doctors, through assistants, to patients.

Until the pandemic, routine dental procedures did not refer to the prevention of pathogen transmission by airborne droplets. For that reason, new and additional methods for prevention of spreading SARS-CoV-2 had to be introduced into the day-to-day work of dentists. These methods involve the use of additional personal protective equipment in the form of face masks, goggles, or special uniforms, as well as new methods for the decontamination of the office environment [5].

In most countries affected by the pandemic, new measures were introduced to deal with the situation, including, among others, the postponement of unnecessary dental treatments, and therefore dental treatments were discontinued and limited only to emergency

cases [6,8]. The healthcare community, including medical, dental, pharmacy, and nursing students, has become the line of first contact with the people infected with the SARS-CoV-2 virus [9].

During the pandemic, many professions, including dental practice, have undergone major changes, particularly with regard to protection measures. The impact of the pandemic on dental professionals has been confirmed by research conducted worldwide. These studies covered the pandemic's impact on various aspects of life, including, among others, financial and professional status, nutrition, and changes in family dynamics [10–12]. Mental health of dental workers (dentists, dental students, and support personnel) during the pandemic has also become a subject of many studies. These studies include the effects of lockdown on depression and the level of perceived stress [13–15].

Fear and anxiety experienced by dental students can be induced by many different factors [16–18], one of them being the transmission of infectious diseases. Since this virus is mostly transmitted by droplets, and dental procedures generate aerosols, dental students may feel stressed about returning to clinical classes while the COVID-19 pandemic continues [19].

It has been noticed that even young people are concerned about getting infected with SARS-CoV-2 due to the possible side effects. Due to the specificity of the dentist profession (mainly clinical practice), dental students may suffer even more in the future due to the lack of training in manual skills [20,21].

Despite the COVID-19 pandemic, dental studies are considered very stressful because, during the curriculum, students must face their practical skills and the ability to establish contact with the patient. An essential element that cannot be learned without direct contact with the patient is the ability to relieve stress in the patient, which often results from empathy [16–18,22]. Dental studies require full-time dedication, especially at the beginning of the curriculum. Freshmen students need to develop practical skills (which takes a significant amount of time) to then participate in patients' visits. The students are pressured with the responsibility for the patient's treatment and possible emerging complications [16]. The factors mentioned earlier influence the higher stress level among dental students comparing to the general population [23–25].

In their study, Abu-Ghazaleh et al. showed an increasing amount of anxiety in dental students at the University of Jordan over the years of training; over the year of studies, the awareness of the responsibility developed and caused increased stress levels [26]. The pressure on dental students is replaced by stress resulting from the need to cope with professional duties and full-time clinical work and to simultaneously carry out continuing postgraduate education [27].

Stress and anxiety affect many aspects of the work of a dental practician, which in effect has an impact on the entire community [28]. Accordingly, it is imperative to determine the stress level of dental students as well as to consider stress management measures [29].

According to Davidovich et al., junior students experience a significantly higher level of stress than experienced professionals. The newcomers rely on their knowledge, which is theoretical and may not yet be sufficient. Moreover, they did not yet receive enough practical training, which causes performance anxiety [29].

Failure to adapt the requirements to the individual's abilities may cause stress, which is a physical, mental, or emotional reaction to change [30]. Stress has become a significant problem of the modern world as it can lead to cognitive impairment, depression, and even cardiovascular diseases [31]. Stress can also affect our daily attitudes and our ability to be involved in work [32–34].

The methods of coping commonly used by dental students are various relaxation exercises as well as emotional support from other people [35,36]. Dental schools also offer ways to reduce one's stress levels, including stress management courses, relaxation techniques, and counselling [37,38].

Despite all the enforced anti-COVID-19, medical students must acquire some skills through practical contact classes. Only in this way are they able to acquire the competences needed to work in the profession for which they are being prepared and educated [39].

Objective

Referring to the issues discussed above regarding, among others, fear of possible infection with the SARS-CoV-2, reduced number of practical classes, difficulties in acquiring theoretical knowledge, and fear for the health of loved ones, we in this paper aimed to assess the level of stress in dental students in relation to the outbreak of the SARS-CoV-2 virus pandemic.

2. Materials and Methods

The study included 164 of 225 dentistry students at the Faculty of Medical Sciences of the Medical University of Silesia in Katowice, Poland.

Thirty first-year students (23 women, 7 men), 19 second-year students (13 women and 6 men), 27 third-year students (22 women and 5 men), 32 fourth-year students (26 women and 6 men), and 56 fifth-year students (35 women and 21 men) participated in the study. The median age of the students was 23 years. The students voluntarily completed the survey, which was available online. The response rate was 0.80. A total of 180 dental students completed the questionnaire. However, due to procedural errors (lack of all responses), 16 questionnaires were not considered in the statistical analysis.

The link to the questionnaire was placed on the website of the Department of Conservative Dentistry with Endodontics of the Medical University of Silesia (available at www.stom.zachowawcza.sum.edu.pl (accessed on 24 April 2020)) and sent by e-mail to the representatives of all years of the study (Years 1–5) with a request to be sent to students. General information about the survey and the study was provided in this e-mail. The consent to participate in the study was part of the questionnaire.

The questionnaire was placed on the e-learning platform of the Medical University of Silesia. The platform is based on the Moodle system, which is a free remote learning management system (LMS) under an open-source license [40]. The system has enormous support from the broadly understood community dealing with distance learning topics. In its present form, the platform was launched in the academic year 2017/2018. The current version of the system was 3.7 in the latest stable update.

The system is based on university server resources, using a virtual multiprocessor environment. This is supported by a stable university computer network. The e-learning platform is available to users continuously, 24 h a day, 7 days a week. Currently, the system covers all the university's faculties, along with most research and teaching units. Currently, there are more than 15,000 active accounts in the system and more than 7500 unique users visit the system every day and actively work with it.

The survey system is also placed on university servers within the information portal with the installed extension, which enables independent design and publication of survey forms. The server is available to users continuously, 24 h a day, 7 days a week.

The Perceived Stress Scale (PSS-10) was used in the survey. This scale is a modified version of the Perceived Stress Scale developed by Cohen [41]. It was used to assess the intensity of stress related to one's own life situation over a month. The authors conducted a survey using the above scale among students between 10 April 2020 and 24 April 2020, during the SARS-CoV-2 virus pandemic state of emergency announced in Poland, as well as globally.

PSS-10 contains 10 questions related to a variety of subjective feelings about personal problems and events, behaviors, and ways of coping. The PSS-10 scale has been used to test the mental status of adults. It is mainly used as a self-assessment method and may also be used as a screening tool to identify people eligible for psychological or medical assistance [42]. The respondents gave their answers by entering the correct digit, that is, 0 meaning "never", 1 "almost never", 2 "sometimes", 3 "quite often", and 4 "very often".

Before the general indicator of the intensity of perceived stress is calculated, a change in the scores should be made in the answers to the positively formulated questions, that is, 4, 5, 7, and 8, according to the rule: 0 = 4, 1 = 3, 3 = 1, 4 = 0. The overall score on the scale is the sum of all points, the theoretical distribution of which ranges from 0 to 40. The higher the score, the greater the perceived stress. To facilitate the interpretation of the results, we interpreted the total sum score obtained according to the properties characterizing the sten scale. The study was designed so that the dependent variable Y represents the Perceived Stress Scale (PSS), which is the most commonly used psychological tool to measure the perception of stress. It is a measure of the extent to which life situations are judged to be stressful. For example, Cohen et al. (1988) show correlations with PSS and stress measures, measures of self-assessment of health and health services, measures of health behavior, smoking status, and behavior in search of help. PSS scores range from 0 to 4 and measure how often participants felt different variables (e.g., 0 = never, 1 = almost never, 2 = sometimes, 3 = quite often, and 4 = very often for X1 = voltage). It is a measure of the extent to which life situations are judged to be stressful. The items are designed to show how unpredictable, uncontrolled, and overloaded respondents find their lives.

According to the PSS-10 scale calculation instruction, scores ranging from 1 to 4 stens (0–13 points on the scale) are treated as low stress levels. Scores within 5–6 stens (14–19 points on the scale) correspond to the average stress level. Finally, 7–10 stens (20–40 points on the scale) indicate a high stress level [43].

The consent to conduct a survey using, among others, the above-described scale in various groups of respondents was issued by the Bioethical Committee of the Medical University of Silesia in Katowice, KNW/0022/KB1/79/18. Students started the study by signing a consent form.

Statistical Analysis

Statistical analysis was performed using Statistica version 9.0 (StatSoft, Inc., Tulsa, OK, USA) and Microsoft Excel spreadsheet (Microsoft Corporation, Redmond, WA, USA). The Mann–Whitney test was used to assess the significance of differences in the values for the PSS-10 point and the sten scale from the point of view of the gender of the respondents and the year of study of the students.

Assessment of the significance of differences in the PSS-10 point and the sten scale with respect to subsequent years of study and the gender of respondents was carried out using the Kruskal–Wallis test. To test the correlation between the stress level of the respondents and age, we used the Spearman correlation test.

A multiple variable linear regression model was used to develop a stress model that can be applied to stress estimation based on PSS-10 variables. Independent variables were selected using a stepwise regression that included a set of regression models in which the choice of predictive variables was carried out using a sequence of F-tests. Once the final data set and independent variables were chosen, a multiple variable linear regression was performed, and a stress model was developed that can be applied to estimate stress levels.

3. Results

To confirm the reliability of the PSS-10 questionnaire, we calculated Cronbach's α for the selected group of respondents, which was 0.86 for students (α = 0.85 for women; α = 0.86 for men). The most difficult question was Question 5 ("How often in the last month have you felt that things were going your way?"). Its elimination could lead to an increase in Cronbach's coefficient, but it would not be a statistically significant increase.

The results of the Mann–Whitney test used to assess the significance of the differences in values for the PSS-10 scale from the point of view of gender of the surveyed students are presented in Figure 1. Women were characterized with a significantly higher perceived stress level than men (p = 0.002).

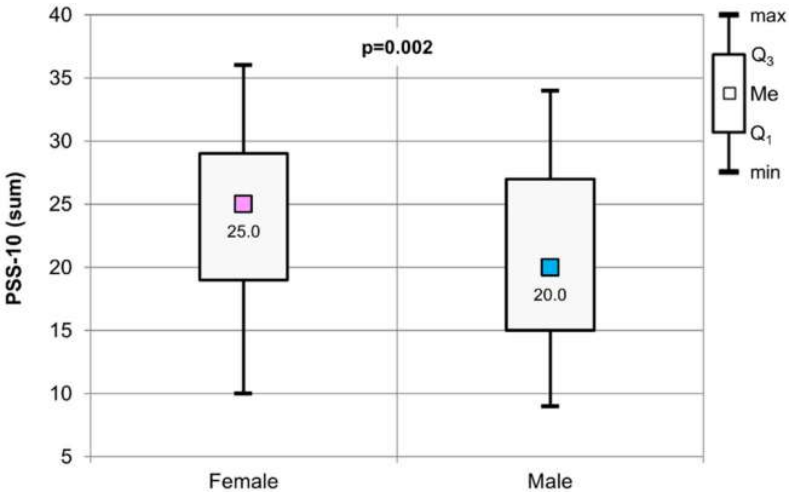


Figure 1. The results of the Mann–Whitney test used to assess the significance of difference values for the PSS-10 (sum) scale in relation to the gender of the respondents.

The median value of the PSS-10 scale obtained for female students was 25, and for male students, 20. The highest number of points on the scale was obtained for female students (36). The highest result on the PSS-10 scale in male students was 34. The lowest point result was 10 and 9 for female and male students, respectively.

Analyzing the results obtained in terms of interpretation on the sten scale, we found statistically significant differences between female and male students (p = 0.002). The median of the sten was 8 for female students and 7 for male students. The highest value obtained on the sten scale for both women and men was 10, while the lowest was 4 in female students and 3 in male students (Figure 2).

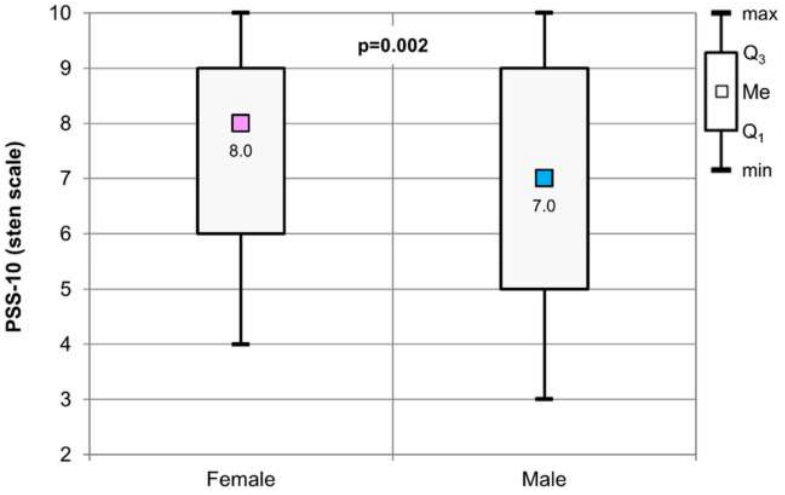


Figure 2. The results of the Mann–Whitney test used to assess the significance of the difference values for the PSS-10 (sten scale) in relation to the gender of the respondents.

Table 1 shows the distribution of respondents according to whether they belonged to the appropriate group of stens. A total of the 73.9% of female students and 51.1% of the male students were characterized by a high level of stress, as evidenced by the results obtained between 7 and 10 stens. To confirm the hypothesis that the gender difference in the sten scale was significant, we applied the χ^2 test of independence. The result of the χ^2 test indicated the significance of examined dependence (χ^2 = 12,884, p = 0.045).

Table 1. The distribution of respondents in different sten scales.

Sten Scale	Female Students	Male Students	Total
1–4	7 (5.9%)	9 (20.0%)	16 (9.8%)
5–6	24 (20.2%)	13 (28.9%)	37 (22.6%)
7–10	88 (73.9%)	23 (51.1%)	111 (67.7%)
Total	119	45	164

The Spearman correlation test showed a positive statistically significant correlation in the group of female students between the age of the respondents and the obtained values of the PSS-10 scale (p = 0.007) and between age and sten values (p = 0.009). The results showed that stress level was related to the age of female students (see Tables 2 and 3).

Table 2. Results of the Spearman correlation test—correlation between age and PSS-10.

	Female Students	Male Students
rs	0.2257	−0.0616
p	0.0068	0.3439

rs—Spearman correlation coefficient.

Table 3. Results of the Spearman correlation test—correlation between age and sten scale.

	Female Students	Male Students
rs	0.2174	−0.0192
p	0.0088	0.4501

rs—Spearman correlation coefficient.

The comparative analysis, considering the gender of the respondents and the year of study using the Kruskal–Wallis test, did not show statistically significant differences between the individual years of study, both in the case of the PSS-10 and the sten scale (Figures 3 and 4).

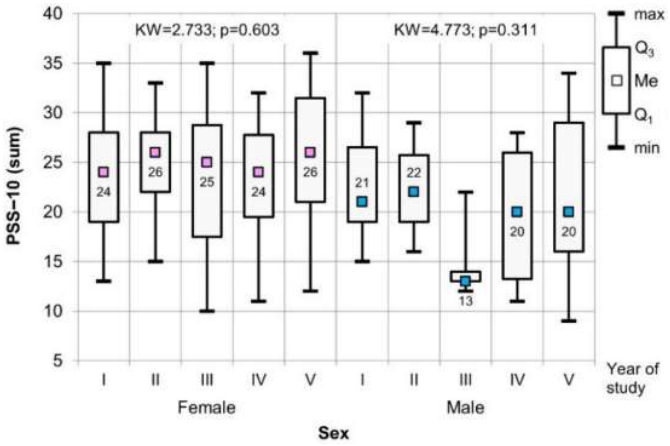


Figure 3. Results of the Kruskal–Wallis test used to assess the significance of difference values for the PSS-10 (sum) scale in relation to gender of respondents and year of study.

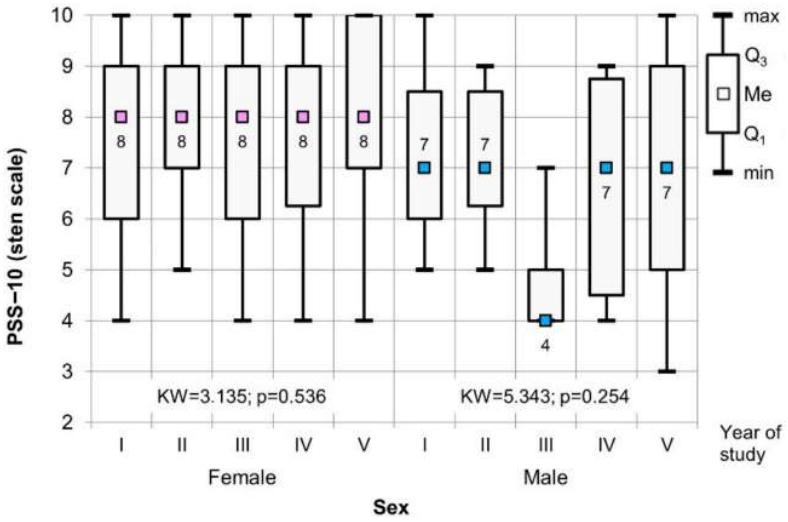


Figure 4. The results of the Kruskal–Wallis test used to assess the significance of the difference values for PSS-10 (sten scale) in relation to the gender of the respondents and the year of study.

A simple linear regression model was developed for each independent variable for the PSS-10, as indicated in Table 4. We performed a stepwise regression starting with the independent variable with the highest F-value. The remaining independent variables were added one at a time in the order of the highest F-value. Independent variables were added when adding them improved the model. The improvement of the model was determined by increasing the R^2 value.

Table 4. F-value and coefficient of determination for each independent variable.

Variables	F-Value	Coefficient of Determination (R^2)
Level of tension (X1)	269.02	0.61
Level of lack of self-control (X2)	247.51	0.59
Level of lack of resilience (X3)	218.91	0.56
Level of anger (X4)	186.33	0.52
Level of ability to cope with uncertainty (X5)	179.02	0.51
Level of lack of ability to cope with responsibilities (X6)	146.52	0.46
Level of ability to cope with irritability (X7)	119.52	0.41
Lack of ability to deal with personal problems (X8)	63.62	0.27
Level of sensation that things were going your way (X9)	51.37	0.23
Level of feeling that everything was going well (X10)	45.72	0.26

The 10 independent variables improved the accuracy of the model, and therefore none of them were removed from the final equation (see Table 5).

Table 5. Multi-regression for stress estimation for PSS-10.

Y = 0.95 + 0.33 * X1 + 0.29 * X2 + 0.3 * X3 + 0.3 * X4 + 0.26 * X5 + 0.25 * X6 + 0.27 * X7 + 0.22 * X8 + 0.27 * X9 + 0.27 * X10	**Coefficient of Determination (R^2) 0.97**

4. Discussion

One of the methods to prevent the spread of airborne infectious diseases is the isolation (quarantine) of infected people and those who meet infected people. However, such isolation, carried out for the benefit of the public, may have disastrous consequences for the individual in the form of psychological, emotional, and financial problems [44]. Due to the specificity of transmission of the SARS-CoV-2 virus, which can cause asymptomatic cases [1], many countries, including Poland, have introduced amass isolation of society, which is also associated with the closure of schools and universities. According to the

regulations of the Minister of Health from 11 March 2020, all classes should be conducted using distance learning methods and techniques [45].

During the coronavirus pandemic, students have been exposed to many stressful situations, such as disturbances during academic activities and limitations of social and family contacts [39]. Limiting academic classes for dental students to only theoretical online classes can be very worrying due to the specifics of the study program, which is largely based on practical classes [46].

Kharma et al. conducted a survey among 315 dental students from Al-Farabi Private College (Jeddah, KSA) on the assessment of anxiety and stress before returning to clinical classes after lockdown. A total of 85% of the participants experienced stress and anxiety before returning to class, 58% of the respondents felt a high level of stress due to the necessity of contact with people outside the academic community, 75% of the students supported the safety procedures while admitting patients introduced by the college, and 43% of the respondents indicated remote classes as the only acceptable form of theoretical classes [19].

In the study by Jum'ah et al., fear related to the high risk of SARS-CoV-2 infection was also observed. According to this study, 92.7% of dental students felt fear of infection, 78.1% of the participants experienced the anxiety of transferring the disease to family members, and 56.1% of the students confirmed that fear of infection caused stress that adversely affected the performance of dental procedures during clinical classes [39].

In our study, female students were characterized by a significantly higher level of stress than male students. Furthermore, a positive correlation was observed between the age of the women and the level of perceived stress. The older the women, the more stress they felt.

Dental students who participated in the study by Hung et al. faced similar problems. Many of them (32%) were concerned about their emotional state. A total of 29% of the participants felt they could not control important things in their lives, while 24.3% of them always or often felt angry due to lack of control, and 37% of the students experienced stress. Almost half of the respondents felt anxious about the state of the pandemic, and 8.3% suffered from depression [47].

Leon-Manco et al. conducted a study on a group of 2036 dentists and 1433 female dental students using the PSS-15 scale. They used descriptive, both two-dimensional and multi-dimensional linear regression analysis to observe factors related to the perception of stress. Mean PSS-14 score was 24.76 ($\pm$11.76). Hierarchical regression models turned out to change significantly along with PSS-14 results, specifically with income levels during compulsory social isolation, having elderly people in care during compulsory social isolation, self-assessment of the level of anxiety related to COVID-19, self-assessment of health, and coffee consumption during the period of compulsory social isolation. The authors of these studies emphasized that the pandemic affected the personal, social, and professional lives of dentists and dental students. Its impact on the mental health of this population is also undeniable, especially when perceived stress is taken into account. Consequently, mental health monitoring strategies and systems need to be put in place for this population [12].

The results of our study showed that a significant proportion of surveyed students (i.e., 73.9% female and 51.1% male) experienced a high level of stress determined by values between 7 and 10 on the PSS-10 scale. The factors that influenced stress to the greatest extent were tension, lack of self-control, and lack of resilience.

Statistically significant differences in the level of perceived stress between men and women were also observed among dental students in Saudi Arabia. Female students were significantly more stressed and experienced higher levels of anxiety and depression. These differences were not observed between years of study, as in our research [48].

The fact of women experiencing higher levels of stress and anxiety is also confirmed in [14,49–52]. The psychological differences between the genders are that women are more likely to express emotions [52]. Female students, especially those in their second and fifth

years, experienced higher stress values than their peers. Third- and fourth-year female students also demonstrated higher stress values when compared to men, but these were only on the border of statistical significance. Similar results were also reported by Saddki et al. and other authors [53–55].

The higher levels of perceived stress among women are likely caused by their higher susceptibility to physical and emotional discomfort [56]. Moreover, the influence of marital status on the level of perceived stress was noticed. Unmarried students (and similarly the ones who were separated/widowed/divorced) showed higher stress levels in terms of factors affecting their future than married students. They were less confident in the decisions they made [57].

Another aspect worth considering is the impact of the COVID-19 pandemic on the education system and thus the level of stress felt by students as a result of new learning conditions. Iosif et al. conducted a cross-sectional study of 878 dental students who assessed their perceptions of the psychological and educational impact of the pandemic period. The authors found a strong psychological influence among the respondents—the level of stress was perceived as high and very high (33.83%, n = 297; 28.59%, n = 251, respectively). Similarly, strong and very high anxiety feelings were noted (26.54%, n = 233; 24.26%, n = 213, respectively). A very high educational impact was noted in terms of acquiring practical skills (48.52%, n = 426) and future career prospects (38.95%, n = 342). Theoretical online learning ability was generally low (37.93%, n = 333). The majority of students rated the effectiveness of lecturers in online courses as neutral (41.12%, n = 361). New dentistry curricula will need to be developed, taking into account the dynamics of the pandemic and its strong impact on students' livelihoods in order to improve both their well-being and the sustainability of dental education.

It is worth noticing that the COVID-19 pandemic has shaken the entire planet, forcing the entire world's population to reconsider all their relationship and interaction habits to avoid the epidemic from spreading. COVID-19 has also left its mark on education and grading methods. Changes in teaching methods that occurred in institutions had to be made suddenly, affecting the stress levels of staff and students [50]. The level of stress of dentistry students in other countries can be implied using the scope of the study, but it should be noted that the subjects were concentrated in a specific geographic area and the results cannot be generalized to the entire globe.

4.1. Limitation of the Study

The limitations of the study include the study group drawn from only one university, the statistical analysis that concentrated on gender differences, and the year of study in students, and there was a predominance of female subjects in the study group. The gender bias in the study group is typical in academic medical programs in Poland [58]. However, the study group should be more heterogenous and with an equal group of male and female subjects in future studies. Moreover, the data related to stress before the pandemic were not available.

4.2. Practical Application

To reduce the levels of stress in society, the authorities must implement psychological first aid strategies in epidemics or natural disasters, and ultimately, the role of telemedicine must become more significant in this case. The COVID-19 pandemic, which has affected the entire world, should influence the development of methods that allow comprehensive epidemiological surveillance and screening of people who may develop mental disorders [59].

A good strategy to reduce stress levels is to train individuals to reduce tension, have more controls of themselves, and be more resilient. These can include strategies that have been shown to be effective, such as biofeedback [60], mindfulness [61], and resilience training [62].

5. Conclusions

This article presents the results of the first academic study conducted at the Medical University of Silesia on the experiences of students in social isolation in early 2020. The survey showed the effectiveness of the PSS-10 scale in screening the level of perceived stress. Regarding female students, the older they were, the higher the level of stress they perceived themselves to have endured. Finally, more than half of the surveyed respondents (67.7%) felt a high level of stress related to the outbreak of the SARS-CoV-2 pandemic. Tension, lack of self-control, and lack of resilience were the most influential factors in the stress levels in the people being surveyed. This analysis indicates that the individual can potentially be in control of his or her own stress level. Stepwise regression analysis also confirmed that all 10 variables on the PSS-10 scale were relevant to explaining stress levels in people. The survey includes follow-up questions on respondents' mental health, such as anger, irritation, tension, or lack of self-control, which are the main contributors to mental health problems.

The primary purpose of the survey was to investigate the impact of the pandemic on mental health. The unique fact is that the pandemic is a memorable period. The results from such a study are non-referential, at least until the next pandemic.

To achieve more accurate results in the future, we consider including additional questions for the survey combined with measurements from blood pressure, heart rate, or any other physiological signal. For the analysis, we hope to involve the use of deep learning methods to achieve higher accuracy and make text responses more arbitrary.

Social distancing and tightening of sanitary standards related to the COVID-19 pandemic have increased the stress among many social groups, including dental students. The situation has beyond doubt affected the world and will have a significant impact on the development of stress-coping techniques, which, as everything indicates, will be more and more needed.

Author Contributions: Conceptualization, S.W. and R.D.; methodology, S.W.; validation, S.W.; investigation, S.W. and R.V.; resources, S.W.; writing—original draft preparation, S.W. and R.D.; writing—review and editing, S.W., R.D., N.P., K.D., S.S., E.T. and R.V.; visualization, S.W.; supervision, E.T.; project administration, S.W. and R.D.; funding acquisition, E.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was carried out according to the Declaration of Helsinki guidelines and was approved by the Bioethics Committee of the Medical University of Silesia in Katowice, Poland (resolution KNW/0022/KB1/79/18, 16 October 2018).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: We would like to thank the students and employees who agreed to participate. A total of 338 were included in the study.

Conflicts of Interest: The author Natalia Piaseczna is an employee of MDPI; however, they did not work for the journal *Healthcare* at the time of submission and publication.

Abbreviations

COVID-19	Coronavirus disease-2019
DASS-21	Depression, anxiety, and stress scale
MERS	Middle East Respiratory Syndrome

OK	Oklahoma
PSQ	Pandemic Stress Questionnaire
PSS-10	Perceived Stress Scale
SARS	Severe acute respiratory syndrome
USA	United States of America
WA	Washington

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Recognition of Drivers' Activity Based on 1D Convolutional Neural Network

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Received: 3 November 2020; Accepted: 21 November 2020; Published: 25 November 2020



Abstract: Background and objective: Driving a car is a complex activity which involves movements of the whole body. Many studies on drivers' behavior are conducted to improve road traffic safety. Such studies involve the registration and processing of multiple signals, such as electroencephalography (EEG), electrooculography (EOG) and the images of the driver's face. In our research, we attempt to develop a classifier of scenarios related to learning to drive based on the data obtained in real road traffic conditions via smart glasses. In our approach, we try to minimize the number of signals which can be used to recognize the activities performed while driving a car. Material and methods: We attempt to evaluate the drivers' activities using both electrooculography (EOG) and a deep learning approach. To acquire data we used JINS MEME smart glasses furnished with 3-point EOG electrodes, 3-axial accelerometer and 3-axial gyroscope. Sensor data were acquired on 20 drivers (ten experienced and ten learner drivers) on the same 28.7 km route under real road conditions in southern Poland. The drivers performed several tasks while wearing the smart glasses and the tasks were linked to the signal during the drive. For the recognition of four activities (parking, driving through a roundabout, city traffic and driving through an intersection), we used one-dimensional convolutional neural network (1D CNN). Results: The maximum accuracy was 95.6% on validation set and 99.8% on training set. The results prove that the model based on 1D CNN can classify the actions performed by drivers accurately. Conclusions: We have proved the feasibility of recognizing drivers' activity based solely on EOG data, regardless of the driving experience and style. Our findings may be useful in the objective assessment of driving skills and thus, improving driving safety.

Keywords: activity recognition; car driving; classification; electrooculography; convolutional neural network; smart glasses; wearable devices

1. Introduction

Driving a car is a complex activity which involves movements of the whole body [1]. The decisions and behavior of drivers regarding the surrounding traffic are crucial for road safety [2]. The factors which affect the road traffic safety can be divided into two categories: the environmental factors and the state of the driver. The environmental factors include weather and road conditions. We define the state

of the driver as driver's alertness, concentration (focus), cognitive abilities and the fact of performing secondary tasks.

To solve the problem of specifying driver's activities, we apply recognition based on tracking eye movements, as most human activities require eyeball movements [3–5]. The analysis of eye movements may help understand the reasons and determine the beginning and the end of activity. However, most eye movements are involuntary and remain out of conscious control [6].

The mainstream method for tracking eye movements in human behavior research is analyzing images registered with a camera [7], because of its advantages: small individual differences, and providing a non-contact of eye measurements. The drawbacks of using a camera to track eye movements are the trade-off between processing time and detection accuracy and the susceptibility to lighting conditions, skin color and sunglasses [8]. Moreover, cameras mounted in vehicles cannot be used to detect the state of a driver outside the vehicle [9]. An alternative method is electrooculography (EOG), a technique for measuring the resting electrical potential between the cornea and retina of the human eye [10]. The EOG signal is registered by electrodes placed around the eyes. The extracted EOG signal is then processed in order to detect the eyeball movements [4,5,11–13].

The reason for choosing EOG to detect eyeball movements was the availability of JINS MEME ES_R smart glasses which can register electrooculograms in a non-invasive way (without attaching the electrodes to the body) while performing various activities (including driving a car) [9,14] and the fact that the eyeball movements contain the most information related to activities related to driving a car [2,4,15]. Another reason for using only electrooculography was to design the system for recognizing drivers' activities regardless of their style of driving and experience and to find the minimal number of attributes required to recognize such activities [16].

To the best of our knowledge, the problem of extracting and selecting appropriate features from electrooculograms in recognition of drivers' behavior has not been thoroughly investigated due to the cumbersome placement of electrodes and the breadth of the topic, which indicates a clear need for further research. The studies conducted by Niwa et al. [9] and Doniec et al. [17] are the only known study on drivers' behavior which used JINS MEME smart glasses. Another recent study on recognizing the gaze on the left turn was conducted by Stapel et al. [18].

Because the average accuracy of the classifier based on k-means clustering and BFS reported in [17] was 85% when analyzing four activities related to driving (driving on the motorway, parking, urban traffic, traffic in the neighborhood), we attempted to improve the accuracy by changing the approach to classification.

In recent years, deep learning techniques, such as recurrent neural network (RNN) [19,20], convolutional neural network (CNN) [7,19], generative adversarial network (GAN) [21], long short-term memory (LSTM) network [20,21], have found their use in classifying the state of the driver based on various signals, such as electroencephalography (EEG) [19,20,22,23], images [20] and EOG [21].

In our study, we apply a one-dimensional (1D) convolutional neural network (CNN) to perform classification on raw EOG signals without crafting features prior to classification [24]. Another advantage of using 1D CNN is the ability to retrain the model on new data sets by using transfer learning [25].

The purpose of this study was to examine whether it is possible to classify drivers' activities in real road conditions based on raw EOG signals and 1D CNN. The performance of the 1D CNN built for classification was evaluated as precision, recall and F_1-score.

The structure is as follows: material and methods are described in Section 2, which includes the experiment setup, data preprocessing and classification. The results in Section 3 consist of the loss and accuracy graphs, the confusion matrix, and receiver operating characteristic (ROC) curves of the proposed 1D CNN model. Finally, we state that, based on the ROC curve and other performance metrics presented in

the confusion matrix, the model was trained without overfitting and underfitting. In Section 4, we conclude the paper by discussing the significance of the results and advantages and limitations of our approach.

2. Materials and Methods

2.1. Experiment Setup

The study was conducted in real road conditions in accordance with Chapter 4 of the Act on Vehicle Drivers of the Republic of Poland [26] on two groups of volunteers: ten experienced drivers (age between 40 and 68) with minimum ten years of driving experience and ten learner drivers who attended driving lessons at a local driving school (age between 18 and 46). The participants gave consent to participate in the study. The candidates for drivers made a statement on their health in a questionnaire submitted to the driving school. Although the candidates for drivers may not reveal the actual health status in the questionnaires, we assumed that the study group did not have any health conditions which may cause a direct driving hazard.

In Poland, the drivers and candidates for drivers are subject to medical examination based on Article 39j of the Act on Road Transportation of the Republic of Poland [27] and Chapter 2 of the Act on Vehicle Drivers of the Republic of Poland [26]. The medical examinations of drivers include the examination of vision, hearing, and balance, the state of cardiovascular and respiratory system, kidneys, nervous system, including epilepsy, obstructive sleep apnea, mental health, symptoms of alcohol abuse, the use of drugs that may affect the ability to drive and other health conditions that may cause a driving hazard.

To avoid distracting the driver during the field study, data were acquired with JINS MEME ES_R smart glasses. The device consists of a three-point electrooculography (EOG) and six-axis inertial measurement unit (IMU) with a gyroscope and an accelerometer. JINS MEME smart glasses acquire ten channels of data: the acceleration and rotation in X, Y and Z axes, and four EOG channels: electric potentials on the right and left electrodes and the vertical and horizontal difference between them. All signals are sampled with the frequency of 100 Hz. The data are transmitted to a computer via Bluetooth or USB and can be exported to CSV file. Electrooculograms were recorded with three-point EOG sensor which consist of left, right and bridge electrodes and were converted into four lead (channel) recording of EOG signal: left, right, horizontal and vertical [14].

Each participant had to perform the same set of tasks while wearing the smart glasses. Sensor data were acquired and linked to scenarios related to driving by the observer sitting on a back seat (see Figure 1). Each learner driver (learner) drove the same car adapted for driving lessons and marked with the L sign. The learners drove the car under the supervision of a driving instructor, whereas other drivers drove their own cars. Sensor data from learner drivers were obtained thanks to the cooperation with a local driving school.

All participants completed their tasks on the same route of 28.7 km in Tarnowskie Góry, Radzionków, Bytom, and Piekary Śląskie in southern Poland presented in Figure 2. The tasks to be completed during the drive were based on the regulations on practical driving tests [28] and included:

- journey through a motorway;
- drive straight ahead in city traffic;
- passage of a section straight ahead outside of the urban area;
- drive straight ahead in residential traffic;
- driving through a roundabout (right turn, driving straight ahead and left turn);
- driving through a crossroads (right turn, driving straight ahead and left turn);
- parking (parallel, perpendicular, angled).

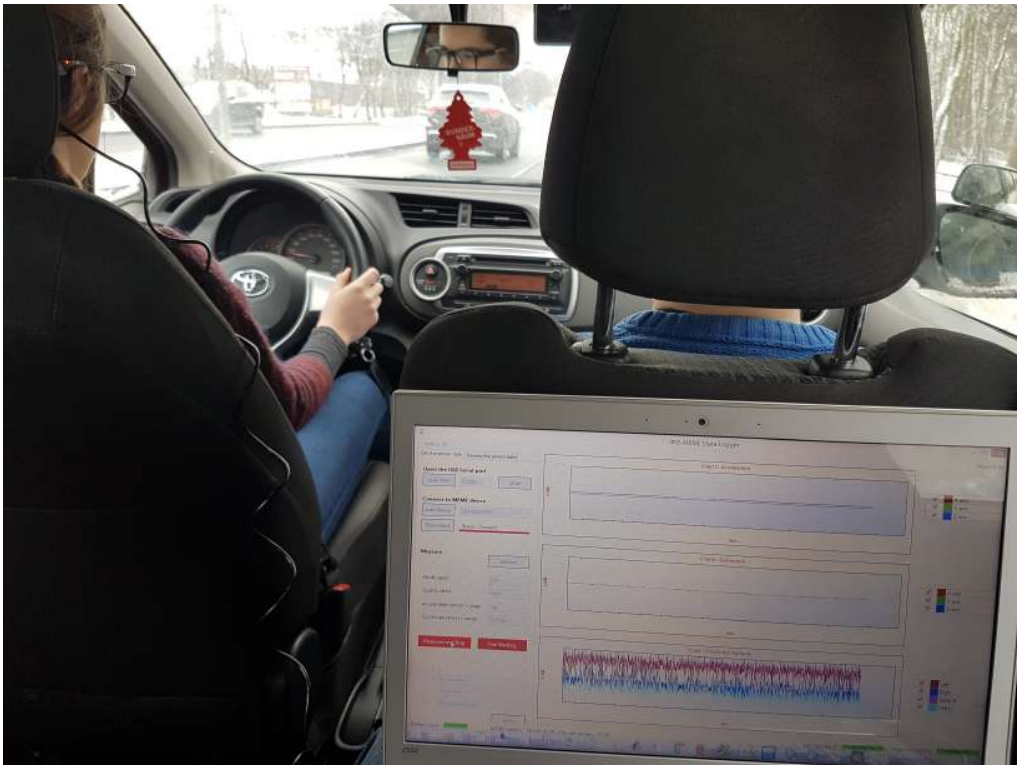


Figure 1. Experiment setup. The driver (left) is wearing JINS smart glasses connected to the computer (foreground) while recording the signals.

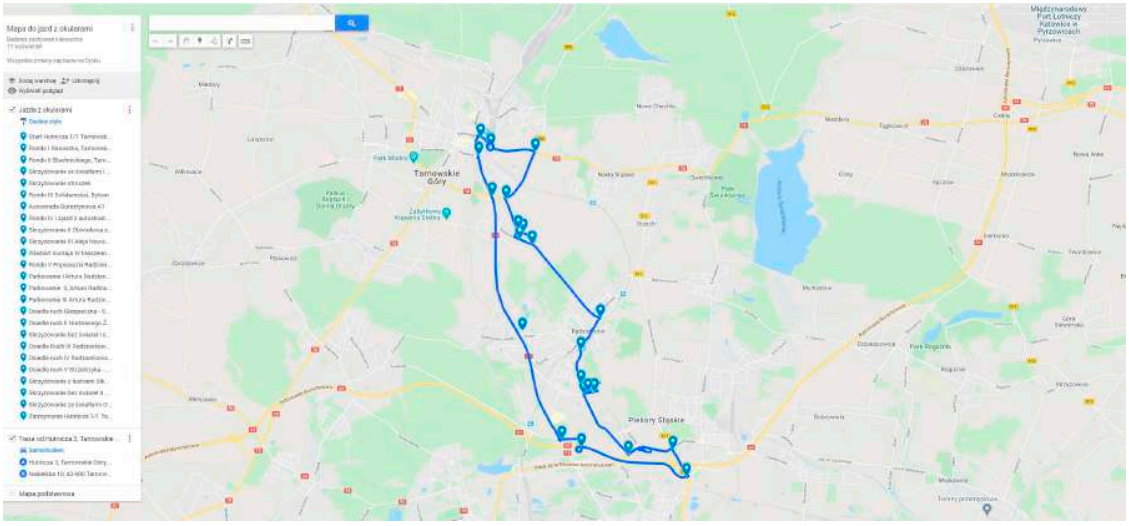


Figure 2. The test route chosen for the study (map data: Google).

The route included roundabouts and parking lots shown as satellite images in Figures 3 and 4. Figure 3 presents the bird's eye view of two roundabouts (small and large) and Figure 4 presents the bird's eye view of public parking spaces with no ticketing along the Artura street in Radzionków (Poland).



(**a**) (**b**)

Figure 3. Bird's eye view of two roundabouts: (**a**) small roundabout (the diameter of circle island: 20 m); (**b**) large roundabout (the diameter of circular island: 54 m). Map and satellite images: Google, CNES, Airbus, Maxar Technologies, 2020.

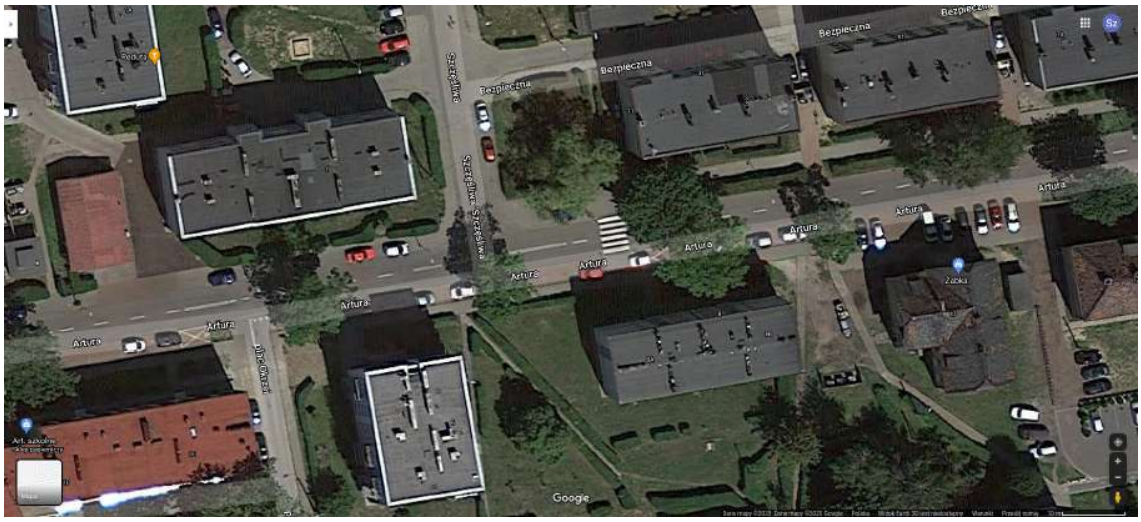


Figure 4. Bird's eye view of the public parking lots at the Artura Street in Radzionków, Poland (map and satellite image: Google, CNES, Airbus, Maxar Technologies, 2020).

Each activity was labeled manually by the researcher during the drive. A pilot (driving instructor in case of learner drivers and in other cases—the researcher) asked the driver to start performing a particular activity, and at the same time, recording began. When the task was completed, the pilot asked to stop the recording. The file with recorded data was named according to the registered activity.

The average time of completing all the tasks during the experiment was 75 min. Experienced drivers generally completed the route faster than learner drivers, regardless of road conditions [17].

The experiment was carried out following the rules of the Declaration of Helsinki of 1975, revised 2013, and with the permit issued by the Provincial Police Department in Katowice. The participants

gave their informed consent for inclusion in the study. Study protocol was approved on 16 October 2018 by the Bioethics Committee of the Medical University of Silesia in Katowice (the resolution number KNW/0022/KB1/18). The identity of learner drivers is confidential under the agreement with the driving school, and the same rule applies for the experienced drivers. Experimental data as Supplementary Materials were made publicly available at IEEE DataPort [29].

2.2. Data Preprocessing

The data set consists of 520 labeled recordings of electrooculograms, acceleration and gyration signals from both experienced and inexperienced drivers acquired with JINS_MEME ES_R smart glasses and is available at the IEEE DataPort [29]. The reason for analyzing the recordings acquired form both experienced and inexperienced drivers is based on the fact that there are no significant differences in overall cognitive and motor skills [30].

The recordings were divided into four scenarios (categories): parking, driving through a roundabout, driving in city traffic and driving through an intersection chosen based on the classification accuracy reported in [17]. By considering only EOG signals, we can distinguish specific patterns associated with analyzed activities, regardless of style of driving, driving dynamics and experience visible in acceleration and gyration.

The recordings were divided into each category as follows:

- parking: 120 recordings,
- driving through a roundabout: 120 recordings,
- driving in city traffic: 160 recordings,
- driving through an intersection: 120 recordings.

Each of these activities can be further divided into categories described in the Section 2.1. We focused on recognizing 4 activities to verify the feasibility of classification based on 1D CNN.

The data were preprocessed before classification in Python 3.7.5 with Pandas, NumPy, Matplotlib and Scikit-learn. The first step was to unify the length of the signals because the length of the original signal vector varies from 320 to 32,357 samples (considering all of the categories). In order to unify the input signals, we took the maximum length value across all the recordings and tiled the shorter vectors to match that value. This approach turned out to be the easiest and the fastest way to standardize input data without losing the inherent characteristics of the signal for each category.

The second step of preprocessing was normalizing the input values to prevent the occurrence of the exploding/vanishing gradient problem [31]. After normalization, the data were divided into training and validation sets. The best performance was achieved with validation split equal to 20%. The number of samples in both sets and for each category was shown in the Figures 5 and 6.

2.3. Classification

In this study, we propose an approach to driver activity recognition using a one-dimensional convolutional neural network (1D CNN). This neural network model has proven its effectiveness in signal classification, yielding state-of-the-art results [32,33]. Because biological signals have non-linear characteristics, convolutional neural networks are an adequate choice, as they are precisely developed for recognizing non-linear patterns in the data [34]. Considering that there have not been established patterns in EOG signals related to driver's activity, we applied 1D CNN due to the ability of automatic extraction of features. By using convolutional layers, we can also visualize the set of filters after training and try to learn which characteristics of the input signal are related to certain activity.

The architecture of the proposed model is shown in Figure 7.

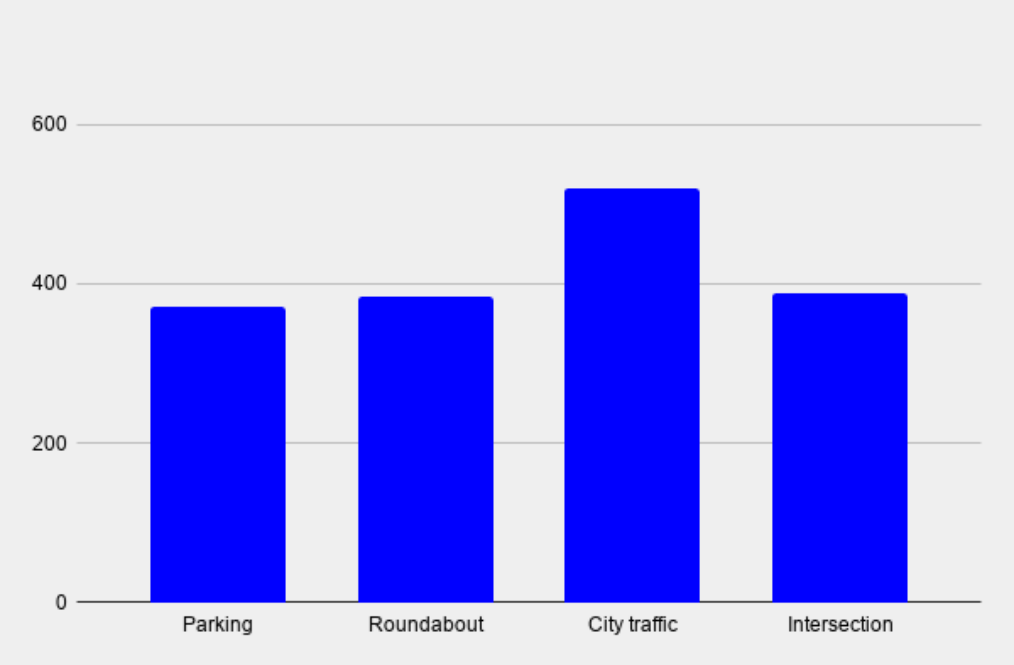


Figure 5. Number of samples in each category in training set.

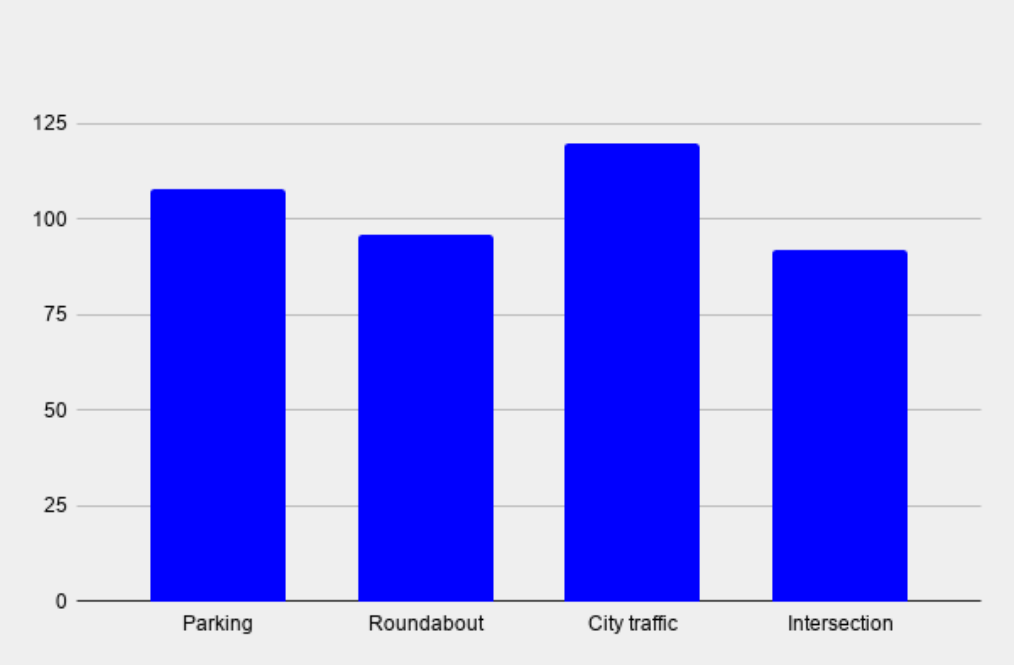


Figure 6. Number of samples in each category in validation set.

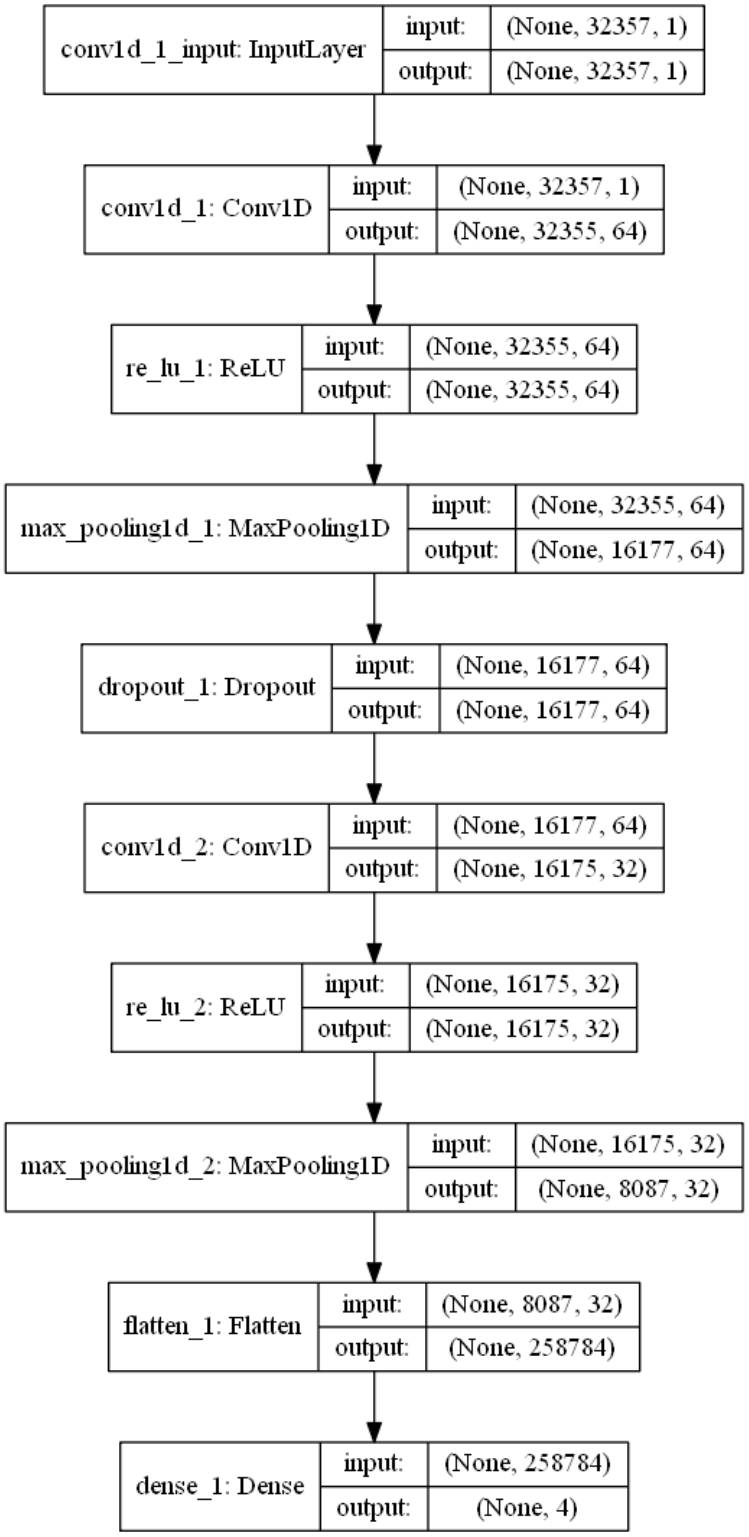


Figure 7. Architecture of the proposed 1D convolutional neural network (CNN) model generated by Keras and graphviz. `None` is the variable batch size.

The architecture consists of the following elements:

- Convolution with max pooling block—first convolution layer produces 64 feature maps which are then processed by activation function in order to capture non-linear patterns and followed by pooling layer with kernel size of two to reduce the extracted information. The second convolution layer generates 32 feature maps with kernel of size three (as in the first block), followed again by rectified linear unit (ReLU) and pooling layer [35]. Although the kernel size of convolutional layer may be much higher in the case of 1D CNN than in their two-dimensional (2D) counterpart, the best results were achieved with the smaller kernel.
- Dropout layer—the dropout layer was set with the rate of 0.5. This layer turned out to be the key element because it prevents overfitting at the beginning of the training phase [36].
- Dense and flatten blocks—after obtaining the data from the second convolutional pooling block, the feature maps are mapped into their one-dimensional representation and classified with the single and final layer consisting of four neurons followed by softmax probability activation function.

The conducted training process lasted 100 epochs, the batch size was 20 and the decaying learning rate was 0.001 at the start. The 1D CNN model was developed in Python 3.7.5 using Keras library with Tensorflow version 2.1 as the backend. To accelerate the computation, we set up the GPU (graphics processing unit) support with Nvidia CUDA (Compute Unified Device Architecture) version 10.1.

Data preprocessing and classification of 520 labeled recordings was run on the Nvidia GTX 1060 with 6 GB of VRAM (Video RAM) and training the proposed model for 100 epochs took circa 10–15 min. The source code of classifier was made publicly available at IEEE DataPort [29].

3. Results

This section provides and describes the results of classification of four analyzed driving scenarios registered in 520 labeled recordings using 1D CNN.

The accuracy on the training set was 99.8% on and 95.6% on the validation set. The performance of the training process was presented as the learning curves and the decaying learning rate curve on Figures 8–10.

The accuracy curve shows the correctness of the model's performance among the epochs. Both train and test accuracy achieved high values (above 90%) after circa 40 epochs.

The loss function is the sum of errors made after each epoch. After circa 40 iterations, loss stabilizes (circa 0 for training set and below 0.2 for validation set).

Figure 10 shows how the learning rate was changed among iterations. In this case, the learning rate was halved after five epochs if the validation loss did not decrease.

The performance of the proposed classifier is presented in the form of confusion matrix (Figure 11) and receiver operating characteristic (ROC) curves for each activity (see Figure 12).

The confusion matrix presents the numbers of cases classified to a specific group (predicted label) in comparison with their real classification (true label). The correctness of the classification is as follows:

- for parking—ten out of 108 signals were classified incorrectly (two as driving through a roundabout, four as driving in city traffic and four as driving through an intersection);
- for driving through a roundabout—two out of 96 signals were classified incorrectly (one as parking and one as driving in city traffic);
- for driving in city traffic—three out of 120 signals were classified incorrectly (as one of each group);
- for driving through an intersection—one out of 92 signals was classified incorrectly (as driving in city traffic).

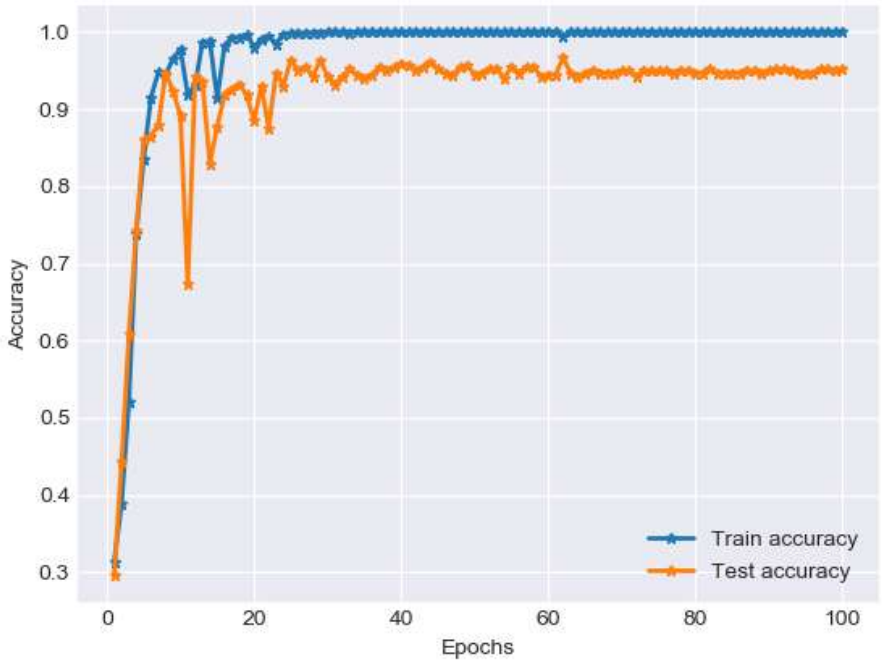


Figure 8. Accuracy of the proposed 1D CNN model.

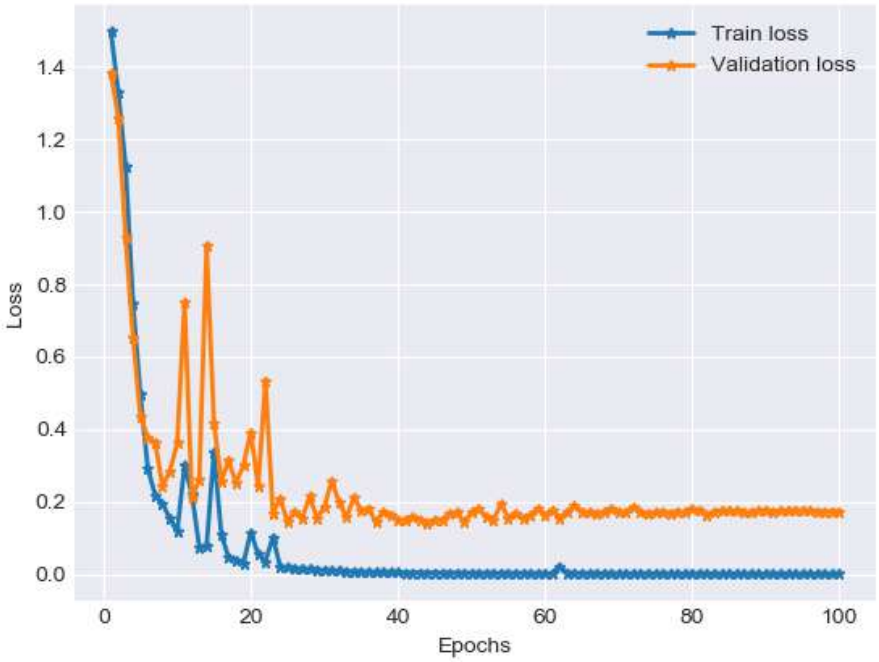


Figure 9. Loss of the proposed 1D CNN model.

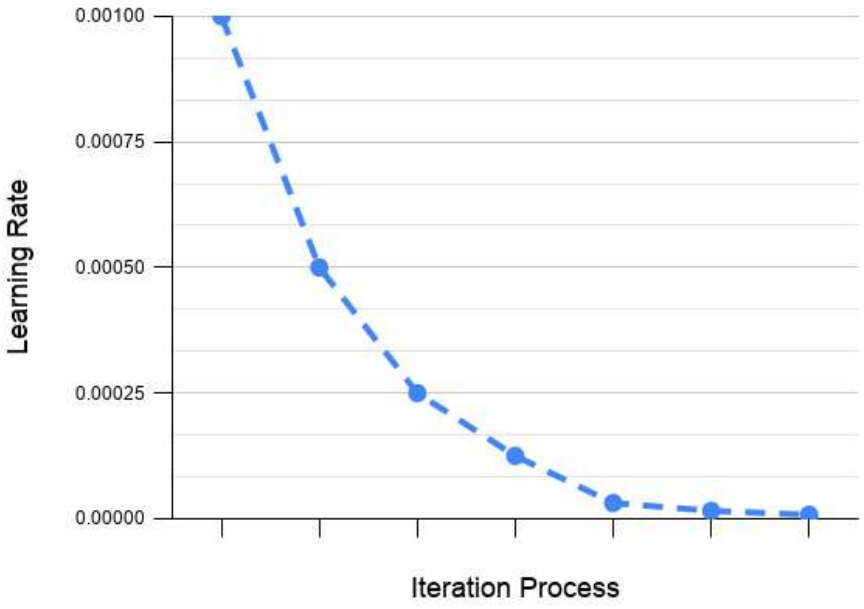


Figure 10. Learning rate decay.

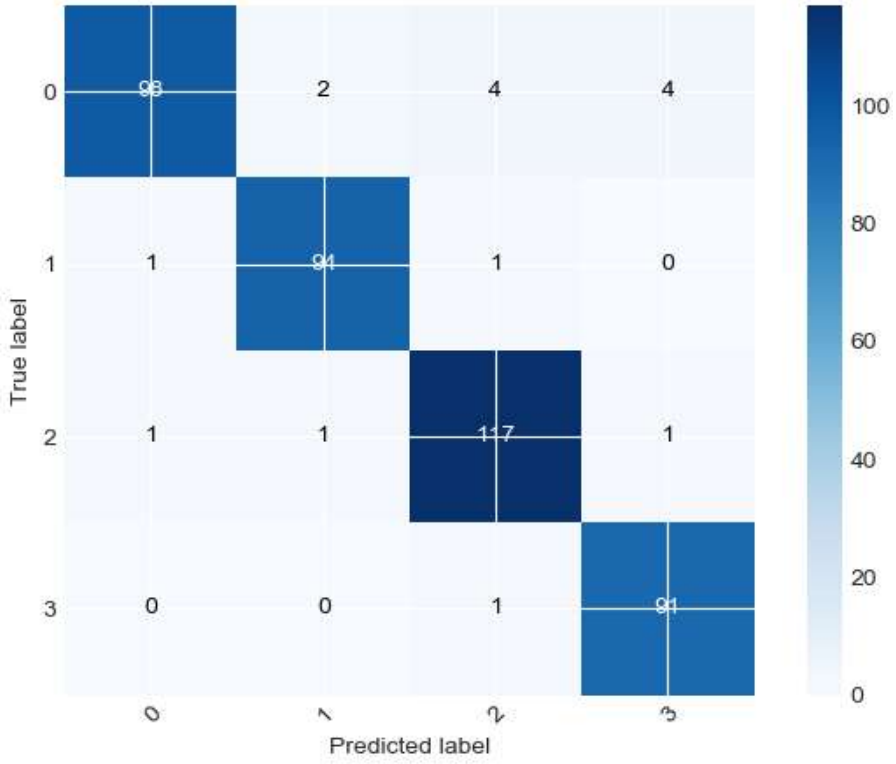


Figure 11. Confusion matrix of the classifier.

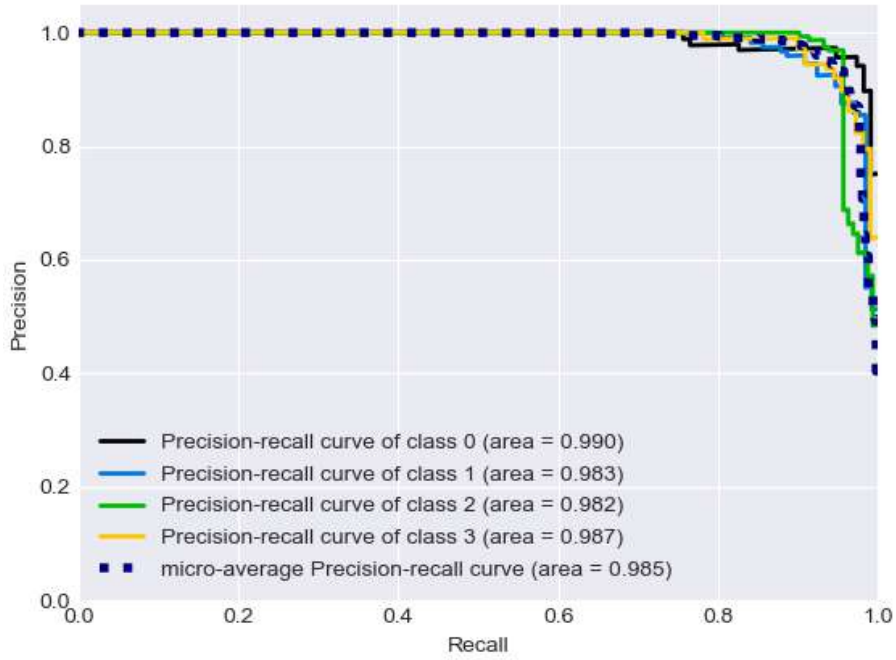


Figure 12. Precision recall curves of the classifier.

Based on the confusion matrix, the following parameters (adapted for multi-category classification) were calculated:

- Precision is the proportion of positive samples out of the retrieved samples (true positive and false positive).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{1}$$

- Recall (sensitivity) measures how accurate is the model within all the positive samples.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

- F_1 score—combination of the two aforementioned metrics which rises when both precision and recall increases.

$$F_{1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

The calculated values of aforementioned metrics are presented in the Table 1.

Table 1. The performance of the classification of four driving scenarios.

Category	Precision	Recall	F_1-Score
0—parking	0.98	0.907	0.942
1—roundabout	0.97	0.98	0.97
2—city traffic	0.95	0.975	0.96
3—intersection	0.95	0.98	0.968

The highest precision was obtained for parking (0.98), the highest recall was obtained for driving through a roundabout and driving through and intersection (0.98 in both cases) and the highest F_1-score

for driving through a roundabout. The lowest precision was obtained for city traffic, and the lowest recall and F_1-score was obtained for parking.

The ROC curve measures the capability of distinguishing given classes by the analyzed model and is presented as true positive rate to false positive rate. With the multi-class problem, we measure this ratio for each single category against all the other categories [37]. The receiver operator characteristic curve shows that the created model was well trained, without overfitting and underfitting. It also shows that there are no unbalanced ratios between true positives and false positives, which again leads to the conclusion that the model was not biased.

Based on the confusion matrix and ROC curve, we can observe that most of the misclassified samples belong to the parking activity (see Figure 11). The reason is the fact that parking can be performed in different ways (angle, perpendicular, parallel) and is also associated with frequent movement of head and eyeballs reflected in the EOG signal. However, the EOG signals linked to parking may resemble the other activities, such as driving on a roundabout.

4. Discussion

We built the classifier of driver's activity based on 1D CNN. Its accuracy was 99.8% on the training set and 95.6% on the validation set. The accuracy of our classifier is higher than in other studies, especially:

- Doniec et al.'s study, which used BFS approach with 2-fold cross validation on seven activities (62% driving on a highway, parking in front, parallel parking, slope parking, driving around a roundabout, driving in city traffic, driving in residential traffic) and four activities (85% for driving on a freeway, city traffic, parking, driving in a residential area) [17];
- Jiang et al. study which used k-nearest neighbors (kNN) and SVM classifying approach on signals from wearable devices (90%) [38];
- Vora et al.'s study which used driver's eye tracking in video recording and CNN-based classifier (95.2%) [25];
- Galarza et al.'s study, which used a video recording of the driver's face, statistical model and Google API-based classifier (93.37%) [39];
- Mulhall et al.'s study, which used binary logistic regression for recognition of lane departures (73%) and microsleeps (96%) during driving in real road conditions [40].

This classifier has proven its high accuracy in classifying four driving scenarios (parking, driving through a roundabout, driving in city traffic and driving through an intersection). Its inherent ability to capture non-linear patterns in the sensor data makes 1D CNN a powerful tool in processing biologically related signals. The main drawback of this approach is the fact that it needs a fixed size input. The performance of 1D CNN deep learning model is at least 14%, better than BFS approach with soft assignment to specific configurations for the same data set. The results obtained for both data sets (training and validation sets) emphasize two points: the superiority of automatically learned functions over manually created ones used in [17], and the stability of 1D CNN deep learning architectures.

The type of dominant features fed to the classifier in [17] depend on the size of the sliding window and the BFS entropy of the extracted data frames. Moreover, the 1D CNN model is among the most efficient methods, which underlines the stability of this model and suggests its good ability to generalize on various data sets [41], including medical data [33]. The accuracy of studies on the drivers' behavior was based on monitoring one or two signals; the accuracy ranged from 60% to 80% [42].

In this study, we have proven the feasibility of driver's activity recognition based solely on EOG data, regardless of his/her experience and style of driving, which can be determined based on accelerometer and gyroscope data. Therefore, this approach may be applied to numerous real-world scenarios, such as building a system that may help improve the driving skills and driving safety, especially in smart vehicles.

Due to the increasing number of vehicles on roads, changing the paradigm of the driver training process is necessary to prevent the growth of road accidents and fatalities. The opportunity to measure the drivers' perception can provide valuable insight into drivers' attention. Accurate and inexpensive driver assistant systems may help encourage safe driving. However, real-time monitoring of behavior and driving conditions imposes technical challenges and the need for monitoring the state of the driver, especially dizziness caused by long trips, extreme changes in lighting, reflections of the glasses or the weather conditions on the road.

In future, we will address the limitations of our study: the need of providing fixed-sized input signals and misclassification of some recordings linked to parking activity. We propose developing a variable-size model which will operate on global pooling instead of a flatten layer to overcome the first limitation. With that approach, we may propose a new method of determining the length of the input vector based on the information from additional sensors. To overcome the second limitation, we propose differentiating variants of parking and providing more robust architecture. Although we achieved satisfactory results with 1D CNN, we consider ensemble classifiers or multi-input deep learning models for recognizing a wider range of activities in the long term.

Supplementary Materials: The research data are available online at IEEE DataPort: https://dx.doi.org/10.21227/q163-w472.

Author Contributions: Conceptualization: R.J.D. and S.S.; Investigation: R.J.D. and K.M.-P.; Methodology: R.J.D., S.S. and K.M.D.; Writing—Original Draft Preparation: R.J.D., S.S. and N.J.P.; Writing—Review & Editing: R.J.D., S.S., K.M.D., N.J.P. and E.J.T.; Validation: K.M.D.; Visualization, K.M.D.; Supervision, E.J.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We would like to thank the volunteers who participated in the study and the driving school for providing the opportunity to acquire signals on learner drivers. We also would like to thank the reviewers for useful comments.

Conflicts of Interest: The authors declare no conflict of interest.

Ethical Statements: The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Bioethics Committee of the Medical University of Silesia on 16 October 2018 (KNW/0022/KB1/18).

Abbreviations

The following abbreviations are used in this manuscript:

1D	One-dimensional
2D	Two-dimensional
BFS	Best fit sequence[s]
CNN	Convolutional neural network
CUDA	Compute unified device architecture
ECG	Electrocardiogram
EEG	Electroencephalogram
EOG	Electrooculography
GAN	Generative adversarial network
GPU	Graphics processing unit
IMU	Inertial measurement unit
kNN	K-nearest neighbors
LSTM	Long short-term memory
MARS	Masking action relevant stimuli
RNN	Recurrent neural network

ReLU	Rectified linear unit
ROC	Receiver operating characteristic
SVM	Support vector machine
VRAM	Video RAM

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Evaluating the stress-response of dental students to the dental school environment

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ABSTRACT

Introduction and Objective. Dentists experience high amounts of professional stress beginning with their student years in dental school. This stress, given its early onset, may negatively impact the personal and professional lives of these individuals, as well as the quality of their clinical work. We sought to create an objective scale to evaluate the levels of stress in students at different stages of their education, as well as in practicing physicians.

Materials and Methods. Thirty dental students participated in this study, with 10 students each selected from junior, mid-senior, and senior classes. They were randomly divided into two groups in which one group was subjected to stressors while the other group was not. JINS MEME ES_R (JINS) smart glasses and Garmin Vivoactive 3 smartwatches were used to obtain data, including electrooculography (EOG), heart rate (HR), and accelerometer (ACC) and gyroscope (GYRO) feedback, while the subjects performed a dental exercise on a phantom tooth.

Results. The heart rates of more experienced students were lower than those of the junior students. The EOG, ACC, and GYRO signals showed multiple differences in the measurement of amplitudes and frequency of episodes.

Conclusion. Our pilot results show that electronic tools, like smart glasses with software and sensors, are useful for monitoring the stress levels of dental students in preclinical operating conditions. We would like to further assess the stress levels in students performing dental procedures on phantom teeth and in later clinical interactions with patients.

Subjects Dentistry, Public Health, Science and Medical Education
Keywords Adaptation, Dental students, School environment, Stress at work

Submitted 15 October 2019
Accepted 25 March 2020
Published 6 May 2020

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Academic editor
Julia Sewall

Additional Information and Declarations can be found on page 16

DOI **10.7717/peerj.8981**

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How to cite this article Mocny-Pachońska K, Doniec R, Trzcionka A, Pachoński M, Piaseczna N, Sieciński S, Osadcha O, Łanowy P, Tanasiewicz M. 2020. Evaluating the stress-response of dental students to the dental school environment. *PeerJ* **8**:e8981
http://doi.org/10.7717/peerj.8981

INTRODUCTION

Dentists experience high levels of professional stress which can negatively affect them from their student years working with phantom teeth through their preclinical and clinical practice years (*Al Faris et al., 2016*).

Stress related to dental school can negatively impact a dentist's personal and professional life, particularly with regard to the quality of their clinical work (*Rada & Johnson-Leong, 2004*; *Piazza-Waggoner et al., 2003*; *Harazin et al., 2014*; *Farokh-Gisour & Hatamvand, 2018*; *Chandrasekaran, Cugati & Kumaresan, 2014*). Stress resulting from external physical or mental factors can affect an individual's physical and psychological well-being and may reduce work efficiency and impact the accuracy of diagnostic and therapeutic decisions (*Rada & Johnson-Leong, 2004*; *Harazin et al., 2014*).

It is difficult to predict and control reactions to external stressogenic situations. During stressful conditions, the hypothalamus-pituitary-adrenal (HPA) axis and the sympathetic nervous system (SNS) are activated. The nervous system becomes aroused in periods of stress or danger, which affects an individual's reactions. Responses to stressful situations vary among individuals due to diverse perceptions of circumstances. The stress response is more highly aroused when a stressor is directed in a personal manner and continues with the ongoing risk of threat (*Martinez et al., 2017*; *Schachner & Singer, 2000*).

Studies have shown that students from medical universities are more prone to psychological problems due to unique stressors, including the demands of their education and special expectations compared to students of humanities and technical faculties (*Piazza-Waggoner et al., 2003*). *Dyrye, Thomas & Shanafelt (2006)*. reported that medical students experience high levels of anxiety and depression. *Mohannad et al. (2019)* and *Brazeau et al. (2014)* confirmed that depression in dental students and interns appears more frequently than in the general population, with evidence of mental health deterioration over the course of their medical training. *Al Faris et al. (2016)* emphasized that the third and fifth years of dental and medical studies are highly associated with depressive symptoms in students.

Dental school is a significant source of stress for dental students who are required to practice in a professional manual workshop for clinical work, establish direct patient contact, and manage patient stress. These stressors are in addition to their rigorous educational challenges, which include providing care for patients and performing treatments that could cause harm if performed improperly.

Dental students must deal with life-threatening conditions, work long hours, undertake a demanding workload, and master an intense theoretical education (*Harazin et al., 2014*). Studies show that young dental students can significantly improve complicated fine motor skills, such as performing dental work while looking in a mirror, with practice (*Lugassy et al., 2019*).

Dental students appear to be more at-risk for stress than students from other faculties, including medical students, because the need to acquire extensive knowledge is combined with manual training, which is practiced in a preclinical simulation center and then in clinical practice (*Ali et al., 2018*).

When training in clinical practice, students have direct contact with patients who may be in pain and fearful of dental examinations and procedures (*Ali et al., 2018*). Our findings support the results demonstrated by *Abu-Ghazaleh, Sonbol & Rajab (2016)* that stress in dental students at the University of Jordan increased over the years of the clinical training; fifth-year students showed especially high levels of psychological stress due to an increased awareness of the expectations and responsibilities of their work. The negative impact of depression on dental students is replaced by stress resulting from the need to cope with professional duties and full-time clinical work, and the need to simultaneously carry out continuing postgraduate education (*Roberts, 2010*).

Stress adversely affects the quality of patient care, patient safety, and professionalism, and its effects extend to the community at large (*Al Faris et al., 2016*). Therefore, given the high rate of depressive symptoms in dental students, stress levels and their causative factors should be determined and preventive measures should be considered (*Davidovich et al., 2015*).

Davidovich et al.'s (*2015*) research comparing students and experienced professionals shows that stress levels are significantly higher among newcomers to clinical practice. Junior students rely on theoretical knowledge from preclinical classes, which may not yet be sufficient, and are typically anxious about using dental equipment with precision (*Davidovich et al., 2015*).

Piazza-Waggoner et al. (2003) and *Davidovich et al. (2015)* investigations confirmed that dental students practicing on patients in a clinical setting have a particularly high level of stress during the implementation of procedures related to invasive work on patients, especially when practicing on a child.

The environment in which students perform their clinical work is also significant. The possibility of being able to perform tasks in silence, under time constraints while being able to complete the task satisfactorily, and the knowledge of how to deal with stressful situations are factors that influence a student's quality of work (*Kiesre & Herbison, 2000*; *Elani et al., 2014*).

Several recent studies have investigated the effectiveness of interventions such as psychoeducational interventions, music therapy, and Progressive Muscle Relaxation (PMR) to cope with student anxiety or stress before academic exams or evaluations (*Labrague et al., 2017*; *Ince & Cevik, 2014*; *Hashim & Zainol, 2015*).

Researchers have not yet confirmed that relaxation or stress management techniques are effective in reducing the fear of working in a clinical setting (*Davidovich et al., 2015*). It is difficult to accurately identify a person's cognitive state but it is important to have an objective real time evaluation for dentists because their cognitive state can influence their performance.

Researchers typically rely on psychological measurements to collect data (*Ishimaru et al., 2015*; *Ogawa, Takahashi & Kawashima, 2016*). However, future research should determine whether differences in the prevalence of severe depressive symptoms among students in different disciplines are due to the innate nature of the discipline, the type of curriculum being studied, or the intellectual and manual skills required (*Al Faris et al., 2016*).

Objectives

We conducted an arbitrary, measurable study of the arousal level of 30 dental students in their third, fourth, and fifth years of study. Results were measured by blink occurrence, speed, and strength; vertical and horizontal eye movement; head movement (rotation roll, pitch, and yaw), and changes in heart rate measured by JINS smart glasses and a GPS smartwatch, with and without stress stimulation. We created our own protocol for stress simulation based on literature data (*Dedovic et al., 2005*; *Ghazali et al., 2018*). The first measured stressor was shaping a cavity in a tooth in a limited time under the careful supervision of a teacher. The second stressor was creating the shape of a cavity similar to the matrix of the cavity. The third stressor was a lack of information on how to prepare the cavity. The control group of students without the stress simulation protocol underwent a session of muscle relaxation, music therapy, and were given full information about the task to be performed. We sought to standardized the measurement method that could be used in further studies using JINS smart glasses.

MATERIAL AND METHODS

Technology used

We used JINS MEME ES_R (JINS) smart glasses with three-point electrooculography (EOG) and six-axis sensors(an accelerometer and a gyroscope) to detect the following actions: blink occurrence, speed, and strength; vertical and horizontal eye movement; and head movement (rotation roll, pitch, and yaw) (*Chen et al., 2012*).

Participant's heart rates (HR) were measured using the Garmin Vivoactive 3 GPS smartwatch with a heart rate sensor located on the back of the device, which displayed the current heart rate in beats per minute (bpm). A graph of the heart rate was also displayed on the device.

Research group

The research participants were third-, fourth-, and fifth-year students (junior, mid-senior, and senior, respectively) of the Dental Division of Silesian Medical University, Katowice, Poland. Ten students were selected from each year group and randomly classified into two equinumerous subgroups: a Management Anxiety Group (MAG) and an Uncontrolled Anxiety Group (UAG). Participation in the study program was determined by the schedule of didactic classes that coincided with the start date of the experiment. Study subgroups were randomly assigned from a closed pool of tickets marked MAG or UAG.

The MAG received a session of PMR and music therapy, detailed and precise information about the task to be performed (analysis of the 3D model, and measurements of the range, shape, and depth of the tooth's cavity, both without any time limit), and recommendations to fully concentrate on precision shape modeling. Relaxation procedures were guided by an experienced physiotherapist (*Gallego-Gómez et al., 2020*): subjects were placed in a room with dimmed lights and sat in chairs to relax the main muscle groups and relieve tension. Relaxing music was also played from a portable audio system using a CD played at a volume of 50–60 DB.

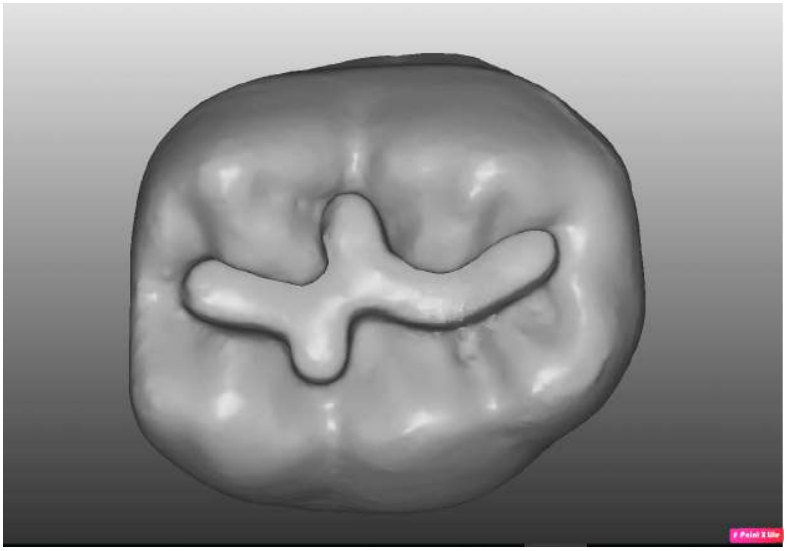


Figure 1 **Matrix with outline of cavity.**

Full-size DOI: 10.7717/peerj.8981/fig-1

The UAG was not given any information or recommendations and did not undergo relaxation training. The UAG was also given a time limit to prepare the cavity. The procedure was conducted under careful teacher supervision but without assistance. The teacher was tasked with informing the students of the passing time at 10 s intervals as well as evaluating their work using the phrase: 'It's bad, not good, hurry up' (*Dedovic et al., 2005*; *Ghazali et al., 2018*)

All participants were equipped with a set of monitoring devices (the smart glasses and smartwatch) during the cavity preparation procedure to measure the vital signs that defined their stress intensity.

Experiment

Students were asked to perform the preparation of a cavity in a standard phantom molar, tooth 36, of a 1:1 scale (Frasaco GmbH, Germany) with limited or unlimited time, depending on the group they were assigned to. The matrix with the outline of the cavity was prepared beforehand (Fig. 1).

They used a Round End Taper NTI Rotary Dental Instruments burr with head length, four mm; diameter, 009 mm; grit, medium.

The participants performed the procedure with high speed ending (350.000 revolutions per minute) and water cooling. A pattern of the cavity outline was presented on a model (Fig. 2) prepared using a 3D printer (Formlabs 2). The model was characterized by the following features: magnification ×10, material: Photopolymer Resin Black FLGPBK04, volume: 389.82 ml, layer thickness: 0.025 mm, number of layers: 3312, print time: 57 h 13 min.



Figure 2 **Printed tooth 36 with matrix.**

Full-size DOI: 10.7717/peerj.8981/fig-2

After a one-week period, the participants switched experimental groups and performed the same procedure, allowing us to determine the differences between MAG and UAG data for the same individual.

Data acquired from the smart glasses worn during the experiment were divided into three parts:

I. electrooculography (EOG),
II acceleration (ACC),
III. gyroscope (GYRO).

The data collected during the first four seconds of the experiment (when the participant started the procedure) and the last four seconds (when the procedure was completed) were not used for analysis, as the largest change in values were observed during that time.

60 experiments were conducted and one common episode that caused rapid rises of amplitude in a signal was chosen to properly evaluate the results. Consent for the experiments was issued by the Ethical Commission of Medical University of Silesia with resolution number KNW/0022/KB1/79/18 on October 16, 2018. All participants gave their written consent prior to the start of the study.

Statistical procedures

Statistical analysis was performed using Statistica Version 9.0 (MUS Katowice, Poland). Results are presented as mean and standard deviation (SD). Statistical analysis of HR values revealed that all distributions were normally distributed. Differences among groups were analyzed using the Student's *t*-test. A Shapiro–Wilk test of normality was performed. A

Table 1 Mean, standard deviation (SD), median and IQR of heart rate measurements in all participants.

			Mean	SD	Median	IQR	*p*-value before/after *t*-student test
Junior (III)	UAG	before	100.6	14.66	101.5	24	$p = 0.36$
		after	97.2	13.91	95.5	18	
	MAG	before	86.0	7.76	84	6	$p = 0.17$
		after	82.8	13.91	82.5	13	
Mid-senior (IV)	UAG	before	92.7	11.98	93	20	$p = 0.02$
		after	80.8	10.56	83	16	
	MAG	before	84.5	13.62	83.5	20	$p = 0.30$
		after	77.4	8.85	78.5	12	
Senior (V)	UAG	before	86.0	6.48	87	9	$p = 0.14$
		after	95.4	18.28	96.5	29	
	MAG	before	83.5	4.06	83.5	6	$p = 0.26$
		after	85.9	6.23	88.5	12	

one-way analysis of variance was used to compare the groups. Fisher's LSD variant was used for two-tailed post hoc tests in justified cases of this test (two cases).

RESULTS

HR data

The Student's *t*-test was used to evaluate the differences in the before and after results from the UAG and MAG groups. Statistically significant differences were only found in the mid-senior UAG ($p = 0.02$) (Table 1). The heart rate in this group gradually decreased while performing the dental task, which implies that stress management training is useful for less experienced students.

The ANOVA test was used to compare HR values among the UAG and it revealed significant differences between the year groups (Fig. 3). The post hoc test results show that significant differences occurred between the third- and fourth-year groups (Table 2).

The results of the ANOVA test in the UAG show significant differences in HR between year groups. The post hoc test results show significant differences when comparing juniors with mid-seniors, and mid-seniors and seniors with mid-seniors. Mid-year seniors had a lower HR than juniors and seniors. There is no statistically significant difference in HR between juniors and seniors (Fig. 4, Table 3).

No statistically significant results were obtained for the MAG (MAG before: $p = 0.69$, MAG after: $p = 0.13$). The anti-stress training indicates that HR values did not differ significantly.

Data from EOG

Data were collected on blinks, squinting of eyes, and probable change of sight directions. There were higher amplitudes and more frequent episodes demonstrated by seven

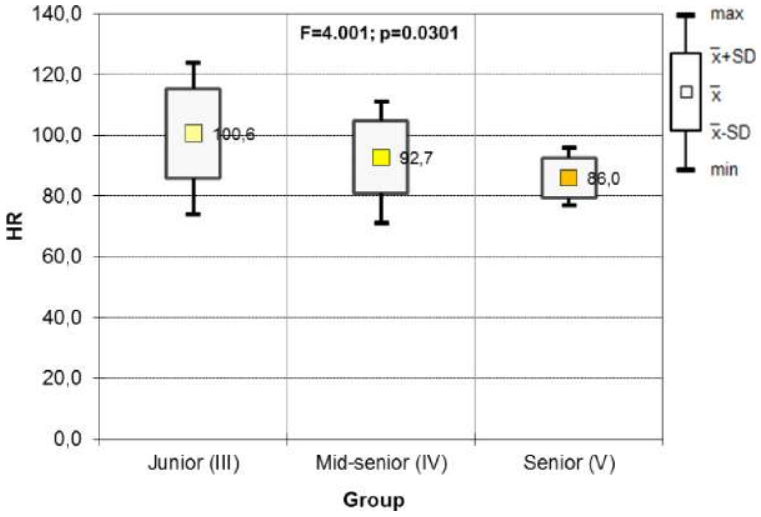


Figure 3 **Results of one-way ANOVA for HR including the year of study in UAG groups (before).**
Full-size DOI: 10.7717/peerj.8981/fig-3

Table 2 **Results of two-tailed post hoc test (LSD Fisher)in UAG groups (before).**

	Junior (III)	Mid-senior (IV)	Senior (V)
Junior (III)		0.01	**0.008**
Mid-senior (IV)	0.01		0.20
Senior (V)	**0.008**	0.20	

participants in the UAG (Fig. 5), while their counterparts in the MAG received lower scores (Fig. 6). There were more frequent blinks and squints, and higher muscle tension in eyes in the UAG.

The number of episodes of saccades and blinks was determined as the number of local maxima of the moving average of the EOG_H signal. EOG_H was used to find these episodes because, according to the producers of the JINS glasses, the greatest changes in EOG while blinking occur in the horizontal component of this signal. The signal processing steps are as follows:

1. Zero-phase 3rd order band-pass Butterworth filter (frequency range 1–35 Hz). Filtration was performed in MATLAB R2019b using the filtfilt function. The frequency range of the band-pass filter was chosen based on (*Nor'aini, Raveendran & Selvanathan, 2007*).
2. Median filtration using 5th order median filter.
3. Moving average FIR (finite impulse response) filter (window-width of 45 samples).
4. Finding local maxima using findpeaks function (Fig. 7).

Based on the comparison of the mean number of peaks, mid-senior and senior MAG students had a lower number of peaks than students from the UAG. The MAG had a higher number of peaks than the UAG in junior-level students (Table 4).

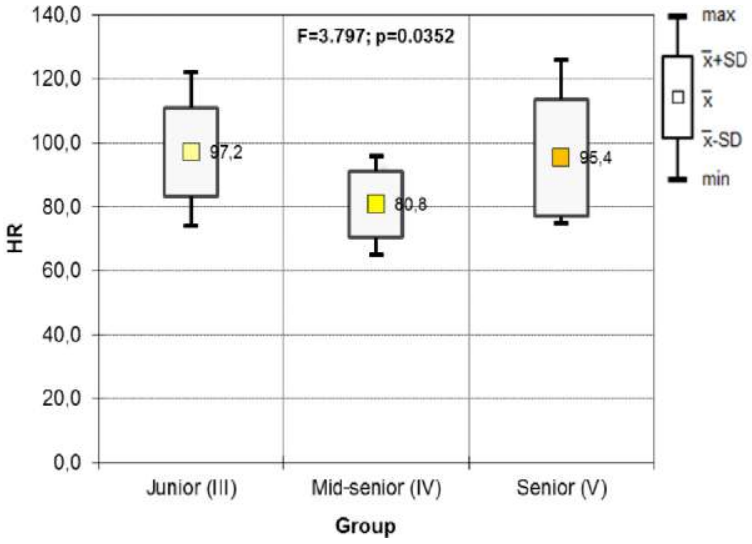


Figure 4 Results of one-way ANOVA for HR including the year of study in UAG groups (after).
Full-size DOI: 10.7717/peerj.8981/fig-4

Table 3 Results of two-tailed post hoc test (LSD Fisher) in UAG groups (after).

	Junior (III)	Mid-senior (IV)	Senior (V)
Junior (III)		**0.01**	0.07
Mid-senior (IV)	**0.01**		**0.03**
Senior (V)	0.07	**0.03**	

Data from ACC and GYRO

Data from the gyroscope were observed as tilts of the head along each plane of the body. Accelerometer data were collected from movements of the head, and their acceleration and intensity. The complete information about the dynamics of the head movements was acquired from both the accelerometer and gyroscope.

The average acceleration (ACC) of juniors and seniors in the UAG and MAG on the x- and y-axes was higher in the UAG than in the MAG, but was lower on the z-axis. The amplitude of the gyration on x-axis head tilts were larger for all students (junior, mid-senior, and senior) in the UAG than for the MAG.

The standard deviations of the head rotation angles were high when considering the average (Table 5).

The ACC_X signal was used in further analyses because of the differences in amplitude among all study groups (Figs. 8–9).

Each of the students who took part in the examination was added to the histogram. Three ranges were proposed from minimum to maximum ACC_X, with the arousal flagged. The mean values of ACC_X signal amplitudes were calculated for each of the students from the UAG and MAG in order to compare his/her stress management abilities (Table 6).

The following ranges were determined based on the data:

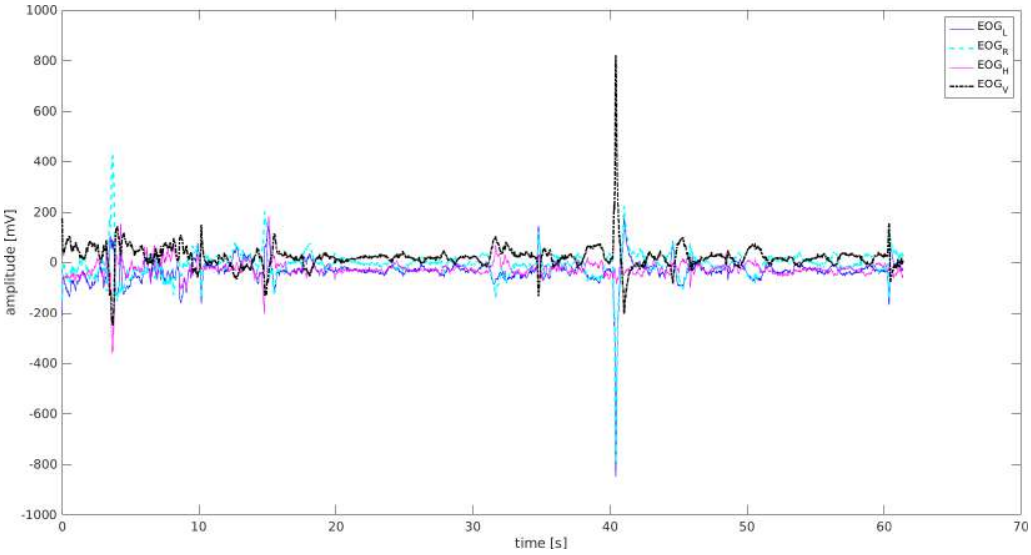


Figure 5 **EOG signal-Mid-senior student UAG.** EOGL, left eye movement; EOGR, right eyemovement; EOGV, vertical eye movement; EOGH, horizontal eye movement.
Full-size DOI: 10.7717/peerj.8981/fig-5

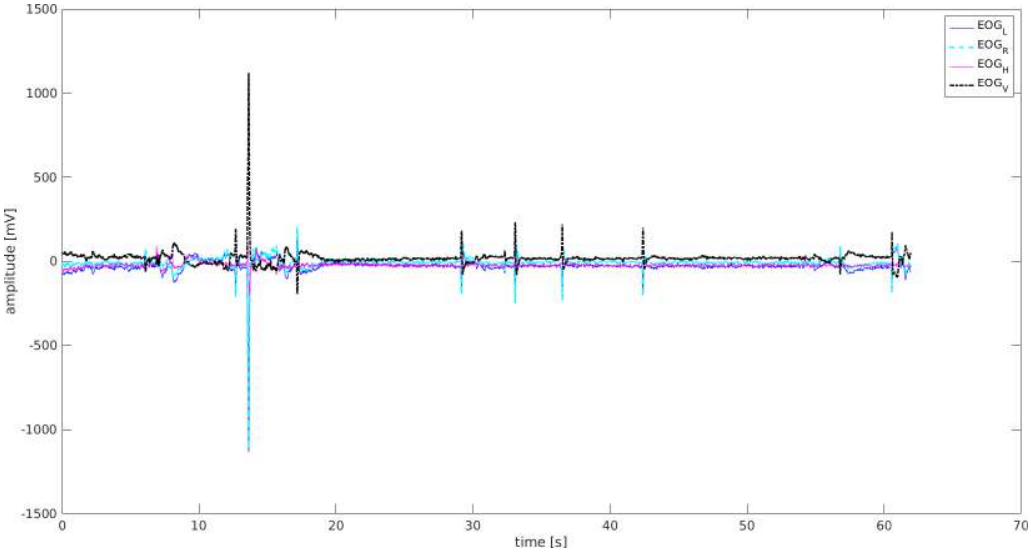


Figure 6 **EOG signal-Mid-senior student MAG.** EOGL, left eye movement; EOGR, right eye movement; EOGV, vertical eye movement; EOGH, horizontal eye movement.
Full-size DOI: 10.7717/peerj.8981/fig-6

1. −1509 to −726: low level of arousal;
2. −726 to 57.7: normal level of arousal;
3. 57.7 to 841: high level of arousal;

Students were classified as having a particular range of arousal based on their medium values. The greatest number of students were characterized by normal arousal levels in

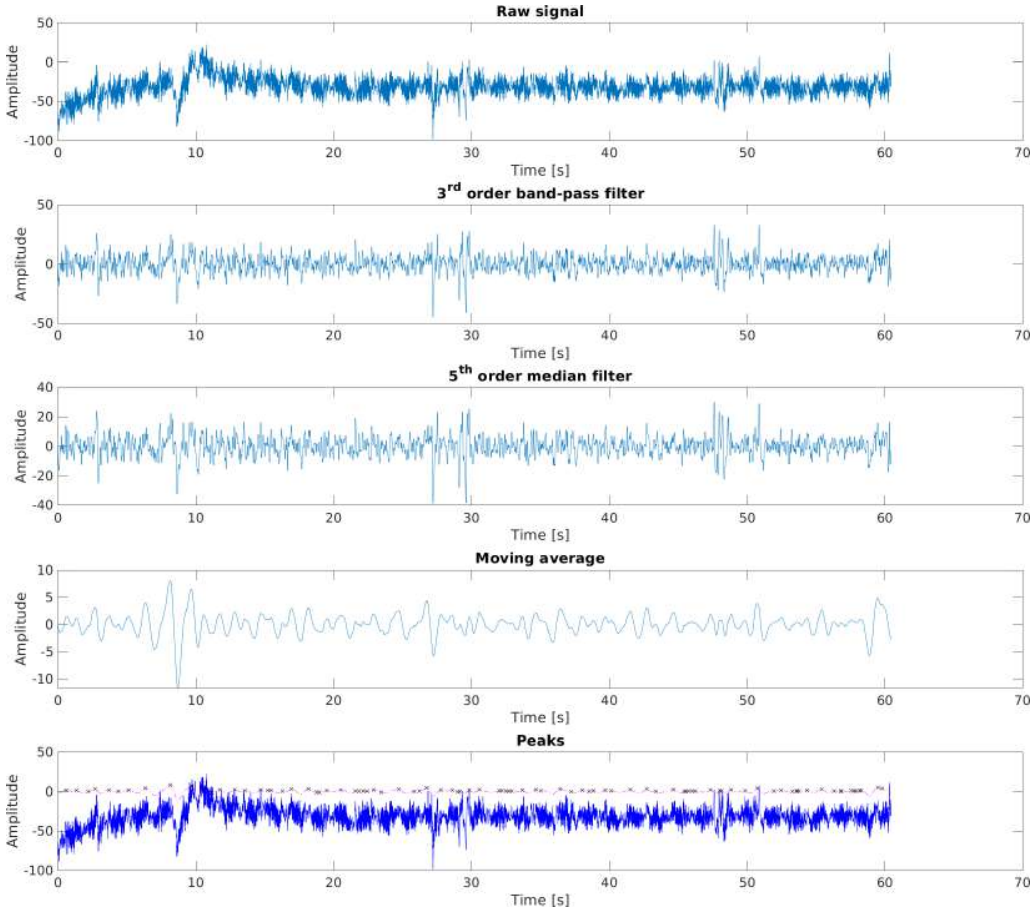


Figure 7 **The steps of processing EOG_H signal.** EOG_H Raw signal. EOG_H 3rd order band-pass filter. EOG_H 5th order median filter. EOG_H Moving average. EOG_H Peaks.
Full-size DOI: 10.7717/peerj.8981/fig-7

Table 4 **Number of peaks in EOGH_signal.**

Participant	1	2	3	4	5	6	7	8	9	10	Mean	SD
Junior UAG	75	40	112	62	71	72	58	76	76	66	71	17
Junior MAG	87	92	80	71	95	69	58	102	100	59	81	16
Mid senior UAG	89	77	69	85	103	69	86	71	75	59	78	12
Mid senior MAG	63	62	70	106	89	60	79	61	87	62	74	15
Senior UAG	73	14	81	47	68	62	105	3	3	91	55	35
Senior MAG	8	16	40	74	69	78	67	105	53	5	52	32

both the UAG and MAG. High level of arousal was observed in three participants: two seniors from the UAG and one senior from the MAG (Table 7).

Simultaneous movements of both eyes in the same direction are called saccades. Typical characteristics of saccadic movements are 400° s for the maximum velocity, 20° for the

Table 5 Mean and Standard deviations of ACC and GYRO signals.

Parameter		Mean (SD) Acceleration			Mean (SD) Head rotation		
		ACCX	ACCY	ACCZ	GYROX	GYROY	GYROZ
MAG	Junior	−561.8 (221.29)	1,227.6 (213.85)	−1,517 (175.97)	−5.88 (101.2)	3.50 (91.83)	−11.54 (232.85)
	Mid-senior	−496.4 (369.56)	1,119.8 (218.99)	−1,583 (199.87)	−4.18 (39.90)	0.70 (39.66)	−12.53 (65.30)
	Senior	−457.09 (444.64)	1,079.42 (613.60)	−1,478.72 (374.89)	−2.37 (153.49)	−2.30 (166.40)	−4.91 (332.81)
UAG	Junior	−620 (303.67)	1,325.4 (304.95)	−1,361 (293.07)	−4.20 (106.12)	−0.19 (111.11)	−1.71 (247.03)
	Mid-senior	−492.8 (358.27)	1,204.7 (278.72)	−1,506 (253.17)	−2.24 (97.78)	5.95 (88.48)	−20.24 (221.69)
	Senior	−573.00 (366.77)	1,307.44 (358.25)	−1,364.05 (291.74)	−1.14 (126.79)	3.57 (162.21)	−7.81 (324.82)

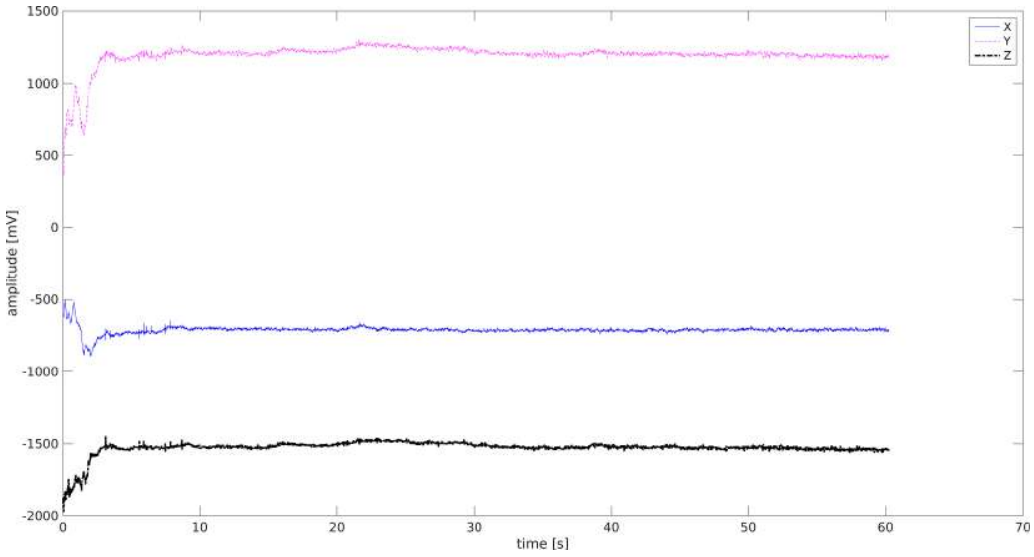


Figure 8 **ACC signal -Junior Student MAG.** X (blue) Y (pink) Z (black)-three spatial dimensions.
Full-size DOI: 10.7717/peerj.8981/fig-8

amplitude, and 80 ms for the duration. Fixations are static states of the eyes during which the gaze is held at a specific location (*Cognolato et al., 2017*). Humans typically alternate saccadic eye movements and fixations while perceiving their environment and the ACC signal and the EOG signal are needed to evaluate these motions.

The pilot scale of arousal was created to determine levels of stress, however, its usefulness should be confirmed in further research. There is an arbitrarily measurable difference in ACC and EOG when using JINS glasses and, inversely, eye movements can be tracked by analyzing the changes in the EOG signal. The electrode pairs capture the horizontal and the vertical components of eye motion.

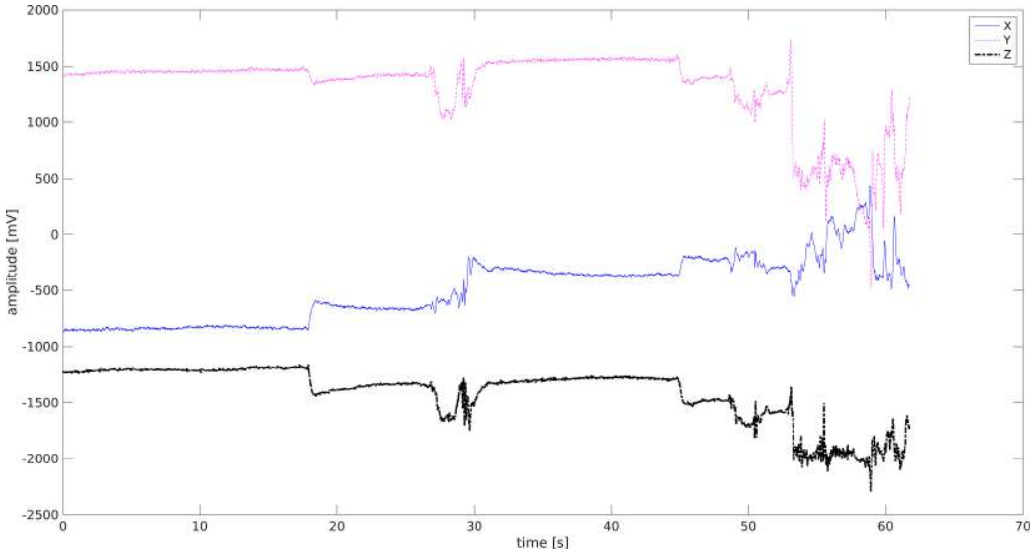


Figure 9 **ACC signal-Junior Student UAG.** X (blue) Y (pink) Z (black)-three spatial dimensions.
Full-size DOI: 10.7717/peerj.8981/fig-9

Table 6 **Mean values and standard deviations (SD) of ACC_X signal of each study participant.**

Participant ID	1	2	3	4	5	6	7	8	9	10
Junior UAG	−229.2 (64.2)	−420.7 (48.5)	−457.6 (12.3)	−509.2 (87.9)	−496.3 (283.1)	−464.7 (185.4)	−843.3 (59.2)	−641.5 (112.9)	−757.5 (23.5)	−795.0 (126.7)
Junior MAG	−204.7 (285.3)	−667.9 (64.7)	−813.6 (116.8)	−737.3 (101.6)	−711.5 (26.6)	−600.2 (62.0)	−1051.0 (159.8)	−183.7 (225.8)	−474.5 (115.9)	−831.6 (59.9)
Mid Senior UAG	−383.2 (74.7)	−1271.6 (140.5)	−332.4 (102.2)	−575.1 (81.3)	−414.2 (108.5)	−874.5 (120.8)	−167.7 (43.1)	−674.3 (169.9)	−78.2 (51.9)	−160.8 (24.0)
Mid Senior MAG	−287.6 (65.8)	−1272.5 (195.3)	−483.0 (121.3)	−694.4 (179.0)	−446.5 (56.5)	−762.2 (311.3)	−190.1 (47.9)	−382.3 (152.6)	−303.5 (54.4)	−134.9 (204.2)
Senior UAG	−474.9 (95.0)	−979.8 (807.8)	−179.1 (34.6)	−445.9 (249.6)	−697.9 (368.0)	−499.9 (79.2)	166.8 (5.5)	435.2 (1,905.9)	−623.5 (201.5)	−1,021.4 (134.6)
Senior MAG	167.8 (5.1)	−802.6 (454.6)	−324.3 (182.9)	−459.4 (152.3)	−963.7 (93.8)	−163.7 (95.1)	−1,049.5 (179.5)	−543.6 (212.9)	−461.6 (241.1)	−458.1 (258.4)

Table 7 **Pilot scale of arousal-distribution of participants.**

	Junior (III)		Mid-senior (IV)		Senior (V)		Total	
	UAG (n)	MAG (n)	UAG (n)	MAG (n)	UAG (n)	MAG (n)	UAG (n)	MAG (n)
Low arousal	3	3	3	2	2	3	8	8
Normal arousal	7	7	7	8	6	6	20	21
High arousal	0	0	0	0	2	1	2	1

EOG requires good electrode placement on the horizontal and vertical axes of eye motion to prevent crosstalk between both components. Typically, the signal amplitudes resulting from horizontal eye movements are larger than those from vertical movements. Therefore, crosstalk affects the vertical component more severely. Signal crosstalk poses problems for the robust detection of eye movement events and eye gaze tracking for which both components need to be analyzed simultaneously. In the human eye, only a small central region of the retina, known as the fovea, is sensitive enough for most visual tasks. There are differences between the measurements of HR and gyration in a student who has knowledge of stress and stress-management techniques and a student who does not (*Bulling, Roggen & Tröster, 2008*).

The statistical tests and histograms obtained from data from the JINS glasses and pulse rates enabled us to systematize and determine a scale for the differences caused by stress.

Summary of the results

We found that stress management training helped one subject from the senior group to progress from a high level of arousal to a low level of arousal and one subject from the mid-senior group moved from the low arousal level to the normal arousal level after training. According to the literature, arousal may be helpful in a high-pressure situation. Body signals resulting from stress, including butterflies in the stomach, increased heart rate, and muscle tension, are associated with an adaptive stress reaction and improved task performance (*Jamieson et al., 2016*). We found no direct relationship between eye movement and the definition of stress. However, we were able to demonstrate with JINS glasses that the training had an effect on eye movement. We also found that mid-senior and senior MAG students had a lower number of peaks, which may indicate the effectiveness of anti-stress training.

DISCUSSION

According to the literature, dental students experience considerable stress and depressive symptoms during their theoretical and hands-on training (*Al Faris et al., 2016*; *Farokh-Gisour & Hatamvand, 2018*; *Chandrasekaran, Cugati & Kumaresan, 2014*; *Elani et al., 2014*). Dental schools are known for their highly demanding and stressful learning environments and high levels of depression among their students which is more pronounced in women (*Al Faris et al., 2016*).

The most common data collection method to evaluate stress levels are questionnaires, such as the Dental Environment Stress (DES) questionnaire (*Manolova et al., 2019*; *Babar et al., 2015*) or the Depression, Anxiety and Stress Scale (DASS-21) (*Basudan, Bnanzan & Alhassan, 2017*). We sought to determine the usefulness of JINS glasses for the assessment of stress levels among dental students when they perform dental procedures. The experiment was performed using phantom teeth to avoid patient contact and remove the stress variable of the subjects' awareness of working on live patients. The student's stress was related to the time restriction and the need to precisely perform the dental procedure. The usefulness of the tools (the smart glasses and the smartwatch) was assessed to measure objective symptoms and to control the vital parameters that confirmed anxiety and stress.

The JINS glasses have been used for the objective evaluation of physical parameters directly related to the intensification of stress (*Ogawa, Takahashi & Kawashima, 2016*). We used JINS glasses for the first time with dental school students during their performance of a task to evaluate and obtain data for analysis and further classification.

There are few reports in the literature on tools used for measuring and analyzing the objective responses of the body to increasing levels of stress and only one pilot study on the subject concerning the area of dentistry. *Hunasgi et al. (2018)* used the sensor and software located in smartphones to record and analyze the heart rate, oxygen saturation, and stress in dental students before and after their university practical exam.

Our own pilot study was conducted using a phantom clinical simulation. The least experienced students felt the highest level of stress while fifth year students who had worked with living patients managed their stress better. These results are consistent with the literature (*Piazza-Waggoner et al., 2003*; *Ali et al., 2018*; *Davidovich et al., 2015*), which indicates that clinical work with a living patient is more stressful than the first contact with mechanical dental equipment and the precise preparation of the cavity in a phantom tooth, despite having additional training or experience.

Our results are similar to those of other studies that also had a limited number of participants and data, and reveal that electronic tools with software and sensors can be used to detect stress levels at any point of time. The JINS glasses were calibrated in preclinical operating conditions, and the graphs were analyzed to preliminarily determine the readings that corresponded with a particular stage of concentration or stress. We intend to continue this study by assessing the stress levels of large groups of students performing dental procedures, including students practicing on phantom teeth and later on patients. We will compare the results to the patterns obtained in this preliminary experiment.

CONCLUSION

Our pilot study shows that electronic tools, such as the JINS glasses with software and sensors, can measure different levels of stress experienced by dental students in preclinical operating conditions. We currently lack a clear definition of the states of stress. However, research using modern wearable devices can record baselines and establish patterns of stresses to allow for accurate assessments and management of stress in the future.

Future research should seek to determine whether the prevalence of severe depressive symptoms among students in different disciplines is due to the innate nature of the discipline, the type of curriculum being studied, or the forms of knowledge and manual skills required.

ACKNOWLEDGEMENTS

The authors wish to thank all of the students who participated in this study.

ADDITIONAL INFORMATION AND DECLARATIONS

Funding

The authors received no funding for this work.

Competing Interests

Marek Pachoński is an employee of Pachonscy Dental Clinic.

Author Contributions

- Katarzyna Mocny-Pachońska conceived and designed the experiments, performed the experiments, analyzed the data, authored or reviewed drafts of the paper, and approved the final draft.
- Rafał Doniec conceived and designed the experiments, analyzed the data, authored or reviewed drafts of the paper, and approved the final draft.
- Agata Trzcionka performed the experiments, authored or reviewed drafts of the paper, and approved the final draft.
- Marek Pachoński conceived and designed the experiments, prepared figures and/or tables, and approved the final draft.
- Natalia Piaseczna, Szymon Sieciński, Oleksandra Osadcha and Patrycja Łanowy analyzed the data, prepared figures and/or tables, and approved the final draft.
- Marta Tanasiewicz conceived and designed the experiments, performed the experiments, authored or reviewed drafts of the paper, and approved the final draft.

Human Ethics

The following information was supplied relating to ethical approvals (i.e., approving body and any reference numbers):

Consent for carrying out the experiments was issued by the Ethical Commission of Medical University of Silesia against resolution number KNW/0022/KB1/79/18 taken on October 16, 2018.

Data Availability

The following information was supplied regarding data availability:

The raw data are available in the Supplementary Files.

Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.8981#supplemental-information.

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The application for reading comprehension and reading speed test

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Abstract. Vision is considered one of the most important human senses. People acquire a large amount of data by reading, so the faster someone reads, the more information he/she should learn. However, this is not always the case. Electrooculography (EOG) plays a significant role in research on reading. We recorded the EOG signals with the JINS MEME ES_R smart glasses from eight subjects who read a text and then completed a reading comprehension test implemented as a multiple-choice test. Reading speed was calculated as the time of reading the text with a constant number of words. The visualization of reading was based on detecting the saccades in the horizontal component of the EOG signal. The algorithm consists of signal preprocessing and FCM (fuzzy c-means) thresholding. Three types of saccades and their duration were detected and associated with blinking, eye movement to the left, and eye movement to the right. The developed application shows the reading process with the use of an animation of eye-walking on the text. The application tests carried out show that it works properly.

Keywords: electrooculography, wearable devices, reading speed, reading comprehension

1 Introduction

Vision is the most important human sense [7] and helps obtain information about the surroundings [23]. The people acquire most data by reading [13]. Therefore, we can state that the faster a person reads, the more information can learn. However, this is not always the case, because the reading comprehension is a complex process, which involves the language phonology and grammar rules [22].

Human eyes move constantly because only the fovea provides a small area of high resolution vision needed in seeing various objects. The most important eye movements for reading are saccades and fixations [22, 4]. Saccade is a fast

movement of the eyes, reaching 500°/s [1], and even 1000°/s, which last 20 ms to 200 ms [5]. The duration of the saccade depends on the angular distance which is linear up to 30° [6]. During the saccadic movement the eye is unable to register the image, therefore they harmonize with the leading movements [16]. Saccades can be forced or spontaneous and may be followed by corrective saccades which are the movements which occur when the eye misses the desired target [3]. The eye movements in reading can be characterized as a sequence of repeated small saccades responsible for the eye movements between the words, separated by large, regressive saccades which occur while going to the next line [4].

Many methods have been designed to measure eye movement, such as oculography. One of them is electrooculography (EOG) which measures the electric potential between the cornea and the retina of the human eye. This potential generates an electric field that changes its orientation as the eye moves [12]. The most important eye movements for reading are saccades and fixations [22]. The EOG plays a significant role in research of reading. Eye movements and eyesight analysis can be used to detect reading [15], measure its parameters, and also help in learning to read to people with impaired vision [24]. Along with the development of technology, many new solutions have emerged in eye tracking, such as smart glasses, which may be used to to test the concentration, sleepiness or reading activities in a non-invasive way [8].

The average reading speed of an adult is 180-250 words/minute [2]. However, there are techniques that can increase the reading speed. Some people are able to read up to 1000 words but it comes at the cost of understanding the text (omitting some words). These techniques include [22]:

- elimination of phonetization, i.e. pronouncing the words read in your mind and its special form — articulation (movements of lips),
- skimming — quickly movements of eyes across the text in search of specific words and key information,
- expanding the peripheral vision of the eyes to reach more words in the eyesight (from a few words to a few lines). However, its limitation is the visual acuity of the fovea,
- shortening the fixation time.

Measurement of reading speed is a simple task performed by counting the number of words of a given text and measuring the time of reading. On the other hand, measurement the effectiveness of reading (reading comprehension), is usually performed as a multiple-choice test that refers to the previously read text [22].

To the best of our knowledge only Kunze et al. performed the study on reading which involved the use of JINS MEME smart glasses [14]. The purpose of our study to provide a method for recording the reading speed and reading comprehension with smart glasses.

2 Material and Methods

2.1 Experiment setup

EOG signals were recorded using the JINS MEME ES_R smart glasses a 3-axis accelerometer, 3-axis gyroscope and three dry EOG electrodes made of stainless steel [13, 10]. The smart glasses are equipped with a Bluetooth module to provide wireless communication with a computer or a mobile device. To establish the connection between the computer and the start glasses via Bluetooth, we connected a USB dongle with a Bluetooth module and used the ES_R Development Kit application available at [11]. The sampling frequency of the EOG signal was 100 Hz [10].

2.2 Signal processing

There are many methods for detecting saccades [19]; In our approach the detection of saccades consists of signal preprocessing, classification and encoding presented as the flowchart in figure 1. The preprocessing phase consists of resampling, baseline drift removal and noise attenuation. The classification phase consists of fuzzy c-means clustering and determining the detection threshold.

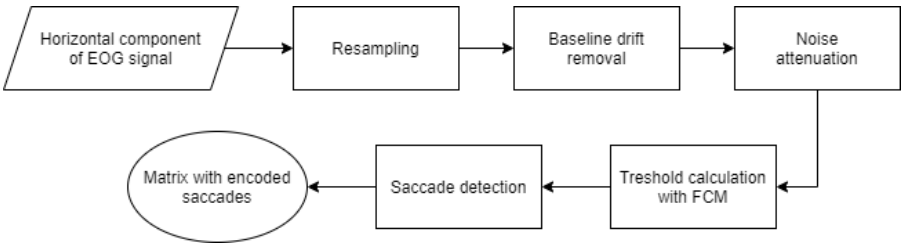


Fig. 1. Saccades detection algorithm flowchart

Due to the uneven signal sampling related to Bluetooth transmission, the signal was resampled by creating a new time vector with a constant sampling rate of 100 Hz. The signal was interpolated using the `interp1` function in MATLAB (Natick, MA, USA). The next step was removing the baseline drift which was estimated by modeling as a polynomial [21].

In our case the baseline drift in horizontal and vertical EOG signals was modeled by a 20th degree polynomial by using the `polyfit` MATLAB function. The values of the estimated baseline drift were calculated using the `polyval` function. Then, the estimated baseline was subtracted from the signal. The 20th degree of polynomial was determined experimentally to ensure the optimal fit to the baseline of the EOG signal.

The noise in the EOG signal may be caused by incorrect electrode placement, muscle activity or power line interference. Aforementioned artifacts affect significantly the quality of the signal, which hampers the recognition of eye movements,

especially saccades. To attenuate the noise we applied discrete wavelet transform (DWT).

Discrete wavelet transform decomposes the signal into an approximation component and details component. The approximation component is implemented as the low-pass filter and downsampling by two. The details component is obtained by performing high-pass filtering and decimation [9]. The wavelet function is defined as:

$$\psi_{ab}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

where ψ is the mother wavelet, a is the scaling parameter, b is translation parameter.

To attenuate the noise we used the `symlet5` wavelet, the scaling based on the noise level estimate based on the first-level coefficients, the fourth level of decomposition and fixed-form threshold for wavelet denoising defined as:

$$th = \sqrt{2}\ln N \tag{2}$$

where N is the number of signal samples.

The classification phase consists of fuzzy c-means (FCM) clustering and determining the detection threshold. Due to the inter-subject variation, we detect the saccades by using the thresholds determined fuzzy c-mean clustering. Our implementation is based on the approach of Pander et al. [20].

The FCM clustering is based on dividing the data set of N elements into c groups of similar objects. The fuzzy membership assumes that an element may belong to more than one group. The membership value u determines the membership of an element to a given set and is between 0 and 1. The group prototype v_i is defined as:

$$\forall_{1\leq i\leq c} \quad v_i = \frac{\sum_{k=1}^{N}(u_{ij})^m x_j}{\sum_{k=1}^{N}(u_{ij})^m} \tag{3}$$

where x_j is the feature vector representing j-th element, m denotes the fuzziness of groups, $u_{ij} \in [0,1]$ is an i-th element of $\mathbf{u}$ matrix (the membership of i-th element to the j-th group) and $w_i = (\forall_i = 1,2,3,\ldots,c)$ are the weights of elements in a group.

Because we can distinguish three types of saccades, we set the number of groups to three, the number of iterations was limited to 20 and the minimum value of membership function value $u > 0.75$. The membership function matrix is defined as:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{||x_j - v_i||}{||x_j - v_k||}\right)^{\frac{2}{m-1}}} \tag{4}$$

where $m > 1$. The FCM algorithm aims to minimize the function:

$$J_m = \sum_{j=1}^{N}\sum_{i=1}^{C} u_{ij}^m ||x_j - v_i||^2, \ 1 \leq m \leq \infty \tag{5}$$

The saccades were detected as the local maxima and minima were detected with `findpeaks` MATLAB function. The saccades below the first threshold were classified as the first type and the saccades above were the saccades of the second type. Local minima were detected for the following parameters: `MinPeakProminence` (minimal amplitude of the peak [17]) set as $p = 0.7|th|$, where th is the threshold value in μV, and `MinPeakDistance` (minimal distance between peaks [17]) was 90 samples.

To detect local maxima, the `MinPeakProminence` value was set to 1.5μV in order to exclude very small peaks related to the possible residual noise. The results are shown in figure 2.

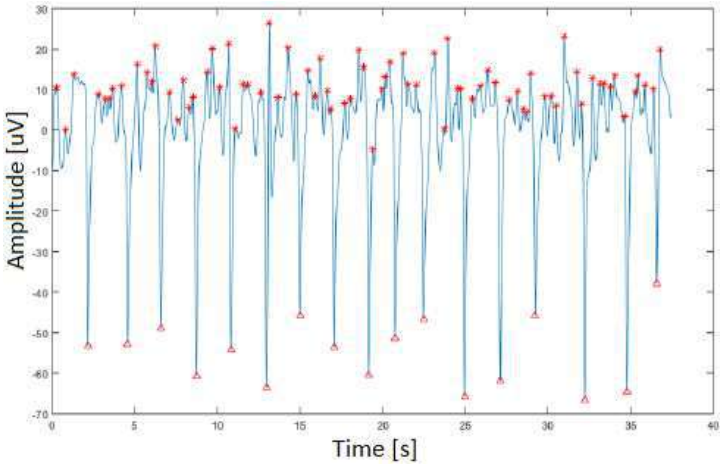


Fig. 2. Detected saccades. An asterisk (*) denotes the eye movement to the right, a triangle dentoes the eye movement to the left

Detected saccades were encoded as follows: zero (0) was assigned to eye movements to the left and one (1) to eye movements to the right.

Reading speed measurement In our study we measured the reading speed by measuring the time needed for reading a predefined text with a known number of words. The text, unknown to the readers, contains information about the biography of Nikola Tesla and consists of 228 words. The time of reading the text was measured as the time between the start of recording and the end of recording. Equation (6) defines the reading speed in words per minute (words/min) as:

$$\text{reading speed [words/min]} = \frac{\text{number of words} \times 60}{\text{reading time [s]}} \tag{6}$$

2.3 Software

We used MATLAB to design signal processing algorithms. The graphical user interface was implemented in .NET Windows Presentation Foundation (WPF) because of the capability to create the animation of reading a text.

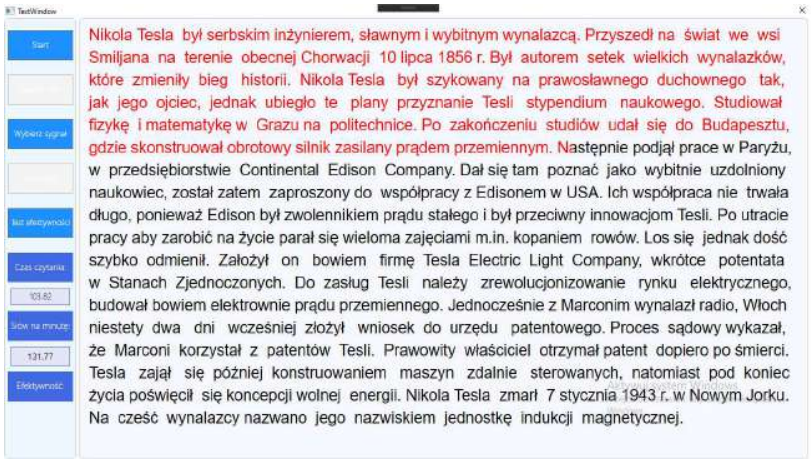


Fig. 3. Graphical User Interface of implemented application; Reading text animation process

Graphical User Interface is presented on the figure 3. The reading speed test starts after clicking "Start" button which launches JINS MEME Academic Logger, the software used to acquire EOG signal. The next step was to choose the COM port of the smart glasses and the device identification number. Then, the text with a constant number of words (228) was loaded into the TextBlock control (WPF widget for text with formatting and effects [18]). The measurement of the reading speed is based on measuring the time (see the equation (6)) after clicking "Choose a signal" button.

Reading comprehension test The reading comprehension test was implemented as a simple multiple-choice test with single-select questions. The test consisted of ten questions about the text used to measure reading speed. After completing the test, the subject is ask to type the name and then, the result is shown as the percentage of correct answers along with the correct answers.

3 Results

3.1 Performance measures of the algorithm

The outcome of saccade detection is considered positive if a saccade is present in the signal or negative if no saccade is detected. Consequently, the method of detecting saccades can be characterized by:

- true positive detections (TP) - number of correctly detected saccades,
- false positive detections (FP) - number of falsely detected saccades (if the detector finds a saccade in a place where there is no real saccade),
- false negative detections (FN) - number of undetected saccades,
- true negative detections (TN) - number of signal changes that the detector correctly classified as a non-saccade.

The performance of measurements were expressed as accuracy (Acc), sensitivity (Se), specificity (Sp), and positive predictive value (PPV) defined as in equations 7, 8, 9, and 10:

$$Se = \frac{TP}{TP + FN} \tag{7}$$

$$Sp = \frac{TN}{FP + TN} \tag{8}$$

$$PPV = \frac{TP}{TP + FP} \tag{9}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

The performance measures of saccade detection are presented in table 1.

Table 1. Performance measures of saccade detection

Subject	TP	FP	TN	FN	Se [%]	Sp [%]	PPV [%]	Acc [%]
1	179	9	68	7	96.24	88.31	95.21	93.92
2	190	7	101	9	95.48	93.52	96.45	94.79
3	63	1	33	5	92.65	97.06	98.44	94.12
4	94	1	60	14	87.04	98.36	98.95	91.12
5	132	2	84	17	88.59	97.67	98.51	91.91
6	136	1	125	40	77.27	99.20	99.27	86.42
7	72	1	51	12	85.71	98.08	98.63	90.44
8	150	1	143	21	87.72	99.30	99.34	93.01
TOTAL	1016	23	665	125	**89.04**	**96.66**	**97.79**	**91.91**

In the table 1 we consider the case of two classes – saccade detection and no saccade occurence (binary classification). The classifier achieved high sensitivity

(over 85%), specificity (over 85%), accuracy (over 86%) and PPV (over 95%) in all subjects. The highest sensitivity was achieved for the subject 1 (96.24%) and the lowest sensitivity was observed for the subject 6. The lowest specificity, PPV and accuracy were observed for the subject 1, subject 1, and subject 6, whereas the highest specificity, PPV and accuracy were observed for the subject 1, subject 8, and subject 2. This set of parameters confirms that the applied classifier is reliable.

3.2 Application performance

In order to test the application, eight people were asked to read the text as quickly as possible and take the reading comprehension test. The results of the reading comprehension tests and measurements of reading speed are shown in table 2.

Table 2. Reading speed in words per minute (words/min) and the results of the reading comprehension test

Subject number	Reading speed [words/min]	Reading comprehension test [%]
1	155.07	80
2	165.20	80
3	169.14	50
4	189.13	40
5	181.12	60
6	365.58	50
7	201.48	60
8	223.76	70
Mean	206.31	61.25
SD	63.56	13.64

The mean reading speed was 206.31 words/min but the most reported measurements were between 150-175 words/min.

4 Conclusion and Discussion

In our study we developed an application for measuring reading speed and testing reading comprehension by using smart glasses, which can visualize the process on reading by tracking the eyes with the EOG. The developed detection algorithm used preprocessing and fuzzy clusterization (namely fuzzy c-means).

The application tests confirmed its reliability. Unfortunately, visualization of reading process was not fully implemented due to the problems caused by the third party application used to record the EOG signals. The reason is probably

the need of pairing with smart glasses. An additional burden is the large selection of measurement options, which strongly affects the user interface. Another limitation was also the inability to test the subjects who wear the glasses.

The proposed detection method is highly efficient and precisely determines the temporal position of saccadic eye movements, even with a low signal-to-noise ratio. The presented method may have potential application in EOG signal processing systems for the determination of visual acuity.

The visualization of reading was determined by the quality of the recorded EOG signal, affected by blinking and the contact of skin and electrodes. The animation of reading the text was reliable in 7 out of 9 cases (77% of cases). Due to the small number of participants the study should be considered a pilot study. However, the developed application works properly as long as the EOG signal has no artifacts.

Eye movement analysis is valuable in both clinical and scientific work. An application with animation for tracking text and then assessing the level of understanding can be useful for research on the level of awareness in learning new content. The applied classifier with the accuracy of circa 92% allows the application to be used in more difficult clinical cases related to rehabilitation after vision loss or visual impairment.

In future studies we will consider adding more texts to be used during the tests of reading speed and comprehension and implementing signal acquisition without using third-party applications provided by the manufacturers of smart glasses. Another issue to be addressed is to include smaller saccades in visualization of reading and consider also other methods for detecting saccades.

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Automatic Assessment of Benton Visual Retention Test Results: A Pilot Study

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Abstract. Visual memory plays an important role in learning to read, write, spell, or draw. The dysfunction of visual memory can be detected by applying tests, such as Benton Visual Retention Test (Benton Test, BVRT), which is based on displaying ten patterns for ten seconds per each pattern and asking the subject to reproduce the displayed patterns. The purpose of our study was to automate the Benton Test by developing a desktop application. We automated the assessment of hand-drawn geometrical shapes (triangles, circles, rectangles) by applying machine learning and image processing techniques, namely, the ResNet50 network trained for recognition of triangles, circles, rectangles and other shapes, filling in the shape, and determining the type of triangle. The proposed algorithm proved its reliability on subjects with limited ability to draw shapes and was the part of a desktop application which may find its use in screening visual perception and visual memory.

Keywords: Benton Visual Retention Test · Image recognition · Automatic assessment

1 Introduction

The brain is a part of the central nervous system which controls the work of the human body. It controls basic life functions such as breathing or eating, body movements, communication, expressing emotions, and also observation and analysis of the environment, memorization and learning [8]. Visual memory plays an important role in remembering what we see [10].

The appropriate level of visual perception enables a person to learn to read, write, and spell [14]. We do not pay much attention to the visual memory until its

Electronic supplementary material The online version of this chapter (https://doi.org/10.1007/978-3-030-83704-4_1) contains supplementary material, which is available to authorized users.

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D. G. Pijanowska et al. (eds.), *Biocybernetics and Biomedical Engineering – Current Trends and Challenges*, Lecture Notes in Networks and Systems 293,
https://doi.org/10.1007/978-3-030-83704-4_1

dysfunctions affect everyday activities [3,6]. There are many diagnostic methods for the assessment of visual memory impairment [1] but in our study, we used Benton Visual Retention Test.

Benton Visual Retention Test (Benton Test, BVRT) is a visual perception and visual memory test published in 1946 by Arthur Lester Benton [9] administered to children, adolescents, and adults [2,10,11]. During the test, the examined individual is shown ten patterns, one at a time, and then asked to reproduce each pattern exactly from memory. The time of the test is unlimited and the results are scored by form, shape, pattern, and arrangement. The invention of BVRT was based on the experiences of psychologist Arthur Lester Benton and neurologist Morris Bender in the treatment of servicemen suffering from traumatic brain injuries [5,9,13].

The aim of the study is to automate the evaluation of the results of the Benton Visual Retention Test by developing a desktop application.

2 Materials and Methods

2.1 Experiment Setup

The study group consisted of 9 residents at the nursing home in Borowa Wieś, a neighborhood of Mikołów (Poland), who can read, write, and draw. Based on the level of disability, they were assigned to three categories: people with diagnosed mild (A), moderate (B), and severe disability (C), as shown in table 1. The degree of disability of each subject was determined by primary care facilities upon admission to the nursing home.

Table 1 The groups of subjects

Group	Subjects
Mild disability (A)	2, 4, 8
Moderate disability (B)	1, 5, 7
Severe disability (C)	3, 6, 9

Each subject was asked to participate in Benton Test which consisted of the following steps:

1. Displaying ten patterns of basic geometrical shapes (triangles, rectangles, circles) or a blank space which appeared in corners;
2. Remembering the pattern in 10 s, regardless of the degree of intellectual disability;
3. Reproducing the pattern without time limit;
4. Repeating steps 1–3 ten times;
5. Evaluating the reproduced pattern.

The geometrical shapes in our implementation of Benton test included circles, triangles, rectangles, and blank shapes (no shape) presented in the four corners

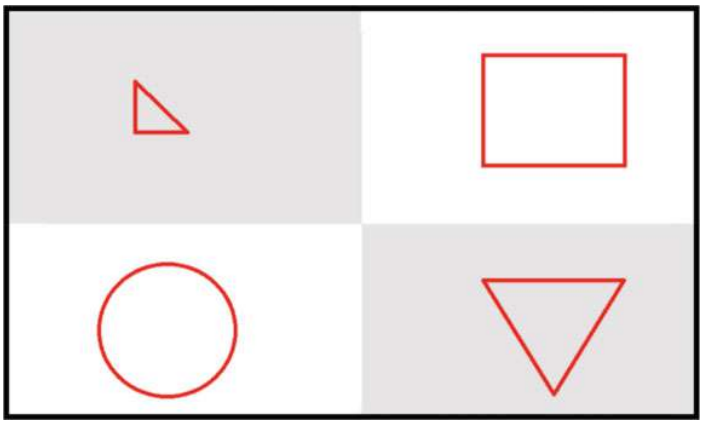


Fig. 1 An example of pattern to be reproduced by a subject

of the pattern. An example of a pattern to be reproduced during the BVRT is shown in Fig. 1.

The experiment outline was approved by the Bioethics Committee of the Medical University of Silesia in Katowice (The resolution KNW/0022/KB1/18) and carried out following the rules of the Declaration of Helsinki of 1975, revised 2013.

2.2 Assessment of Results

The ability to reproduce the pattern as accurately as possible is measured by the number of errors found in the reproduced shapes. These errors are divided into six categories (omission, distortions, repetition, shifts, rotations, and wrong size) indicating disorders of visual perception [2].

In our study, we automate the assessment of geometrical shapes reproduced by a subject by preprocessing and applying deep neural network (DNN) to recognize them. Then, the errors are classified based on the following principles:

- The omission occurs when a subject did not draw a geometrical shape in a designated area.
- Wrong size means that the reproduced geometrical shape is significantly smaller or larger than in the presented pattern.
- Distortion occurs when the reproduced figure does not reflect the sample (e.g., a triangle instead of a rectangle).
- Rotation error is defined reproducing a shape in a direction which does not reflect the sample.

The next step is listing the detected errors and displaying them to the user and the set of actual and correct answers with the occurrence of a type of error (Fig. 2).

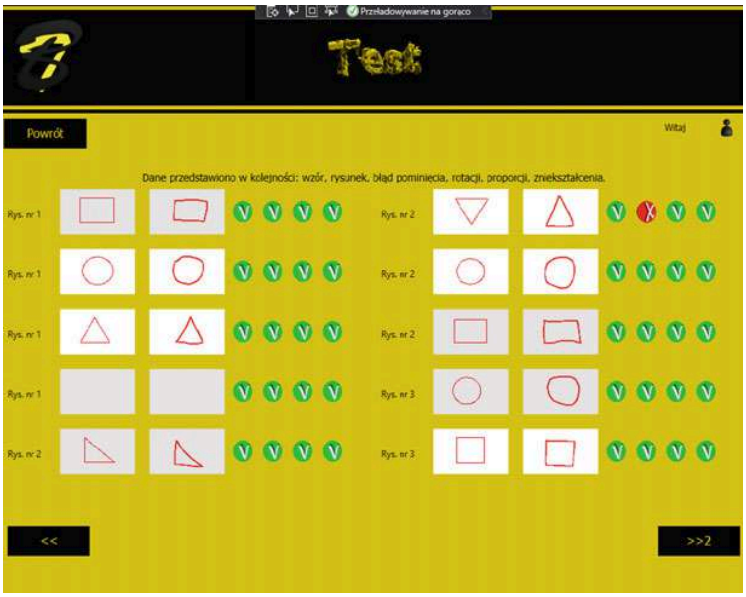


Fig. 2 The indication of errors in a graphical manner. The tick (✓) mark indicates the correct reproduction whereas the cross (✕) mark indicates the occurrence of error (omission, rotation, size, distortion)

2.3 Image Processing

Recognition of shapes consists of preprocessing and applying the DNN trained on 40 samples of triangles, rectangles, circles, and other figures painted in red. Each geometrical shape was represented by 10 samples. The preprocessing consists of changing the color of the background to white and filling in the area with red color because the lines are red, as in the training set. After this operation, the geometric shape area was calculated.

The geometrical shapes after preprocessing are fed to a classifier based on deep artificial neural network (DNN). The DNN was implemented in C# which uses TensorFlow to implement transfer learning [7] using ResNet50 network described in detail in [4]. The output of the DNN was the label describing a shape ("p" for the rectangle, "t" for a triangle, "o" for circle, and "i" for other shape). Then, the triangles were divided into six categories.

Triangle Type Coding. Because the DNN could not recognize the rotation of a triangle, we proposed a new approach to address this problem; the triangle was divided into nine parts by three horizontal and three vertical lines (see Fig. 3). If most pixels in the horizontal axis (from right to left) were in the first part, the figure was given the number 100 (1 which represents the first part with the

maximum number of pixels and zero (0) for other parts). A similar rule applies for the vertical axis (from top to bottom). The codes and triangle rotations are presented in Fig. 4.

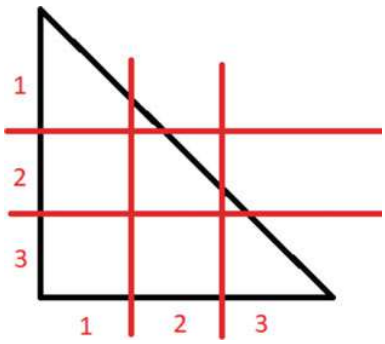


Fig. 3 The division of a triangle into nine parts

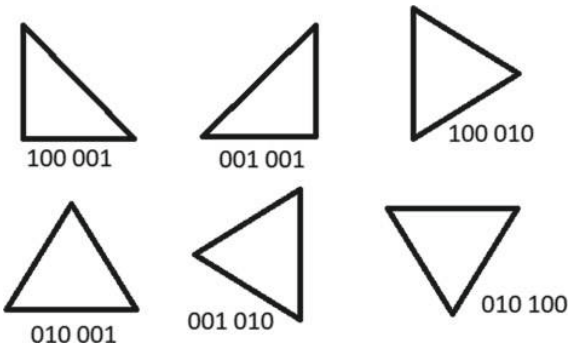


Fig. 4 Triangle rotation codes

3 Results

3.1 Shape Recognition

The results of BVRT were evaluated based on the description published in [2]. The number of correctly recognized rotations, distortions, changes of size, omissions, triangles, circles, and rectangles was 10 out of 10 evaluated geometrical shapes for each category. The number of correctly recognized incorrect rotations was 6. Figure 5 shows an example of misclassification of rotation errors.

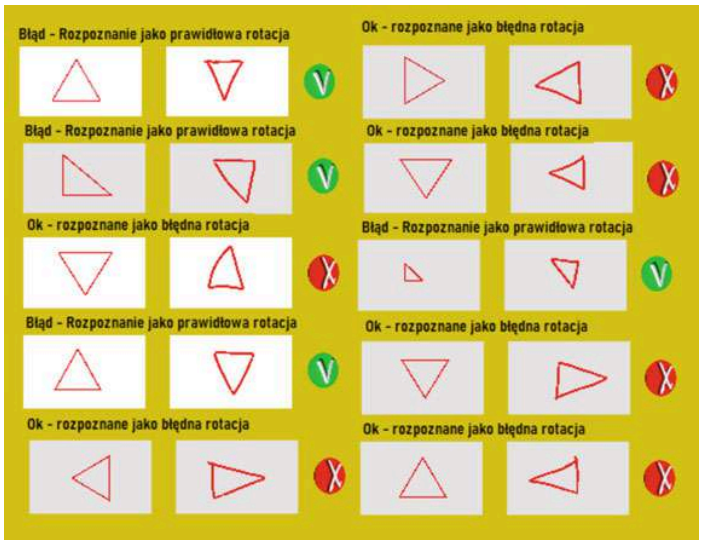


Fig. 5 Examples of correctly and incorrectly recognized geometrical shapes and the anomalies (errors in reproducing the shape)

The screenshot provided in Fig. 5 shows that the incorrect rotation in four cases was recognized as a correct reproduction of the shape (left image in the column). This type of misclassification was caused by incorrect coding of the hand-drawn triangles.

Four cases of triangle classification were incorrect because of incorrect recognition of a correct rotation.

3.2 Evaluation of the Study Group

The Table 2 shows the number of errors (divided by their category) committed in each group category. It can be observed that in the group of mildly disabled people, which was significantly different from the group of moderately and severely disabled people, there is also a difference in the type of errors made. In group A, the most common were rotation errors, and in groups B and C – distortions and omissions.

4 Discussion

The purpose of our study was to automate the evaluation of Benton Visual Retention Test by developing an algorithm and a desktop application. We proposed an algorithm based on image processing and deep neural network implemented in C# using ML.NET and Tensorflow libraries and ResNet50 neural

Table 2 Number of errors made in each group

Error category	Group A	Group B	Group C
Distortion	3	13	15
Omission	0	13	12
Rotation	8	2	5
Shifts	4	2	1
Wrong size	0	5	2

network. The proposed algorithm recognizes the geometrical shapes drawn by a subject and then classifies them as a triangle, circle, or rectangle.

The next step is verifying whether the shape drawn by the examined person is consistent with the pattern. The proposed algorithm proved its reliability on subjects with limited ability to draw shapes in a careless and sloppy manner. However, in some cases, the algorithm classified the geometric shapes incorrectly because some hand-drawn geometric shapes such as a circle, square, or triangle may look quite similar [12].

Another disadvantage of the proposed algorithm is the incorrect recognition of the triangle rotation in some cases, which works properly only for basic rotations, presented in Fig. 4. Nevertheless, the proposed algorithm can recognize the hand-drawn geometrical shapes (triangles, rectangles and circles) and errors in reproducing them which may be used to assess the dysfunctions of memory and recommend the appointment with a psychologist.

Since the intelligence index affects visual perception, and this is closely related to the degree of impairment, we expected to notice a large difference between the three study groups. Nevertheless, a significant difference in the test results was visible between the group of mildly disabled people and the other two groups. On the other hand, the outcomes in groups B and C were similar. The result obtained in this way suggests that visual perception in people with different degrees of impairment is not different and there are no significant differences between them.

The most significant limitations were the small number of subjects in the study group (only 9 people) and incorrect recognition of triangle rotations in some cases. In future work, we consider including the recognition of more geometrical shapes, their modifications (distortions, rotations, and scales), and extending the study groups by including more subjects.

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The Classifier Algorithm for Recognition of Basic Driving Scenarios

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Abstract. This paper concerns three common but not recognizable driving practices based on sequences of signals from accelerometers, gyroscopes and electrooculograms obtained using state-of-the-art smart eyeglasses. As a result we obtained recordings from twenty volunteers with a set of flagged data assigned to specific actions taken while driving a car during driving lessons.

Keywords: smart glasses, driving, pattern recognition, wearable devices

1 Introduction

Recognition of activity is not a new field; it can be stated unequivocally that categories of activity recognition have already been created [1,2,4]. Particularly well described are those primarily related to our basic needs and everyday life: breathing, eating, sleeping, walking [5–7], and so on. In this paper, we define a sequence of such basic activities as a scenario.

In addition to vital signals, each person can be characterized by his or her cognitive abilities. Cognition, a term that describes mental processes, typically reasoning, consciousness, perception, knowledge, intuition and judgment, is a vital feature of a driver [15]. Using this well-established convention, we decided to analyze activities accompanying the common task of car driving.

The challenge was to recognize the discrete scenarios that take place during a driving session. This task involved the need to acquire a sufficient amount of data using JINS MEME glasses [8,9] and analyzing the data in order to extract the scenarios.

We originally intended to take up the challenge of examining as many scenarios as possible related to driving a car, but ultimately selected four scenarios which we believed had the highest levels of activity recognition.

2 Material and Methods

2.1 Technology used

We used the JINS MEME ES_R (eye sensing for researchers) smart glasses to acquire the data. The device contains the three-point electrooculography and six-axis inertial measurement unit (IMU) with an accelerometer and a gyroscope [16]. The JINS MEME is a micromechanical patented technology [10] thanks to which we can register and detect:

- blink occurrence, its speed and strength,
- vertical and horizontal eye movement,
- head movements.

Technological advances and the availability of various mobile devices allow us the unprecedented opportunity to continuously record sensor data [14].

2.2 Experiments

The experiment was carried out in accordance with the recommendations of the Ethics Committee of Medical University of Silesia. The experiment was conducted on 20 volunteers of which ten were experienced drivers with a minimum of ten years' driving experience (age between 40 to 68 years), and ten were students who attended a driving school (age between 18 to 46 years). We gave each driver a set of defined tasks to perform while wearing the JINS MEME glasses and acquired sensor data to the computer. The sensor data were linked to the tasks by observing the driver from the rear seat. The tests were conducted under real road conditions in accordance with the Chapter 4 of the Act on Vehilcle Drivers [18]. The cognitive aspects of driving lessons were assessed by tracking head, eye and eyelid movements as the indicators of driver's performance reduction and concentration due to fatigue or stress.

Driving tests were performed on a route of 28.7 km which was followed by all the participants and the average journey took approximately 75 minutes. To ensure the comfort of drivers during the test, experienced drivers drove their own vehicles and learner drivers drove the same car under a supervision of a driving instructor. The car for learner drivers was properly marked and adapted for driving lessons (see fig. 1).

The following basic driving scenarios were isolated based on the data acquired with the JINS MEME glasses and observing the drivers in action:

1. driving through a roundabout:
   - turning left,

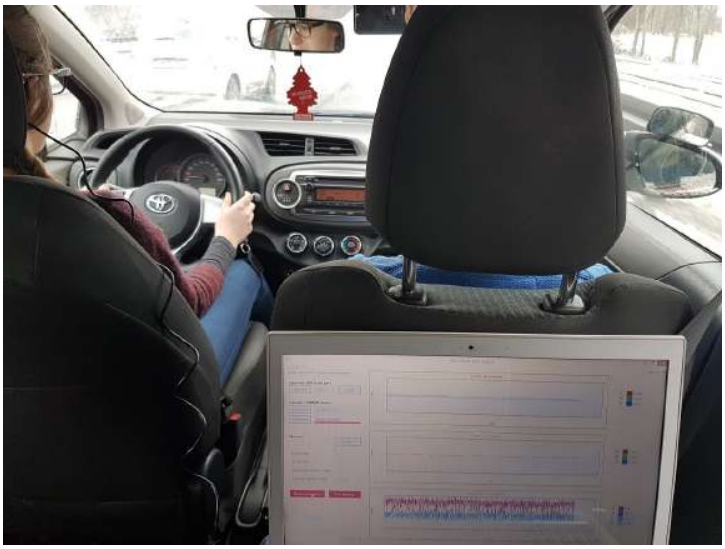


Fig. 1. Experiment setup. The driver (left) is wearing JINS MEME glasses connected to the computer (foreground) while recording the signals.

   - driving straight ahead,
   - turning right;
2. driving through a crossroads:
   - turning left,
   - driving straight ahead,
   - turning right;
3. parking:
   - parallel,
   - perpendicular,
   - slant.

In addition, compound scenarios included:

- journey through a motorway,
- drive straight ahead in city traffic,
- passage of a section straight ahead outside of urban area,
- drive straight ahead in residential traffic.

It should be added that experienced drivers generally completed the route faster than learner drivers, regardless of road conditions.

2.3 Classifier

Classification of activities and scenarios was based on the designation of Best Fit Sequence (BFS) from a sequence of features derived from data acquired using

the JINS MEME glasses. Best Fit Sequence approach is based on the codebook approach described in papers [2–4, 17]. The features are further separated by a time window for a given quantity or signal and results from a series of subsequences of windows shifted in time. From this set of subsequences, we can separate a set of the most similar sub-specificities that will establish a BFS. Because it is usually not possible to determine in advance which BFSs are specific to a particular activity, it is necessary to recognize them at the beginning of the data set classification process and to build a Best Fit Sequence Dictionary (BFSD) from the discovered Best Fit Sequences. The final step of classification is training and testing in accordance with the fact that the subsection represents a specific signal characteristic and can be considered as a reference point for the multidimensional space of the subsequence of features to be checked. The classifier draws a line between accurately marked activity classes and others (see Fig. 5). Constructing a vocabulary book (BFSD) was part of the training phase and took place on the unmarked data.

The first step in constructing a BFSD is to find the right BFSs. Each BFS equals the length of subsequence data sets from the classifier training data set, which matches the size of the time window (w) after a tested signal; a time window that is moved from the beginning to the end of the set of selected and analyzed data (see Fig. 2).

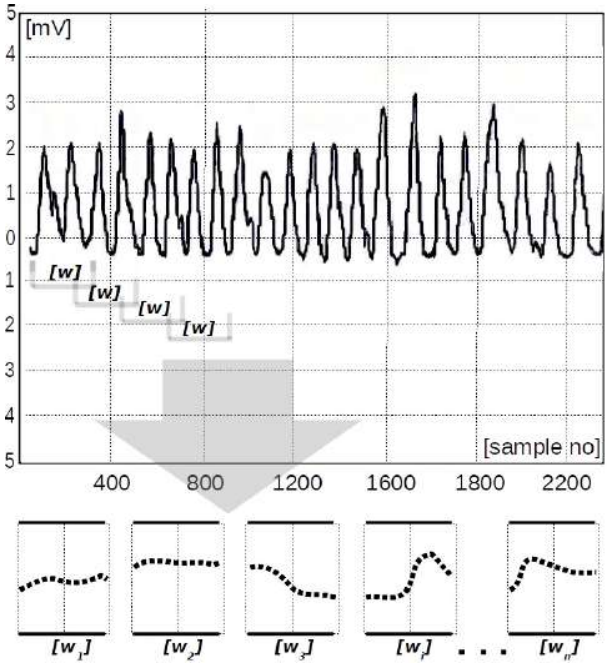


Fig. 2. BFSD construction. Source: [4].

After each driver performs a set of defined tasks wearing the JINS MEME glasses, we use the sequence of data obtained during specific time windows corresponding to the specific activity we are attempting to map to begin creating our BFSs. We made sure to use large overlaps with adjacent activities (or subsequences) as dense sampling of subsequences has been shown to lead to better results than rare sampling with little overlap of time windows [12]. It should be noted that the size of the window (w) and the sliding size (i) are the parameters of the parent and must be chosen accordingly. The second classification step grouped all extracted subsequences into N different clusters (see Fig. 3). In the presented implementation of k-means, clustering is performed on N clusters consisting of similar subsequences.

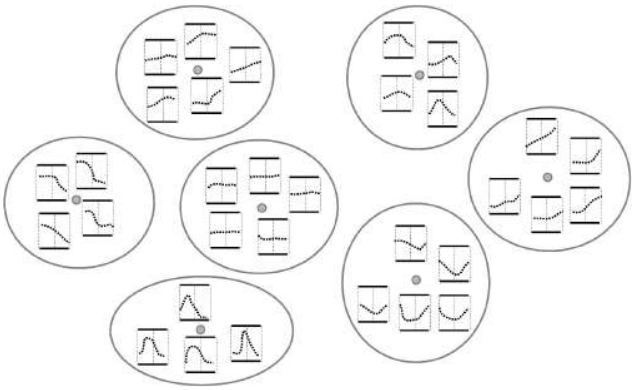


Fig. 3. Illustration of k-means clustering of sequences.

The distance between the two sub-sequences is measured as the Euclidean distance. Because k-means clustering depends on the initial cluster centers that are randomly determined, it is performed tens or even hundreds of times in order to select the best result. This result is the minimum Euclidean sum, distanced between sub-sequences and the cluster centers assigned to them. Based on the best grouping result, a BFSD consisting of N BFSs is thus obtained, with each focusing center equal to one BFS. The optimal number of BFSs (N) must be determined experimentally.

After grouping subsequences into clusters, each cluster center becomes a BFS. Each subsequence is then assigned in a given sequence to the most similar BFS. Then we extract the histogram representing the frequency of each BFS (see Fig. 4).

After assembling our BFSs into a BFSD, we used a small set of labelled data to train the activity classifier related to driving, based on sequential, multidimensional data from sensors that corresponded to measurements of three quantities (measured by the 3-axis accelerometer, 3-axis gyroscope and four-channel EOG). It should be noted that the BFSD may contain more base vectors (x, y, z – see

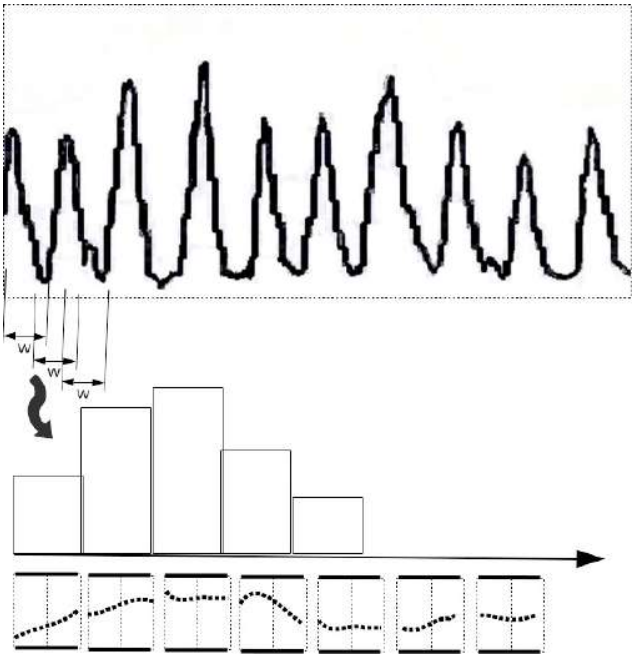


Fig. 4. Plotting a histogram from Best Fit Sub-Sequences.

Fig. 1) than the input data dimension. Excessive completeness reduces sensitivity to noise, while the use of sparse coding makes it possible to move away from the pure linear dependence between input and output to obtain a BFSD structure that captures the optimal order of data patterns [13].

3 Results

The investigation obtained for n BFSs uses the previously proposed method using the subsequence of pre-processed data. We changed not only the size of time windows ($w \in \{8, 16, 32, 64, 128\}$ bits), but also the way that the windows were chosen (in sequence or randomly).

The next step was to calculate the entropy from each window. The common formula for the entropy of random variable x into set of values $x_1, x_2, \ldots, x_n$ is:

$$H(X) = \sum_{i=1}^{n} p(x_i) \log_r \frac{1}{p(x_i)} = -\sum_{i=1}^{n} p(x_i) \log_r p(x_i) \tag{1}$$

$$\lim_{p \to 0^+} p \log(p) = 0 \tag{2}$$

where, according to the theory of information, $r = 2$ and entropy unit is a bit.

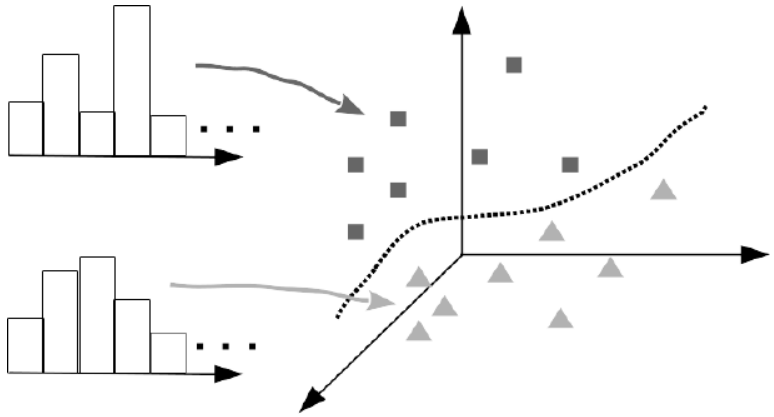


Fig. 5. BFS assignment.

The data presented includes several features: high probabilities (p) and low entropy (H) in each activity class. The desired situation is low entropy and indicates that the probability in one activity class is significantly higher than in other classes.

In the first experiment in which seven activities were analyzed, experiments were carried out on the data from the driving school. The data were analyzed by dividing into seven classes, namely:

- highway driving,
- parking in front,
- parallel parking,
- slope parking,
- driving around a roundabout,
- driving in city traffic,
- driving in residential traffic.

The main goal was to recognize the activity by classifier from the raw data generated. Unfortunately, the results were not very promising – the maximum that we managed to achieve was 62% of activities that were classified correctly, even before averaging the results of two runs (2-fold cross-validation). Therefore, in the next experiment, only 4 classes of activity were used:

- driving on the motorway,
- parking,
- urban traffic,
- traffic in the neighborhood,

to which the collected data were assigned and we managed to achieve much better results, with the best average probability value (i.e. percentage of correctly classified activities) from two runs being 85%.

In summary, we are able to recognize four activities related to driving a car with a sufficiently high probability. To improve our method, so we can recognize seven activities, we need to collect data from many more subjects.

4 Conclusions

Comparing our investigations to research (including literature review and related works), it should be noted that we operated on a similar number of subjects within each experimental group. The differences were in the number of signals taken from sensors and monitoring devices. We mainly relied only on signals from the accelerometer, EOG and gyroscope positioned in the JINS MEME glasses. The experimental results presented in this article show that the BFSD approach can be successfully used to diagnose activities related to driving a car. In the case of only EOG data from the accelerometer and gyroscope, the proposed method achieved a high level of accuracy in results, predicting appropriate activity classes in approximately 85% of cases without prior knowledge. What is more, a test based on entropy BFSs turned out to be an easy-to-use analytical tool to acquire knowledge about the time window characteristic for a given class of activities. These can be used to build a knowledge base on cognitive activities related to driving a car; currently, there is an insufficient number of studies and research about the characteristics of particular classes of cognitive activity in this area.

Future work will build on the current implementation and contribute to the development and decoding of more difficult and complex activities related to driving a car, e.g. mobile phone calls, avoiding road obstacles or responding to traffic incidents. An even more interesting area of research may be an approach related to individual driver traits, such as specific dysfunctions and diagnosed diseases including diabetes, narcolepsy and vision defects. Deterministically assigning each area of samples (data collection intervals) to the most adapted BFS would also be a valuable approach. This method should provide flexibility with respect to areas of uncertainty (where the driver's activity being tested shows similarity to more than one BFS). We plan to solve this problem with a soft assignment, smoothly assigning the width of the data window being tested to many BFSs.

Additionally, the discrete approach to the signal itself seems potentially useful in further research. In particular, the probabilistic approach can solve the problem of the precise distribution of BFSs and corresponding activities, which the current simple function based on histogram production and analysis does not provide.

Our main goal for the future is to create a system for the arbitrary evaluation of a person's ability to learn how to drive a car. We believe that this kind of system cannot only monitor but also increase the efficacy of learning outcomes in many driver training and examination centers.

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Classification of Recorded Electrooculographic Signals on Drive Activity for Assessing Four Kind of Driver Inattention by Bagged Trees Algorithm: A Pilot Study



Rafał Doniec, Szymon Sieciński, Natalia Piaseczna, Konrad Duraj, Joanna Chwał, Maciej Gawlikowski, and Ewaryst Tkacz

Abstract The act of engaging in secondary activities while driving can cause safety risks on public roads due to the driver's distracted attention. The objective of the research was to predict changes in driver concentration levels caused by secondary activities (eating, drinking, bending, and turning toward the rear seats) using the electrooculographic (EOG) signal. Four subjects, consisting of one male and three females between the ages of 23 and 57, performed distracting driving activities using a driving simulator. The EOG signals were recorded using JINS MEME Academic Pack smart glasses, and machine learning techniques (boosted trees, bagged trees, subspace discriminant, subspace KNN, RUSBoosted Trees) were used to classify the occurrence of secondary activities. The results show that the highest accuracy (87%) has been achieved for the bagged tree (ensemble classifier).

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P. Strumiłło et al. (eds.), *The Latest Developments and Challenges in Biomedical Engineering*, Lecture Notes in Networks and Systems 746,
https://doi.org/10.1007/978-3-031-38430-1_18

Keywords Electrooculugraphy · Driving safety · Classification of EOG · Biomedical signal recognition · Automatic assessment

1 Introduction

Road safety remains one of the top priorities in society. The number of drivers distracted by smartphones or elderly drivers on the roads is increasing, for example, drivers aged 16–19 years and drivers over 85 years of age had per vehicle mile fatal crash rates of 4.7 and 7.6, respectively, compared to a rate of only 1.4 fatal crashes per 100 million miles traveled for those aged 45–49 years [1, 2].

Behavioral and physical restrictions at the age of retirement from professional activity significantly affect the level of road safety. To drive safely, you must be sufficiently aware of your surroundings, pay constant attention to the road and traffic, and be alert enough to react to unexpected circumstances. Age and inattention of the driver are still key factors that contribute to accidents and fatal accidents. Much attention has been paid to the dangers caused by the use of the phone while driving; here, the focus is on more common scenarios of secondary activities that are also causes of dangerous events on the roads [3–5].

Road safety is a crucial issue for seniors, who are at increased risk of accidents due to age-related declines in cognitive and physical abilities. According to the National Highway Traffic Safety Administration, in 2018, drivers 65 years and older accounted for 18% of all traffic fatalities in the United States. Machine learning has emerged as a promising approach to address road safety challenges for seniors using large-scale data to develop predictive models that can help identify drivers at risk and improve road safety [6].

According to the latest data from the National Highway Transportation and Safety Administration (NHTSA), distributed driving claimed the lives of more than 3,000 people in 2020 in America, accounting for 8.1% of all road accident deaths. Furthermore, approximately 324,000 people were injured due to driver inattention [7].

Basic driving activities refer to tasks that are directly related to maneuvering a vehicle, such as acceleration, braking, and steering. Human activity recognition (HAR) techniques can be used to automatically detect and classify basic driving activities using vehicle sensor data [8].

Secondary driver activities refer to actions that drivers perform while driving that are not directly related to driving the vehicle, such as using a cellphone, eating or drinking, adjusting the radio or air conditioning, and engaging in conversations with passengers. These activities can distract drivers and reduce their ability to operate the vehicle safely, increasing the risk of accidents [3, 5].

Observations show that 14% of the drivers were involved in some secondary activity, the most common activity being the use of a mobile phone (5%). Involvement in secondary work was significantly more common among drivers without passengers (15%), compared to 9% among drivers with passengers [9].

Human activity recognition (HAR) using machine learning is a challenging task due to several factors. HAR involves identifying and classifying human activities based on sensor data collected from wearable devices or other sources. Some of the challenges in HAR using machine learning include:

- Variability in human activities: Human activities can vary significantly in terms of duration, intensity, and complexity. HAR algorithms must be able to account for this variability to accurately classify activities [10, 11].
- Sensor noise and variability: The wearable sensors used in the HAR can produce noisy and unreliable data due to factors such as sensor placement, sensor drift, and environmental factors. This can make it difficult to accurately classify activities based on sensor data [12, 13].
- Data sparsity and class imbalance: HAR datasets are often sparse and imbalanced, and some activities occur less frequently than others. This can make it difficult to train machine learning models to accurately classify all activities [14].
- Subject variability: Different individuals may perform the same activity differently, making it difficult to generalize HAR models across different subjects [15].
- Context Awareness: Human activities are often performed in specific contexts, such as indoor or outdoor environments, and different contexts can affect the performance of HAR algorithms. HAR models must be able to take context into account to accurately classify activities [16–18].
- Real-time performance: HAR algorithms must often operate in real time, with low latency and high accuracy requirements. This can make it difficult to develop machine learning models that can classify activities quickly and accurately [19, 20].

Many machine learning techniques have been used to recognize human behavior. It is important to have appropriate labels for data for training and testing. Developing a reliable classifier to recognize activity patterns requires a large data set. First, a certain amount of data is needed to distinguish important characteristics for the neural network to distinguish important characteristics, and second, it is necessary to provide a wide range of classification of signal characteristics [21].

The purpose of the study was to automate the evaluation of machine learning classification results by developing the best cooperation of functions in the set to examine features corresponding to real driving activities based on EOG signals.

2 Material and Methods

2.1 Experiment Setup

The study was carried out in a controlled environment that consisted of a car simulator, JINS MEME ES_R smart glasses (JINS, Inc., Tokyo, Japan), and a laptop for the acquisition of signals. The study group consisted of four volunteers (one male and



Fig. 1 Driving simulator setup

three female) between the ages of 23 and 57. All of them had no health contraindications to drive a car, nor a driver's license to drive motor vehicles up to 3.5 tons. Four activities were considered in our study: eating, drinking, turning, and bending. We chose these activities because they can affect the attention of a driver and do not require the use of a car.

Each subject was asked to participate in second driver scenario which consisted of the following steps:

- Eating (1, class 0)—Taking a bite of any food;
- Drinking (2, class 1)—Taking a sip of water or any drink;
- Turning (3, class 2)—Turning back and reaching to a passenger's seat;
- Bending (4, class 3)—Bending and picking up a fallen object.

During the experiment, we sought to distinguish between secondary driving activities (activities not directly related to driving) in a controlled environment consisting of a car simulator. All participants had normal or corrected-to-normal vision. The setup of the experiment is shown in Fig. 1.

The outline of the experiment was approved by the Bioethics Committee of the Medical University of Silesia in Katowice (the resolution KNW/0022/KB1/79/18) and carried out following the rules of the Declaration of Helsinki of 1975, revised 2013.

2.2 Assessment of Results

The format of the data is as follows; first, the data acquisition parameters are presented, followed by the header describing the content of each column that contains the sample number, the date in the format: dd.mm.yyyy:hh:mm:ss, then the 3 channel accelerometer components:

- EOG_L—left eye raw EOG signal,
- EOG_R—right eye raw EOG signal,
- EOG_H—the difference between the left and right eye potential ($EOG_L - EOG_R$),
- EOG_V—negative arithmetical mean of the left and right eye potential—$(EOG_L + EOG_R)/2$.

2.3 Preprocessing

Before feature extraction and classification, the signal was preprocessed by applying the median filter and bandpass filter.

The first step was to apply the median filter with a window width of 11 samples. The median filter was applied due to the efficiency in removing the spikes in the signal. The EOG signals were preprocessed using a digital Butterworth filter implemented using the scipy.signal module. A third-order low-pass filter with a cutoff frequency 20 Hz was used to remove high-frequency noise and artifacts. A band-pass filter with a passband from 0.1 30 Hz was used to remove DC offsets and electrode polarization. The filter coefficients were obtained using the "butter" function with a sampling frequency 100 Hz. The filtered signals were then evaluated to ensure that the filtering did not introduce any unwanted artifacts or distortion.

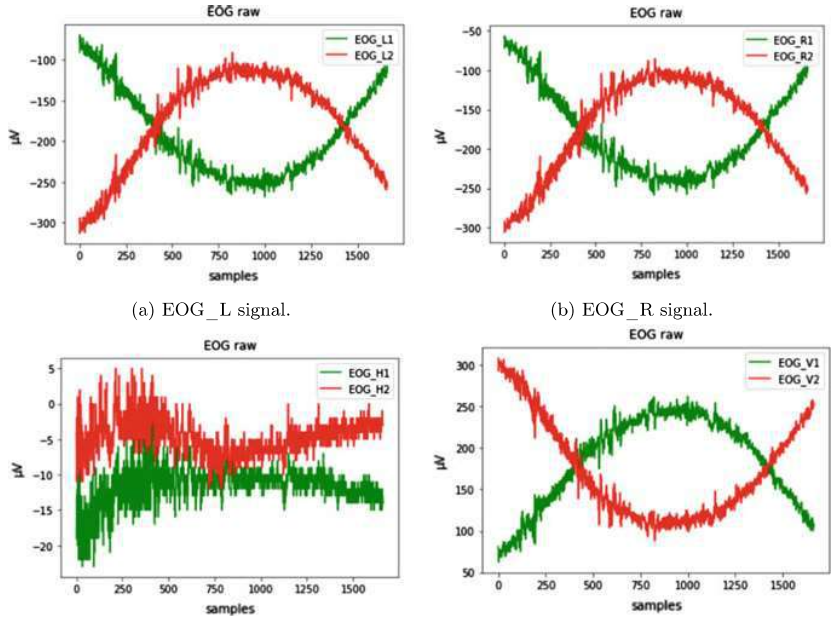
There are numerous potential reasons for this, such as electrode polarization or interference with background signals [22].

Using a technique called detrending by differencing a time series, this objective was accomplished. The new value at the current time step is determined as the difference between the current and previous observations.

Then, the signal data were normalized with the Z-score normalization and the first and last samples were discarded due to the artifacts. The mean and standard deviation of each signal were calculated, and the values of the samples are replaced with the newly determined values using the following formula:

$$x' = (x - \mu)/\sigma, \tag{1}$$

where μ is the mean of the signal, σ is the standard deviation, x is the current value of a sample and x is the new value, so that the new mean of all values is 0 and the standard deviation is 1.



(a) EOG_L signal.

(b) EOG_R signal.

(c) EOG_H signal.

(d) EOG_V signal.

Fig. 2 Raw EOG signal of going straight at a roundabout

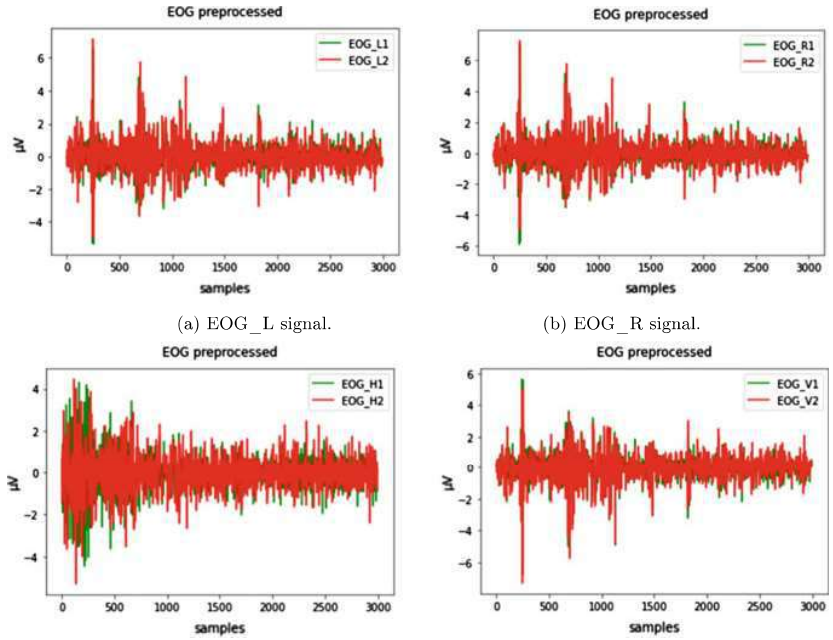
2.4 Signal Processing

The raw EOG signal presented in Fig. 2 contains different types of artifacts that must first be filtered out.

To reduce the noise of electricity lines, baseline wander and other potential types of noise in the EOG signal, we applied a second-order low-pass Butterworth filter with the pass band between x Hz and Y Hz. The filter was applied twice: once forward and once backward. This filter has twice the order of the initial filter and zero phase [23]. An example of the processed EOG signal is shown in Fig. 3.

3 Results

The results were obtained using four different classifiers: Boosted trees, RUSBoosted trees, bounded trees, subspace discriminant, and subspace KNN, based on 24 of 60 features, were chosen based on ANOVA results. The hyperparameters of the models are shown in Table 1 and their performance is shown in Table 2 and Figs. 4 and 5.



(a) EOG_L signal. (b) EOG_R signal.

(c) EOG_H signal. (d) EOG_V signal.

Fig. 3 Preprocessed EOG signal of going straight at a roundabout

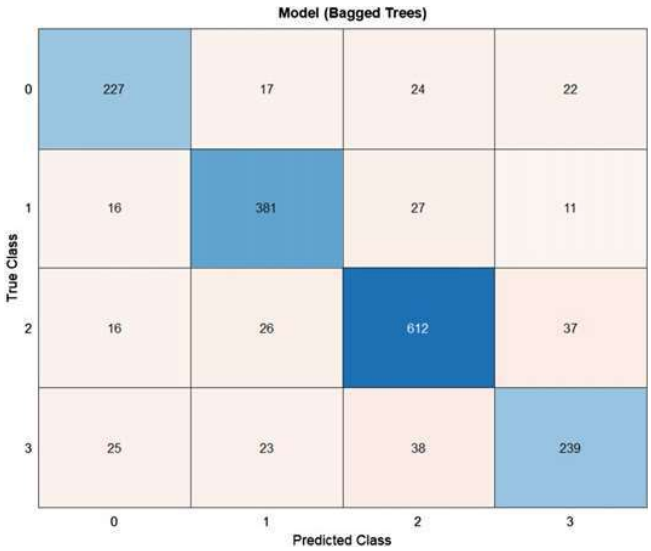


Fig. 4 The confusion matrix

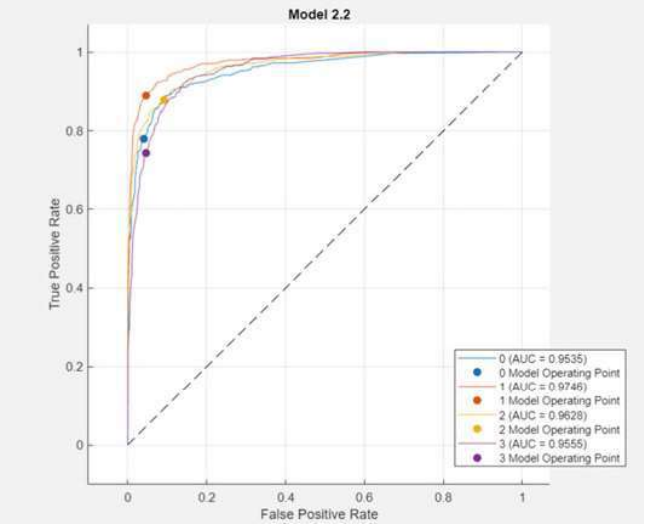


Fig. 5 ROC curves for four classes of activities

Table 1 Performance models hyperparameters for the validation and test data set

Preset	Ensemble method	Leaner method	Max. number of splits	Number of learners	Learning rate
Boosted trees	AdaBoost	Decision tree	20	30	0.1
Bagged trees	Bag	Decision tree	1740	30	–
Subspace discriminant	Subspace	Discriminant	-	30	–
Subspace KNN	Subspace	Nearest neighbors	–	30	–
RUSBoosted trees	RUSBoost	Decision tree	20	30	0.1

Table 2 Performance parameters for the different types of trees classifiers

Class	Accuracy	
	Validation	Test
Boosting	73.3%	73.1
Bagged	**83.8** %	**87.0%**
Subspace discriminant	61.2 %	56.5%
Subspace KNN	64.4 %	55.4%
RUSBoosted	74.9 %	70.0%

Table 3 Performance parameters for the test dataset

Class	Accuracy	Recall	Specificity	Precision	F1 score
1	0.9174	0.8000	0.9509	0.7500	0.7741
2	0.9482	0.8979	0.9652	0.8979	0.8979
3	0.9223	0.8961	0.9397	0.9078	0.9019
4	0.9430	0.8378	0.9679	0.8611	0.8492
Overall	0.9327	0.8695	0.9559	0.8292	0.8558

To determine the performance of our classifier, we used several standard evaluation metrics derived from the confusion matrix of the classifier (shown in Fig. 3). This matrix shows the number of instances in the test dataset that were classified into a particular group (predicted label) compared to their actual class label (true label) (Fig. 5).

ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

1. True Positive Rate,
2. False Positive Rate.

True Positive Rate (TPR) is a synonym for recall and is therefore defined as:

$$TPR = \frac{TP}{TP + FN}, \tag{2}$$

where TP is True Positives (the actual value is Positive and the predicted value is also Positive) and FN is False Negatives (the actual is Positive but the prediction is Negative, called Type 2 error) [24, 25].

False Positive Rate (FPR) is calculated as follows:

$$FPR = \frac{FP}{FP + TN}, \tag{3}$$

where FP is False Positives (the actual is negative but the prediction is positive, called the Type 1 error) and TN is True Negatives (the actual value is negative and the prediction is also negative) [25].

- Class 1, FPR = 0.0399724, TPR = 0.7793, AUC = 0.9535
- Class 2, FPR = 0.0459418, TPR = 0.8896, AUC = 0.9746
- Class 3, FPR = 0.0914286, TPR = 0.8784, AUC = 0.9628
- Class 4, FPR = 0.0459040, TPR = 0.7446, AUC = 0.9555.

Furthermore, we calculate the accuracy, recall, specificity, precision, and F1 score (see Tab. 3). Finally, we used the receiver operating characteristic (ROC) to evaluate the classifier precision (see Fig. 5).

Among the evaluated classification decision trees, the best-performing model was Bagged Trees (83.8% and 87.0% of accuracy for validation and test sets, respectively) and the worst performing model was the subsequence discriminant (61.2% and 56.5% of accuracy for validation and test sets, respectively).

4 Discussion and Conclusion

In this study, our objective was to determine whether it is possible to distinguish driving activities by tracking eyeball and head movements. Using simple light-weight preprocessing and machine learning methods, a series of secondary driving activities were recognized with high precision.

In the experiment, we provided 700 samples that were evenly distributed between classes. One participant provided 100 samples in each class, the remaining 25. In total, 2,100 samples were collected in this study. Signal flagging and acquisition, as well as real calculation data with timestamps and header indicating what is represented by the specified value and volunteer.

The model performed outstandingly with respect to binary classification and yielded very good results when grouping activities by type. The main objective of the study, recognizing all secondary behaviors, bending, drinking, eating and turning back, showed relatively good performance, precision, precision and the f1 score at the level of 87%, considering the high complexity of the imbalanced data.

The findings of our study demonstrate that detection of driver inattention is feasible using easy-to-wear commercial eyeglasses with an IMU affixed to the temples and EOG electrodes affixed to the bridge of the nose. All necessary components are readily available, portable and small in design, and the program is created entirely from open source parts, demonstrating that it is possible to avoid using expensive proprietary technologies [8, 26].

Although preliminary results on activity detection are promising from an application perspective, they still require confirmation in larger investigations. This study did not include participants over the age of retirement (in Poland, the age limit is 60 for women and 65 for men) and did not consider age as a variable. However, as a pilot study, its goal was to explore potential new routes for the next steps.

Future research should include examining a wider variety of subjects due to the user-dependent characteristics of the signal and the determination of cognitive and behavioral differences related to driving at the end of professional activity, that is often related to exclusion from social activities [27, 28]. Additionally, the model should also be trained and tested in a real world setting to improve robustness.

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Evaluation of Intoxication Level with EOG Analysis and Machine Learning: A Study on Driving Simulator*

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Abstract— **Driving after consuming alcohol can be dangerous, as it negatively affects judgement, reaction time, coordination, and decision-making abilities, increasing the risk of accidents and putting oneself and other road users in danger. Therefore, it is critical to establish reliable and accurate methods to detect and assess intoxication levels. One such approach is electrooculography (EOG), a non-invasive technique that measures eye movements, which has been linked to intoxication levels and holds promise as a method of estimating them. In recent years, machine learning algorithms have been utilized to analyze EOG signals to estimate various physiological and behavioural states. The purpose of this study was to investigate the viability of using EOG analysis and machine learning to estimate intoxication levels in a simulated driving scenario. EOG signals were measured using JINS MEME_R smart glasses and the level of intoxication was simulated using drunk vision goggles. We employed traditional signal processing techniques and feature engineering strategies. For classification, we used boosted decision trees, obtaining a prediction accuracy of over 94% for a four-class classification problem. Our results indicate that EOG analysis and machine learning can be utilized to accurately estimate intoxication levels in a simulated driving scenario.**

I. INTRODUCTION

Intoxication from alcohol and drugs is is a major cause of traffic accidents, leading to severe injuries and death [1]. Therefore, it is important to develop reliable and accurate methods to detect and measure intoxication levels. One such method is electrooculography (EOG), a non-invasive technique that measures eye movements. EOG has been shown to be related to the level of intoxication and has potential as a method for estimating intoxication levels [2]. The aim of this study was to evaluate the feasibility of using EOG analysis and machine learning to estimate intoxication levels in a simulated driving environment [3], [4].

EOG is a technique that measures the electrical potential difference between the front and back of the eye. This electrical signal is generated by the movement of the eye and reflects changes in the orientation of the eye relative to the head. EOG has been used in a number of applications, including the assessment of cognitive and neurological function, the evaluation of sleep and wakefulness, and the study of eye movements in various disorders. EOG is a non-invasive and relatively inexpensive method for measuring eye movements, making it a useful tool for various research and clinical applications [2].

In recent years, machine learning algorithms have been applied to EOG signals for the estimation of various physiological and behavioral states. Machine learning algorithms are able to analyze large amounts of data and identify patterns and relationships that might not be immediately apparent to the human observer [5], [6]. In the context of EOG and intoxication, machine learning algorithms could be used to identify characteristic patterns in EOG signals that are associated with different levels of intoxication.

II. MATERIALS AND METHODS

A. Study group

The study group consisted of nine healthy subjects: seven males and two females, aged between 20-25 years old. All participants had a valid driver's license and provided their informed consent prior to participating in the study.

B. Technology used

EOG was measured using JINS MEME_R smart glasses (see Fig. 1a). The technology utilized by these smart glasses was previously described as a reliable and effective tool for measuring EOG signals. Smart glasses with built-in eye tracking technology, such as JINS MEME, use sensors and algorithms to track eye movements and convert them into electrical signals. These signals can then be analyzed to obtain information about eye position, gaze direction, and other aspects of eye movement [7]. The use of smart glasses for EOG measurement has the advantage of being non-invasive and allowing for measurement of eye movements in real-world scenarios, as opposed to traditional EOG measurement techniques, which require electrodes to be placed around the eyes. However, the accuracy and reliability of EOG measurement using smart glasses can vary depending on factors such as the design and quality of the sensors and the processing algorithms used. Intoxication levels were simulated using drunk vision goggles (see Fig. 1b).

The subjects were tested on a driving simulator while wearing drunk vision goggles to mimic the effects of intoxication [8]. The stand for the car driving simulator consisted of: a computer with Windows 10 (central unit equipped with an i7 processor and a graphics card with an NVIDIA processor and the 3D VISION system, additionally standard computer peripherals and LED backlight), a spatial structure made of steel and an adjustable chair, a Logitech set: steering

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*This research was carried out under the initiative "Involving students in scientific research through scientific clubs and project-based learning", in connection with the participation of the Silesian University of Technology in the Excellence Initiative - Research University program (contract No. 08/IDUB/2019/84 of December 16, 2019).



(a) JINS MEME_R smart glasses (b) drunk vision goggles

Fig. 1: Technology used for the study

wheel, pedals, and gearbox, 3 LED 27 monitors adapted to long work, dedicated software, including routes in the city and beyond, also a maneuvering area. The experimental setup is presented in Figure 2.



Fig. 2: Experimental setup

Each of the study participants performed nine different activities (maneuvers) wearing:

- smart glasses alone,
- smart glasses and three types of drunk vision goggles simulating blood alcohol concentrations of 1, 2 and 3 per mille, respectively.

Participants repeated the study process several times. As a result, we obtained about 220 signals for each class of intoxication level (0, 1, 2 and 3).

C. Data processing

The data obtained with the JINS MEME_R smart glasses included three accelerometer channels recorded with a sampling frequency of 100 Hz and four EOG channels recorded with a frequency of 200 Hz. For this study, we used only EOG signals.

Before extracting the features, each signal was normalized and filtered with a third-order median filter. The signals were then divided into windows of 200 samples (1 s), with a stride of 50 samples. In each window, we calculated the following features:

- signal amplitude,
- skewness,
- kurtosis,
- variance,
- μ of a normal distribution fitted to the data,
- and σ of a normal distribution fitted to the data [9].

The result was a 22679x24 matrix of features that was then split into train (70%), validation (20%) and test (10%) dataset, which were then used to create a classifier.

D. Classification

To choose the right classifier for this problem, we used a built-in MATLAB tool called Classification Learner, which enables the quick training of many different classifiers. After initial testing, we observed that the best results are obtained using decision trees. For that reason, we decided to continue working on this group of classifiers. For choosing the best hyperparameters we performed optimization process using Bayesian optimization – in each iteration the set of hyperparameters was changed and minimum classification error was calculated. The optimization process is presented in Fig. 3. Finally, we chose the classifier with the lowest minimum classification error value, which was decision tree with adaptive boosting, 443 learners, 2073 splits, and learning rate 0.92409.

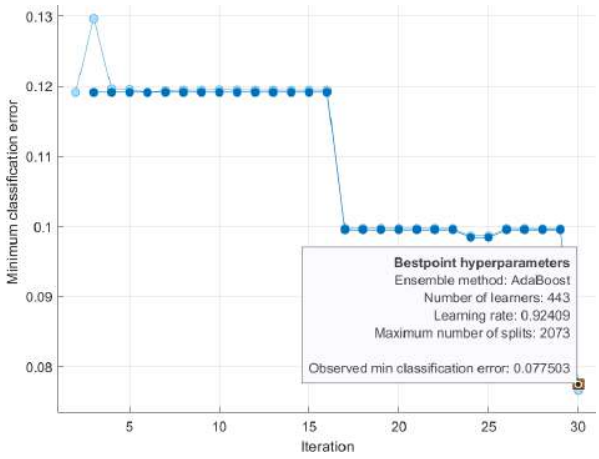


Fig. 3: Hyperparameter optimizing process

AdaBoost (Adaptive Boosting) is a popular ensemble learning method for classification problems in machine learning. It combines multiple ”weak” decision trees into a single ”strong” classifier. A decision tree is a tree-like model that makes a prediction by asking a series of questions about the input data, with each internal node in the tree representing a test on an input feature and each leaf node representing a prediction. In the AdaBoost algorithm, each decision tree is trained on a different subset of the training data, with

the weight of each data point in the subset adjusted based on the performance of the previous trees. This means that subsequent trees give more weight to the data points that were misclassified by previous trees, effectively allowing the algorithm to ”focus” on the harder-to-classify data points. The final prediction made by the AdaBoost classifier is a weighted combination of the predictions made by each individual decision tree. The weights are adjusted based on the accuracy of each tree, with more accurate trees having a greater influence on the final prediction.

III. RESULTS

To determine the performance of our classifier, we used several standard evaluation metrics derived from the confusion matrix of the classifier (depicted in Fig. 4). This matrix shows the number of instances in the test dataset that were classified into a particular group (predicted label) compared to their actual class label (true label).

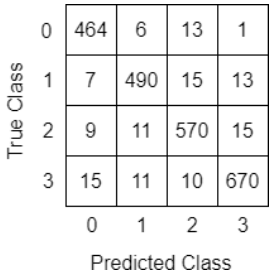


Fig. 4: Confusion matrix for the test dataset

Additionally, we calculated the accuracy, recall, specificity, precision, and F1 score (see Tab. I). Finally, we employed the receiver operating characteristic (ROC) to evaluate the accuracy of the classifier [10]. The ROC provides a comprehensive view of both sensitivity and specificity and can be represented as a graph showing the relationship between the true positive rate and false positive rate.

TABLE I: Performance parameters for the test dataset

Class	Accuracy	Recall	Specificity	Precision	F1 score
0	0.9374	0.9374	0.9890	0.9587	0.9479
1	0.9459	0.9459	0.9806	0.9333	0.9396
2	0.9375	0.9375	0.9796	0.9421	0.9398
3	0.9585	0.9585	0.9778	0.9490	0.9537
Overall	0.9457	0.9448	0.9817	0.9458	0.9453

In a multi-class problem, the Receiver Operating Characteristic (ROC) curve is employed for each class against the rest of the classes, in a one-vs-all approach (see Fig. 5). The ROC curve plots the True Positive Rate (TPR) versus the False Positive Rate (FPR) for each class, and the area under the ROC curve (AUC) is calculated for each class as well. The AUC values give an estimate of the classifier's performance in terms of its ability to distinguish the positive instances of a class from the negative instances of all other classes.

The results of a four-class classification problem indicate high performance metrics:

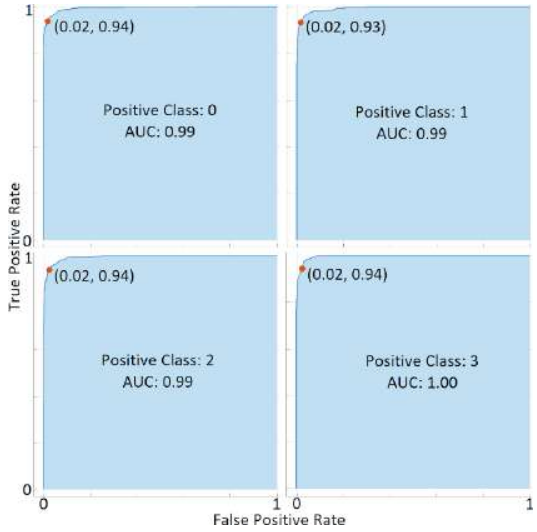


Fig. 5: ROC curves for four classes

- Accuracy: 94.57% of the test instances were correctly classified by the classifier;
- Recall: the classifier was able to correctly identify 94.48% of the positive instances in the test data;
- Specificity: the classifier was able to correctly identify 98.17% of the negative instances;
- Precision: 94.58% of the instances that the classifier classified as positive were indeed positive;
- F1-score: 0.9453 is a balanced measure of the precision and recall.

These results suggest that the classifier is performing well for the four-class classification problem and is making very few false positive or false negative predictions.

An AUC score of over 0.99 means that the classifier is able to distinguish the positive instances of that class from the negative instances of all other classes with high accuracy. It means that the classifier is making very few false positive and false negative predictions for that class.

IV. CONCLUSIONS

Driving is considered a valuable skill. It provides individuals with the ability to travel freely, increase mobility, and access various opportunities for work, education, and recreation. Having a driver's license is also seen as a symbol of independence and freedom. However, it is important to remember that driving is a responsibility that requires proper training and attention to road safety rules.

Driving a car after drinking alcohol is dangerous because it impairs your judgement, reaction time, coordination, and ability to make split-second decisions. This increases the risk of accidents, putting not only yourself but also other road users in danger. The exact number of accidents caused by drunk drivers varies depending on the location and time frame. However, drunk driving is estimated to be a factor in a significant portion of road accidents worldwide. According to the World Health Organization (WHO), globally, alcohol is a factor in approximately 20-30% of road traffic deaths.

In the United States, the National Highway Traffic Safety Administration (NHTSA) reported that in 2020, over 10,000 people were killed in crashes involving a drunk driver (with a blood alcohol concentration (BAC) of 0.08 g/dL or higher). Drunk driving is a preventable cause of accidents and deaths on the road, and efforts to reduce drunk driving, such as education and enforcement of laws, continue to be a priority for many countries [11], [12].

Systems that recognise the level of intoxication, such as breathalyzers and sobriety tests, can play an important role in preventing drunk driving. These tools provide law enforcement with a means to quickly and accurately determine whether a driver is impaired and over the legal limit of alcohol consumption. This information can be used to take appropriate actions, such as making an arrest or ordering a driver to pull over and wait for a designated driver. Some countries have introduced mandatory alcohol interlocks in vehicles, which prevent a vehicle from starting if the driver's breath alcohol concentration is above a pre-set level. These systems have been shown to be effective in reducing drunk driving and preventing accidents caused by impaired drivers [13], [14], [15], [16] . However, the implementation and use of such systems can also raise privacy and technical issues that need to be considered.

Eye movements (EOG) can be a sign of alcohol impairment, but it is not a definitive method to determine if someone is drunk. Alcohol affects various cognitive and motor functions, including eye movements, but other factors such as fatigue, drowsiness, and medical conditions can also cause similar symptoms. Currently, the most accurate way to determine if someone is drunk is still by a breathalyzer or blood test.

This study demonstrates the feasibility of using EOG analysis and machine learning to estimate intoxication levels in a simulated driving environment. The results suggest that this approach has potential as a reliable and accurate method for detecting and measuring intoxication levels, which could be useful in reducing the number of traffic accidents caused by drunk or drugged drivers. Machine learning algorithms were able to distinguish between different levels of simulated intoxication with high accuracy. Furthermore, the EOG signals contained useful information for estimating intoxication levels, even when the visual input to the driver was altered by the drunk vision goggles.

Studies have demonstrated that Electrooculography (EOG) signals obtained from smart glasses can be utilized to identify various scenarios related to driving a car [10], [17], [18], [19]. This finding supports the feasibility of creating a comprehensive system for driver activity recognition relying solely on smart glasses without the requirement for supplementary sensors.

Further studies are needed to validate these findings and to evaluate the performance of this method in real-world driving conditions.

ACKNOWLEDGMENT

We would like to thank all the participants for taking part in the study.

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The Stress Level Assessment Based on Socio-demographic and Gender Factors Among Polish and Taiwanese Female and Male Junior Dental Students

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Abstract. The aim of this study was to assess the perceived levels and sources of stress for Polish female and male dental Junior students, who study in Polish and compare the results of those students with Taiwanese female and male Junior students, who study in English which is not their native language. The procedure was done by the usage of the JINS MEME ES_R (eye sensing for researchers) device. That device is equipped with three-point electrooculography (EOG) and six-axis IMU (a 3-axis accelerometer and a 3-axis gyroscope). GPS Smartwatch Garmin Vivoactive 3 was used to measure the heart rate. All the participants of the experiment received, precise information about the task to be performed (filling in a close test on dental knowledge composed of 5 questions with five descriptors, analysis of the 3D model; range, shape and depth of the cavity; explanation about the time limit of preparation) and the recommendations to fully concentrate on the precisive shape modeling.

Keywords: Dental students · Gender · Socio-demographic factors · Stress level.

1 Introduction

Dentists are prone to professional burnout, anxiety disorders and clinical depression, owing to the nature of clinical practice and the personality traits common

among those who decide to pursue careers in dentistry. The professional stress is beginning in dental school. This stress may negatively affect their personal and professional lives — in particular with regard to the quality of their subsequent clinical work [1–5]. The results reported by Boran et al., show that the specialized dentists had a lower level of stress, compared to the students and general dentists, who are in line with the [6]. Dyrye et al. in their systematic review reported that medical students experience the highest levels of anxiety and depression [7]. The dental environmental stress can be greatly influenced during the undergraduate study program (program for Junior Students).

Clinical training, in particular, can affect dental students' performance due to their exposure to different patient-related stressors which are similar to the ones faced by dental practitioners [8, 9]. Unless necessary steps are taken, the dental environment-induced stress can negatively affect the students' well-being. If stress persists, students may be unable to continue working, may find difficulty to interact with their patients.

Ultimately, elevated levels of stress can deteriorate academic achievement and reduce career options and life style choices [10, 11]. It can also be expected that students from other countries who have had to deal with a foreign environment and who are additionally exposed to stress from socio-cultural confrontation may be less resistant to stress in contact with the patient, for example due to language barriers. The females showed a higher level of stress as compared to the males. These findings are in alignment with those obtained by Gambetta-Tessini et al. reported that women are more responsive, sympathetic, and supportive toward the patients, which causes them to show higher level of the stress [12]. Myers and Myers revealed that the patient's stress is significantly correlated with physician's stress and that increased stress in the patients lead to elevate stress in the dentists [13].

The aim of this study were to assess the perceived levels and sources of stress for Polish Female and Male Dental Junior Students, who study in Polish and compare the results of those students with Taiwanese Female and Male Junior Students, who study in English which is not their native language.

2 Material and Methods

During the experiments blink occurrence (its speed and strength), vertical and horizontal eye movement and head movement (rotation roll, pitch and yaw) were assessed. The procedure was done by the usage of the JINS MEME ES_R (eye sensing for researchers) device. That device is equipped with three-point electrooculography (EOG) and six axis inertial measurement unit (IMU) which consists of an accelerometer and a gyroscope [14].

JINS MEME ES_R (produced by JIN Co. Ltd.) acquires electrooculographic (EOG) data and acceleration/angular rate. In order to acquire data, the subject needs only to wear the device [15]. GPS Smartwatch Garmin Vivoactive 3 was used to measure the heart rate. That device has the heart rate sensor located on

its back, which enables to measure current heart rate in beats per minute (bpm) which is displayed on the watch in a form of a graph.

2.1 Research Group

The study was conducted on 20 Polish and Taiwanese students of a third year of Dental Division of Silesian Medical University in Katowice who were divided into four equal groups: Polish Female Junior Students (PFJS), Polish Male Junior Students (PMJS), Taiwanese Female Junior Students (TFJS) and Taiwanese Male Junior Students (TMJS). The Taiwanese students were included to examine the influence of communicating in English as an additional stressor.

All the participants of the experiment received, precise information about the task to be performed (filling in a close test on dental knowledge composed of 5 questions with five descriptors, analysis of the 3D model; range, shape and depth of the cavity; explanation about the time limit of preparation) and the recommendations to fully concentrate on the precise shape modeling. Polish students from PFJS and PMJS groups were given all the information regarding the test in their native language, the test itself was also in Polish, while the test prepared for the Taiwanese students (groups: TFJS and TMJS) was in English. All the participants of the experiment during both filling in the test and the cavity preparation procedure were equipped with a set of monitoring appliances (the smart glasses and the smartwatch) in order to control the vital parameters defining stress intensity.

2.2 Experiments

In the first stage of the research students were asked to fill in a test composed of 5 questions regarding the knowledge required from the third year dentistry students in 5 minutes. Then students from all groups were asked to perform a task of preparing a cavity in a standard phantom tooth in type of molar tooth 36 in 1:1 scale (Frasaco GmbH Germany) in limited or non-limited time. The matrix with the outline of the cavity has been prepared. (See Fig. 1) Each student used the same type of the burr (Round End Taper NTI Rotary Dental Instruments, head length 4 mm, diameter 009, medium dirt), turbine with water cooling (350,000 revolution per minute). A model tooth with prepared cavity was prepared (shown in Fig. 2 and Fig. 3) by the usage of 3D printer (Formlabs 2). The characteristics of the model are as follows:

- magnification x10,
- material: Photopomyler Resin Black FLPBK04,
- volume: 389.82 ml,
- layer thickness: 0.025 mm,
- number of layers: 3312,
- print time: 57h 13min.

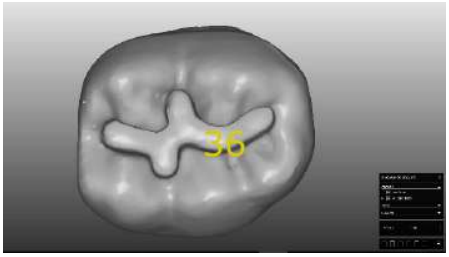


Fig. 1. Matrix with outline of cavity.



Fig. 2. Printed tooth 36 with matrix (top view).



Fig. 3. Printed tooth 36 with matrix (side view).

3 Results

The mean time of filling the test in PFJS group was 2 minutes and 11 seconds. Due to the decision that 60% of proper answers results in satisfactory mark, the results obtained in that group were: two good marks, one satisfactory and two students failed. In the PMJS group the obtained results were: two failed tests, one satisfactory mark, two good marks. The mean time of filling the test was 2 minutes and 13 seconds. In case of TFJS group the mean time of writing was

2 minutes, students obtained: two good marks, two satisfactory marks and one student failed. In TMJS group there were four good marks and one satisfactory, the mean time of filling the test was 2 minutes and 25 seconds.

The central trend is pointed by a single value that defines the data set. In our case we used the arithmetic mean as the most probable measure of central tendency. The analysis of the heart rate has shown no statistically significant differences between the groups. However, higher heart rate measured in beats per minute (BPM) was observed in women in comparison to men when performing the same tasks (Table 1 and Table 2). The heart rate was measured before the procedure started (shaping tooth or writing a test) and after they were finished.

Table 1. Mean heart rate in women.

	PFJS		TFJS
	Heart rate [BPM]		Heart rate [BPM]
	Before	After	Before
Shaping a tooth	106.2	107.8	103.4
Writing a test	105	105.8	90.8

Table 2. Mean heart rate in men.

	PFJS		TFJS
	Heart rate [BPM]		Heart rate [BPM]
	Before	After	Before
Shaping a tooth	92.4	85.6	92.2
Writing a test	86.8	81.8	87.8

Data received from electrooculography (EOG), gyroscope (GYRO) and accelerometer (ACC) are presented in Table 3 and Table 4. Then, we performed the normality test on acquired data.

Data from electrooculography marked as H describe the movement of eyeballs in horizontal axis (right-left), while marked as V describes the movement of eyeballs in vertical axis (up-down). In Tables 1-4 the mean values of signal amplitude are shown. We can observe higher amplitudes of the signals in women both Polish and Taiwanese in comparison to men.

The arithmetic mean is in normal distribution the most common value, although it may not be observed in the data set. However, one of its important properties is minimizing the value prediction error in the data set. An important feature of the mean is including each value in the data set as part of the calculation and is the only measure of the central tendency in which the sum of deviations of each value from the mean is always zero. Thanks to this property,

Table 3. Mean values of EOG, angular velocity and acceleration amplitudes in women.

	Shaping a tooth		Writing a test	
	PFJS	TFJS	PFJS	TFJS
EOG H	50.64	32.68	111.38	91.39
EOG V	54.23	21.81	97.86	37.34
GYRO X	37.57	21.55	44.15	41.10
GYRO Y	31.79	21.25	40.17	29.40
GYRO Z	62.95	26.14	53.09	30.49
ACC X	89.88	75.42	126.02	106.70
ACC Y	114.85	70.78	145.26	122.55
ACC Z	67.02	74.60	158.72	171.58

we can instantly identify in the single experimental data set the fundamental differences in the mean of men and women.

Table 4. Mean values of EOG, angular velocity and acceleration amplitudes in men.

	Shaping a tooth		Writing a test	
	PMJS	TMJS	PMJS	TMJS
EOG H	13.10	36.80	41.66	42.36
EOG V	24.58	24.55	52.18	40.37
GYRO X	21.47	16.51	29.84	36.58
GYRO Y	19.09	11.05	37.02	27.32
GYRO Z	13.42	8.95	23.78	27.33
ACC X	108.76	41.58	97.46	92.14
ACC Y	70.17	41.32	87.50	117.30
ACC Z	66.69	41.00	118.20	147,44

The mean for subsequent signals from JINS MEME smart glasses for women who deal only with tooth shaping generally does not exceed 100. Signal from the accelerometer had the amplitude for women given to the test is 30% greater than the group of women who were not given a stressful stress in form of the test. However, raw data control suggests that this mean value may not be the best way to accurately reflect differences in the range 60 to 171. The mean is skewed by an amplitude of 114.85 for a "comfortable" situation. In the case of the same signal, in a "stress" situation is even worse. Therefore, in this second situation, the median has been used as a better measure of central tendency.

The mean amplitude of the same signal from the accelerometer for men after the test is up to 50% greater than the group of men who were not given a stressful stimulus. This suggests that the mean value may not be the best way

to accurately reflect differences in the range and is expressed by the amplitudes of 108.76 and 147.44 for both situations in which the test was conducted. Therefore, we should look at an mean standard error. Statistics provide factual information including numbers in our case, these are data in the form of a sequence of signal amplitude values for time intervals.

The confidence interval for the difference between the two measures determines the range of values in which there can be a difference between the means of two populations, in our case two genders, two different circumstances of conducting the test. To examine the statistical significance of the differences in the mean response in the analyzed groups we performed the for the two means with known standard deviations. The results are shown in Table 5.

Assuming that the level of significance $\alpha = 0.1$ (for which the expected value is 1.65) it can be told that the means marked with underlining present statistically significant differences in groups. When the level of significance is 0.2, the values of means marked in italics are statistically important differences.

Table 5. The results of statistical analysis withe the test for the two means with known standard deviations.

	PFJS/PMJS tooth	PFJS/PMJS test	TFJS/TMJS tooth	THJS/TMJS test
EOG H	2.489534434	1.931145871	-0.228119075	*1.317322796*
EOG V	*1.533486051*	*1.397699732*	-0.245794753	-0.182593327
GYRO X	0.677187666	1.157962265	0.619880545	0.356139606
GYRO Y	0.687886454	0.161895801	*1.448000259*	0.323574644
GYRO Z	0.985782466	1.755563572	*1.330254924*	0.36605361
ACC X	-0.360999099	0.709298385	0.931657124	0.388047072
ACC Y	0,688147565	*1.251796546*	0,962902413	0,115737019
ACC Z	0.008385653	1.195780508	0.957832141	0.490580689

Some examples of the electrooculograms in particular groups are presented in Figures 4-11. Figure 4 presents the EOG signal acquired during shaping a tooth and Figure 5 shows the EOG signal registered while writing a test in subject A (PFJS). Electrooculograms acquired on subject B (PMJS) are shown in Fig. 6 (shaping a tooth) and in Fig. 7 (writing a test). In Fig. 8 the EOG signal acquired while shaping a tooth is shown and in Fig. 9 the EOG signal registered while writing a test in subject C (TFJS). EOG signals registered on subject D (TMJS) are shown in Fig. 10 (shaping a tooth) and in Fig. 11 (writing a test). The higher amplitudes of the signals can be seen in case of writing the test which was more stressful than shaping a cavity.

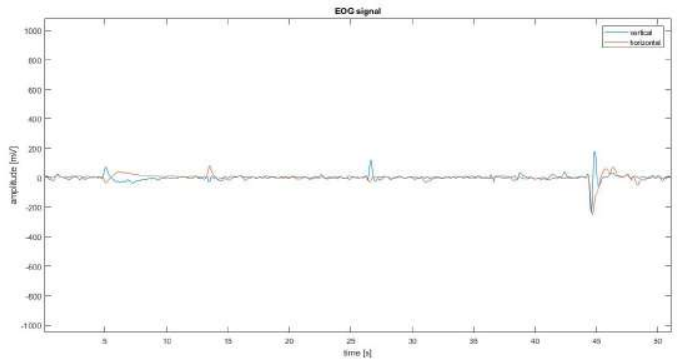


Fig. 4. Data from EOG-PFJS-shaping a tooth in subject A.

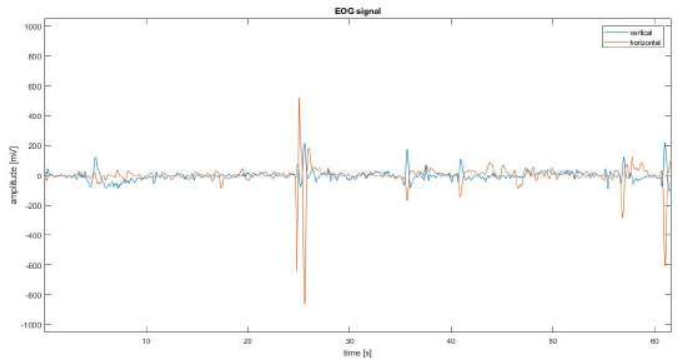


Fig. 5. Data from EOG-PFJS-writing a test in subject A.

4 Discussion and Conclusions

The main objective of this experiment was to assess the level of stress among dental students — with regard to gender and socio-demographic environment, the country of origin and place of study. Dental students need to obtain training in both theoretical and surgical aspects of dental care, including performing treatments on patients to qualify as competent dental professionals. In the preclinical years, dental students need to manage laboratory requirements that require a significant amount of time and manual skills. These factors contribute to significant amounts of stress for dental students that put them at additional risk for psychological problems like anxiety, depression, and burnout [14]. Sometimes the support provided by medical faculties for foreign students vary greatly in type and extent. Offered support may be insufficient in coping with the needs of the international students in many cases [16].

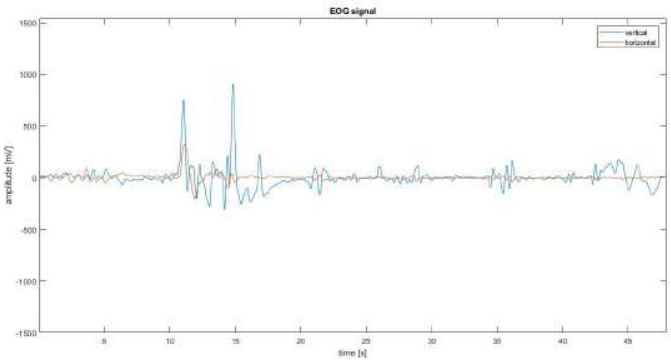


Fig. 6. Data from EOG-PMJS-shaping a tooth in subject B

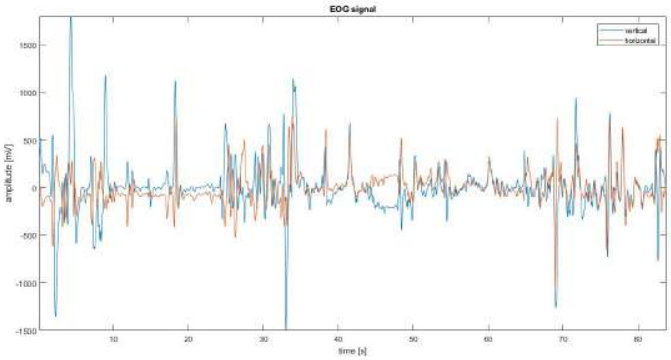


Fig. 7. Data from EOG-PMJS-writing a test in subject B.

The number of women applying to dental schools and entering the profession of dentistry increases globally. Women dentists aim to advance their careers; however, differences exist between men and women dentists regarding for resistance to stress [17]. Such literature reports confirm the results of our research. Results of te Brake et al. showed male dentists to report a higher score on the depersonalization dimension of the Maslach Burnout Inventory than female dentists did [18]. Pool research carried out in the United States on a group of 300 men and 300 women (the selection of respondents) provides some interesting observations. The most common reason for stress was the interaction between doctor and patient (90%), for both women and men. Conflict situations were more accurately and sooner noticed, felt and resolved by women. They were the ones who better dealt with their patient's "pain" (empathy at a higher level of sensitivity) therefore it was not a source of as intensive stress as it was in the case

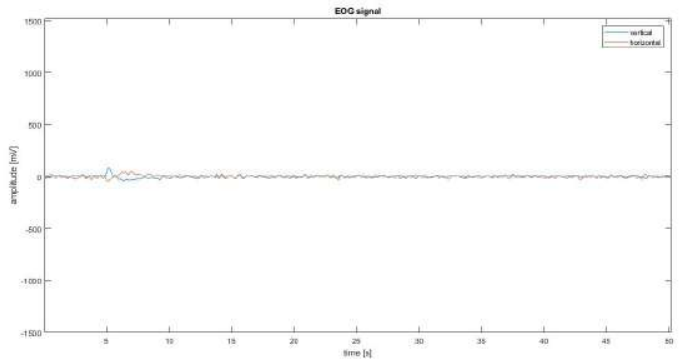


Fig. 8. Data from EOG-TFJS-shaping a tooth in patient C.

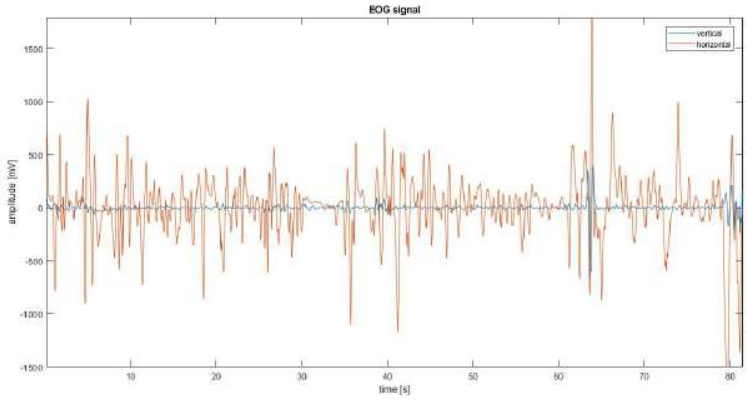


Fig. 9. Data from EOG-TFJS-writing a test in subject C.

of men, who often became aware that the result of their actions was a physical discomfort to their patients when it was too late [19].

From the static point of view, the method of comparing means or standard deviations is reliable when we want to compare and separate two groups of data. It is fast and in its simple way is not unreliable, giving results immediately. The method of means comparisons in the case of statistical inference for one population parameter, zero hypothesis, confidence intervals and significance tests for two unknown data sets and known standard deviations seems to be an adequate tool. However, in this process we lose a lot of important information, such as the reasons for the creation of limit values, which may be the result of measurement error as well as real measurement in special circumstances. Therefore, further research on other classifiers based on artificial intelligence, such as fuzzy sets,

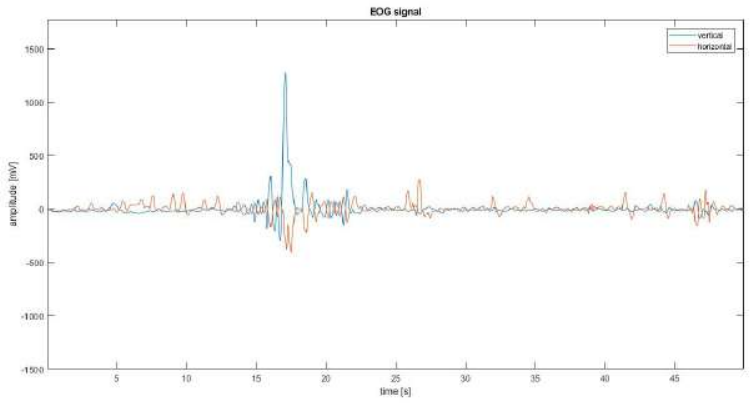


Fig. 10. Data from EOG-TMJS-shaping a tooth in subject D.

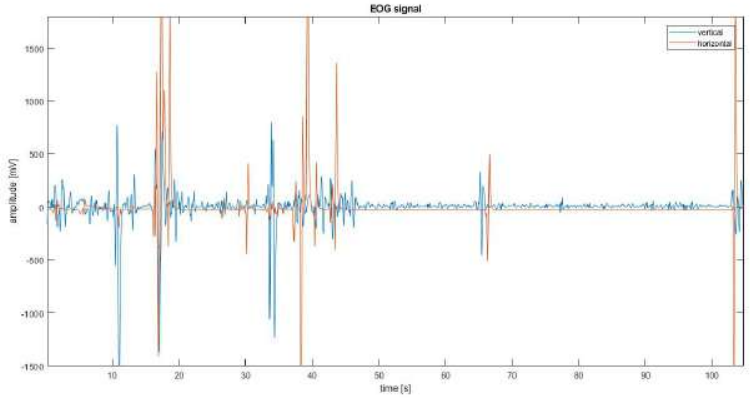


Fig. 11. Data from EOG-TMJS-writing a test in subject D.

expert systems, or other machine learning tool based on advanced statistical data mining would be beneficial.

The future research needs to consider more precise measures of stress level to aid in better understanding dental students' experience and accordingly improving their learning environment. Hence, a better coverage of international students as well as further research efforts to the specific needs and the effectiveness of applied interventions seem to be essential. Both Polish and Taiwanese female students were more prone to stressful situations than male students. We observed that writing a test was more stressful for students than shaping the cavity.

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