A Driver Fatigue Recognition System, Based on an Artificial Neural Network

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Abstract: The paper proposes a method for monitoring the state of a driver, based on the use of neural networks. An intelligent automated system based on a fuzzy inference algorithm has been developed. The relevance of the study is considered. It is carried out a review of studies on this topic and the history of the problem development. Ensuring road safety, is one of the priority State tasks, for the Republic of Kazakhstan. The goal of the study based on the review was set: the development of an automated system for monitoring the driver's condition using artificial neural network (ANN). The theoretical-empirical method was chosen as the research method. As a result of the study, an ANN containing 3 layers was developed: an input layer of 7 elements, a hidden layer of 14 elements, and an output layer of 2 elements. Based on the constructed model, the software "Intellectual system for monitoring the state of a person during work associated with increased danger" was developed. All considered methods and algorithms are implemented in the software package in C#. The obtained results are discussed, and it is concluded that the developed ANN-based assessment model is able to reliably assess driver fatigue and can be applied in real conditions.

Keywords: artificial neural network (ANN); transport safety; fuzzy logic; automation; monitoring; image recognition

1 Introduction

1.1 The Relevance of the Research

A person is no longer in adequately control of the situation due to fatigue or distraction of attention in the case of monotonous, routine work [1] [2]. Such dangerous situations take place when guarding objects in front of security camera monitors, when the driver of a vehicle is driving for a long time, etc. The relevance of increasing the level of safety of the population employed in jobs associated with increased danger (protection of facilities, the driver of a vehicle, etc.) in real time with the involvement of modern digital technologies is beyond doubt. The study examined the work of the driver.

One of the priority state tasks of the Republic of Kazakhstan is ensuring road safety. According to the Committee on Legal Statistics of the Republic of Kazakhstan (press@kgp.kz), for 8 months in 2021, 8307 road accidents were registered in the country, in which 12205 people were injured, and in 87% of cases the drivers were found guilty of the accident (7256 facts).

The object of the research is the process of automated recognition of a person's state. The subject of the study is models and methods of information technologies for an automated system for monitoring the state of a driver.

1.2 Purpose and Tasks of the Research

Monitoring and warning the driver about the onset of a dangerous condition, for example, falling asleep at the wheel, is an urgent and demanded task.

The purpose of the work is developing an automated system for monitoring the state of a person at work associated with increased danger.

The tasks of the work: to study the following questions:

- A review of research by domestic and foreign authors in the field of automation systems for monitoring the state of a person driving a vehicle
- Development of a method and algorithm for monitoring the driver's condition
- An automated system for monitoring the driver's condition creation in real time.

1.3 The History

This scientific direction originates in the mid-1970s, when the University of Bloomington in Indiana, USA, commissioned by the National Highway Traffic Safety Administration for one county of Monroe, carried out a study of 420 accidents [3]. This study can be considered the first large-scale study of the causes of road accidents.

The results showed that the human factor, i.e., mistakes and inattention was the likely cause in 90-93% of accidents. After this study, many works appeared where the causes of accidents were studied, and the human factor was singled out as one of them. For example, in 2009, German scientists from the Medical University Hannover, Germany studied and analysed 248 car accidents in the country [4]. This study showed that the human factor is responsible for 97% of all accidents.

Chinese researchers Li Yaqiu, Zhang Junyi, Lu Yunpeng, Jiang Ying made a great contribution to solving the problem of safe driving and assessing the driver's condition [5] [6].

The issues of safe monotonous work are being actively studied by scientists from different countries, for example [7]. During 2018-2024, about 80 publications in this field were registered in the Web of Science database, 52 in Scopus, and 58 in the RSCI. It was obtained 40 patents in Europe and USA. The general idea of existing solutions is processing a video stream by applying a set of algorithms.

The development of driver condition monitoring systems today goes in three directions: driving style; brain activity and eye to eye. Each direction has its own advantages, requires certain equipment and its implementation difficulties. All systems are usually equipped with a notification unit, which includes an alarm signal in sound, light, or tactile form, and sometimes contains a combination of signals.

It is worth noting that mobile applications that are used to monitor the driver’s condition, for example, developed by Google and Apple, have a few disadvantages. The main one is that mobile applications cannot interfere with the vehicle control process and thereby respond more quickly to emergency situations that occur while driving. Another disadvantage of this kind of solutions is that the accuracy of recognizing dangerous conditions is noticeably lower compared to modern driver assistance systems. While there are many ready-made driver monitoring solutions available, they have several disadvantages: some come as an in-vehicle system and cannot be used in another vehicle, other handheld devices physically interfere with the driver's control, and almost all are expensive.

Thus, the development of a Kazakh system for monitoring driver behaviour, which determines the dangerous state of the driver in the vehicle cabin and warns him about the possibility of an emergency using a smartphone, is an urgent and in demand task.

Currently, automobile manufacturing companies are actively developing their driver condition monitoring systems, but these systems are not portable, which makes it impossible to use them on another car. Basically, all the considered developments have one common drawback - the complexity of the implementation as a whole or individual blocks included in the driver's condition monitoring system, as well as the high cost.

2 Research Methods

2.1 Brief Review

The classic approach to the problem of emotion classification is based on the classification of key points of the human face. The location of key points records rigid and non-rigid facial deformations due to head movements and human facial expressions. To implement the classical approach, algorithms such as PDM, CML, AAM, DPM or CNN can be used to obtain key points of the human face. The next stage of recognition in the classical approach is the classification of key points. Support Vector Machine works well for this. It is necessary that the position of the face in the image is aligned to use the classical approach: the person is looking straight, the face is located exactly in front of the camera. This situation is not always possible.

An alternative to using the classical approach is an approach based on convolutional neural networks, which represent the architecture of artificial neural networks aimed at effective pattern recognition through the operation of calculating a new value for a selected pixel, taking into account the values of surrounding pixels. Convolutional networks are a good baseline solution for classifying various visual data and are used in this work. The convolution operation can be described by the following formula, where f is the original image matrix; g is the convolution kernel (matrix), l is the layer, k is the number of the convolution kernel, m x n is the dimension.

$$(f * g)[m,n] = \sum_{k,l} f[m-k, n-l] \cdot g[k,l] \tag{1}$$

The approach is based on the principles and algorithms of fuzzy logic.

2.2 The PERCLOS Parameter and the Duration of Closed Eyes

The theoretical-empirical method was chosen as the research method. An artificial neural network was built on the basis of observational data and fuzzy set theory. A selection of indicators was made to form the input layer of the ANN. The PERCLOS parameter is a proven and reliable criterion for determining driver drowsiness, which is confirmed by many studies. PERCLOS characterizes the fraction of time that the driver's eyelids are more than 80% closed, as judged by an observer, or related application. This is the first indicator. If the PERCLOS indicator is observed more than 28% [8] [9] of the time within one minute, then it is considered that the person is in a state of drowsiness [10-12]. Thus, the duration of closed eyes is the second indicator. Membership function formula for close eyes:

$$\mu_1(x) = \frac{1}{1+kx^2} \tag{2}$$

where k – interval hit rate.

2.3 The Frequency of Blinking and Yawning

The frequency of blinking the eyes is an additional criterion for determining drowsiness. The safe interval for the driver during which blinking of the eye is allowed is from 0.5 seconds up to 0.8 seconds [13] [14]. The increase in blinking time characterizes the degree of driver fatigue [15]. This will be the third indicator. The presence of yawning [16] will also be an indicator of determining the state of drowsiness [17] [18], i.e., fourth indicator. We assume that the driver has signs of fatigue if he makes more than 3 yawns within 30 minutes while driving the vehicle. One of the noticeable signs of a decrease in attention is the moment when it becomes difficult for the driver to keep his head in the usual position [19] [20]. If the application detects that the driver made more than 2 head nods within 2 minutes, it is considered that a dangerous condition has been detected. This will be number five. The membership function of class s is defined as:

$$s(x;a;b;c) = \begin{cases} 0, \quad x \le a, \\ 2\left(\frac{x-a}{c-a}\right)^2, a \le x \le b, \\ 1-2\left(\frac{x-a}{c-a}\right)^2, b \le x \le c, \\ 1, x \ge c, \end{cases} \quad where\ b = \frac{a+c}{2} \tag{3}$$

For example, let's calculate the membership function of the class s = "the driver keeps his head straight" for the values x=0.7, a = 0, c = 1, b = 0.5:

$$s(o.7, 0,0.5,1) = 1 - 2\left(\frac{x-c}{c-a}\right)^2 = 1 - 2\left(\frac{0.7-1}{1-0}\right)^2 = 0.82 \tag{4}$$

2.4 The Position of the Driver's Head and Duration of Monotonous Activity

The condition of the driver takes into account three indicators: the percentage of eye closure, the time during which the driver was with his eyes closed, and the position of the head.

The term "inattentive driving" refers to the driving of the vehicle by not fully focused on road conditions driver.

Researchers have identified three types of inattentive driving. It is used to determine the position of the driver's head relative to the body. Normal is the situation in which the driver's head should be directed straight in the direction of movement of the vehicle. If the head does not look in the direction of the vehicle for more than two seconds, or if it is not directed to the vehicle turning, this indicates a weakened driver's attention [21] [22]. In another case, the driver's passage of turns to the left and right is monitored by tracking the direction of the vehicle movement and fixing its turns to the left or right. If, when turning the vehicle, the angle of rotation of the driver's head is less than 15° in the direction of movement of the vehicle or is simply absent, then it is assumed that the driver has signs of impaired attention.

The process of rebuilding the vehicle into the adjacent lane is also controlled, while the driver must make sure that the manoeuvre is safe by checking the presence of cars using side mirrors.

It was found that constant driving for 4 hours reduces the speed of the motorist's response to changes in the traffic situation by 2 times, and within 8 hours - up to 5-7 times as a result of research by the authors of [23] [24]. Duration of monotonous activity (driving) will be the sixth indicator. We also take into account the time of day due to the circadian rhythms of sleep and wakefulness of a person to build an ANN, which will be the seventh indicator.

2.5 ANN Layers

Thus, the following indicators were selected to create the ANN input layer: yawn, PERCLOS – percentage of eye closure, duration of close eyes of a driver, $t_{eyecl,}$ head nodding angle, $Ang_{hn,}$ frequency of head nodding, $fr_{hn,}$ time of a day, $day_{time,}$ duration of monotonous activity (driving), $t_{trip.}$ (Figure 1).

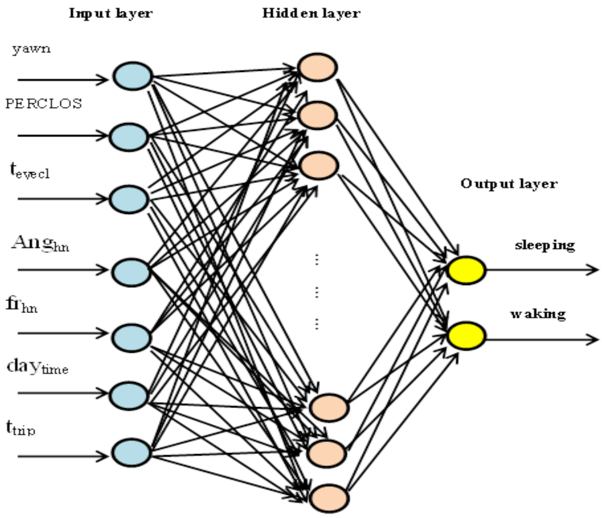

Figure 1
ANN architecture

A detailed mathematical description of the model is considered in [25] and discussed at the AIS symposium in November 2021.

The hidden layer of the ANN is auxiliary and contains 14 elements. The output layer includes two elements characterizing the state of the driver: sleeping or awake.

The process of ANN training is on the Figure 2.

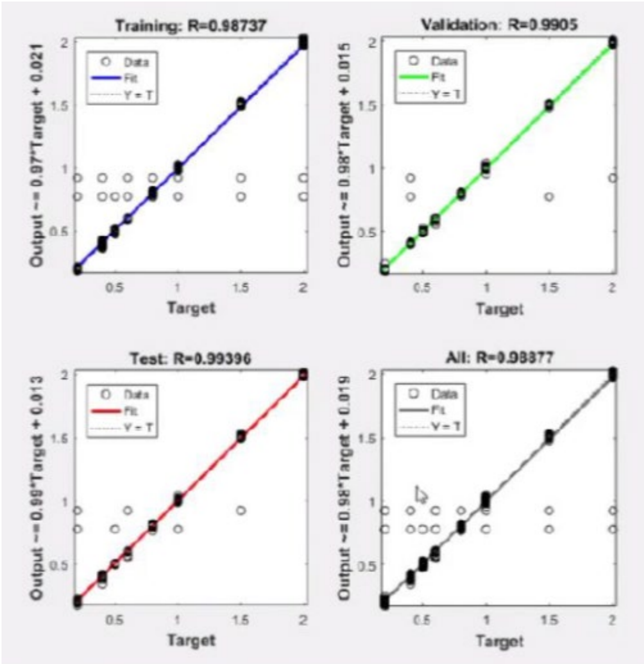

Figure 2
ANN training

3 The Software and the Experimental Setup

3.1 Intellectual System for Monitoring

The software product "Intellectual system for monitoring the state of a person during work associated with increased danger" was developed based on the constructed model. The application architecture was developed and reviewed in [25].

System requirements:

- Any version of Microsoft Windows 7, 8, 10, 11
- Processor x64, x86
- A Screen resolution of at least 1536 by 864 pixels, at 100% scale

The Window of program settings is presented on Figure 3: path, filters for active and sleeping person etc.

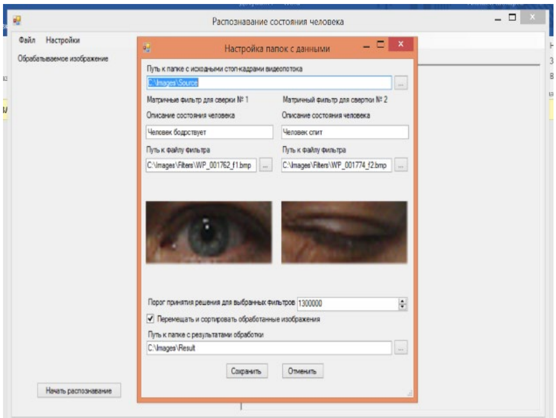

Figure 3
Window of program settings

Images matching filter 1 will be placed in the “Filter1” subfolder; corresponding to filter 2 - to the “Filter2” subfolder; that do not match any of the filters - to the “Unrecognized” subfolder (see Figure 4).

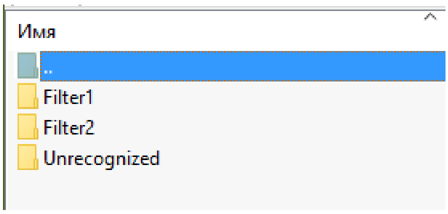

Figure 4
Subfolders

It is possible to start image recognition after saving the settings.

In this program, the method of selecting the maximum element (max-pooling) was used – the entire feature map is divided into cells of 2x2 elements, from which the maximum values are selected. Formally, the layer can be described as follows:

$$x^i = f(a^i \cdot subsample(x^{i-1}) + b^i) \tag{5}$$

Here x is the output of the layer *f()* is the activation function, *a, b* are the coefficients, *subsample()* is the operation of sampling local maximum values.

Log of the data processing is presented below (Figure 5).

All considered methods and algorithms are implemented in the software package in the C# programming language.

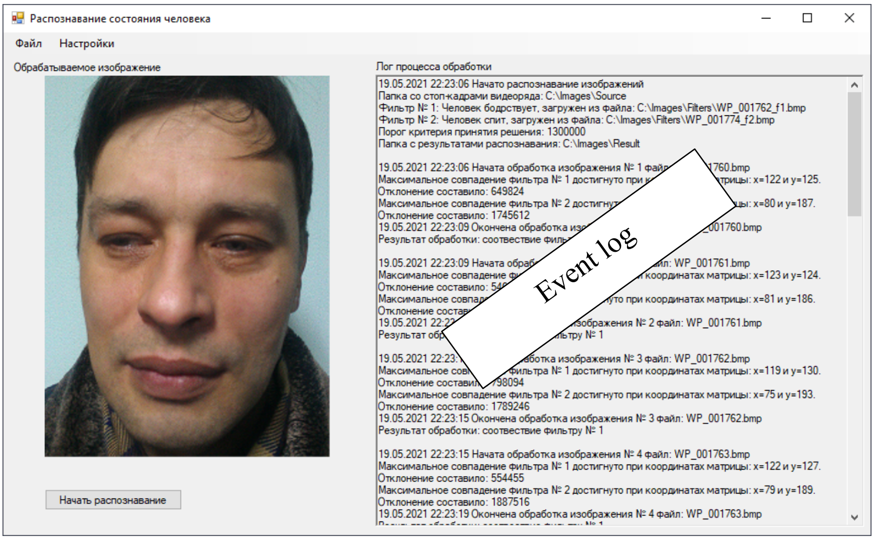

Figure 5

Checking if an image matches a filter 1

3.2 Intellectual System on Android Platform and Experimental Setup

It is clear after testing that for comfortable software exploitation that transferring to the Android platform for using a smartphone without additional connection to a laptop is needed.

That is why the program was rewritten with Java and Kotlin programming languages from JetBrains, which is fully compatible with Java because it runs on its virtual machine (JVM).

This system consists of a mobile phone, a recorder, and a fitness bracelet. After connecting the recorder, the video sequence in the form of a stack of frames will be transferred to the application on the smartphone for further processing.

The ML Kit tool is used for image processing. It is a mobile SDK that brings Google-developed machine learning tools to Android and iOS devices. The ML Kit APIs run on the device, allowing them to be used in real time, for example, to process a camera stream. This also means that the functionality is available offline. Since this model is optimized for mobile devices, one of its main advantages is the recognition speed. Facial contours (sets of points that repeat the shape of facial features) and the angle of the head along two axes (Euler X and Euler Z) are used to determine the factors for falling asleep.

The following parameters are used when recognizing falling asleep: closing the eyes, eyes opening, head tilt.

Since the visual factor is a priority, when the time threshold is exceeded in accordance with one of these parameters, a wake-up sound will be played.

A fitness bracelet connected via Bluetooth is configured to periodically synchronize with the application (with an interval of 1 minute) to transmit heart rate data. When a heart rate drops below the acceptable threshold, a notification tone will sound.

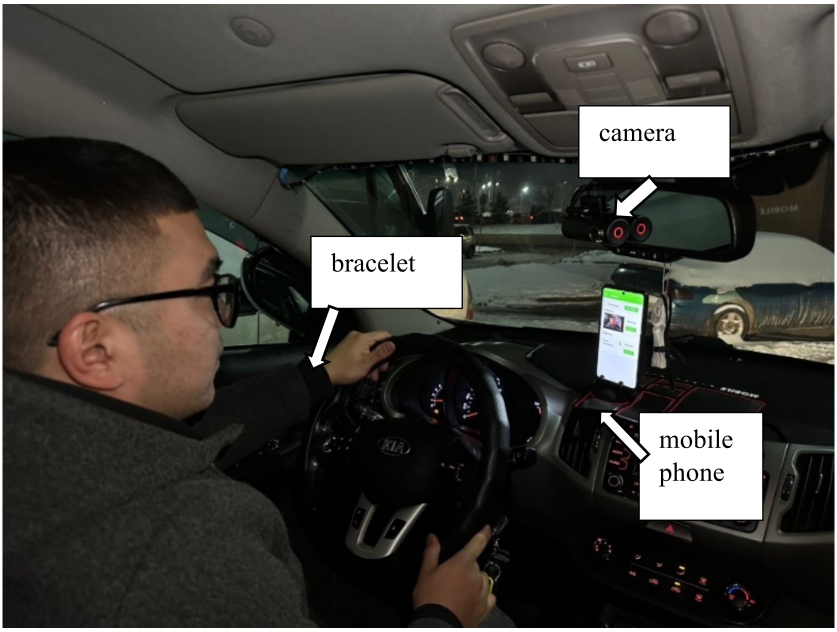

Figure 6
Experimental setup

All thresholds in the application are configurable.

Main technical characteristics:

1) A touchscreen phone (Android OS) with at least 500 MB of free RAM
2) A recorder with Wi-Fi access point and RTSP protocol support
3) A fitness bracelet or smart watch, with a heart rate measurement function

The examples of screenshots in different situations present below: right side – asleep, left side – active (Figure 7).

An LED strip was added to the system to attract the driver's attention. In the “sleeping” state, the system gives signals to the driver: sound and light (Figure 8).

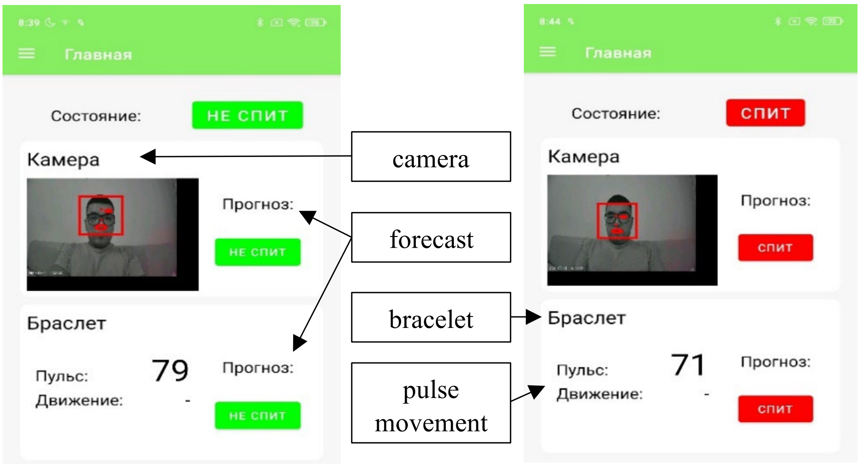

Figure 7
Screenshots

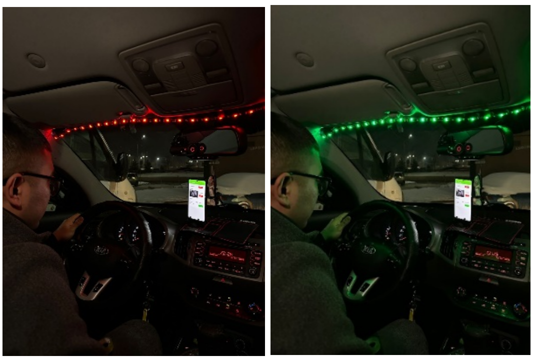

Figure 8
Alarms to the driver

The application requires an Internet connection on a smartphone to work correctly to use it in real conditions. Also, for the entire algorithm to work, it is necessary to add a count of the number of frames with the “sleeping” state. This is due to the human need to blink and trigger the algorithm only if there is a sequence of frames with the “sleeping” state.

It can be used quality metrics for a classification such as accuracy, precision and recall F1-score (see Table 1).

The existing monitoring systems were estimated based on a review [9].

Table 1

Contains the result of comparing in pairs with the final result

Metrics	PERCLOS	The angle of the head	Google Driver support	Our model
Accuracy	0.89	0.88	0.89	0.92
Precision	0.8802	0.875	0.884615385	0.9108
Recall	0.8982	0.8936	0.901960784	0.9293
F1-score	0.8891	0.8842	0.893203883	0.92

4 Results

As a result of the study, an ANN containing 3 layers was developed: an input layer of 7 elements, a hidden layer of 14 elements, and an output layer of 2 elements. When conducting an experiment using the developed software product based on ANN, the following results were obtained: 5 drivers were tested: 4 men and 1 woman. Photos of the video sequence during testing are shown in Figure 9.

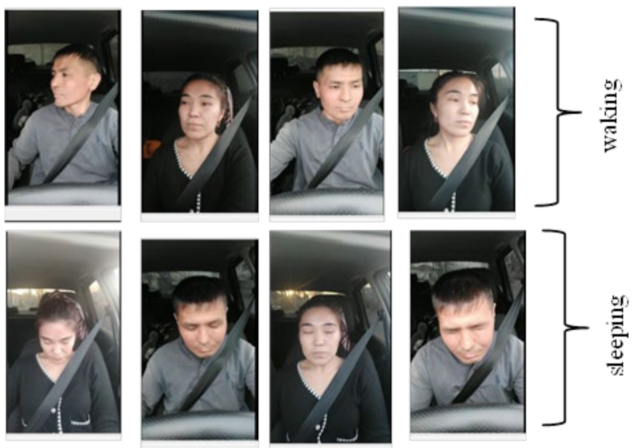

Figure 9

Photos of the video sequence during testing

100 actual driving trips (20 trips per driver) were evaluated over a 6-month period to test the performance of the model. Drivers' smartphone cameras were used for video filming. A laptop was connected via Bluetooth to analyse the dangerous state of the driver in real time during the trip. A notification system was also implemented through a sound signal through the laptop's speakers. Photos from the control sample are shown in Figure 10.

Figure 10
Photos from the control sample

For safety net, one of the product developers, B. Smakanov, was sitting next to the driver during the driver’s trip in a state of fatigue.

92 driver state samples were correctly identified. 92% of states of wakefulness and 88% of states of falling asleep while driving was correctly assessed.

If we evaluate the developed model for determining the states of wakefulness and sleepiness, then in comparison:

- With estimation models based on PERCLOS, the accuracy is 89.2 and 88.9%, respectively.
- With models, estimates for the angle of the head nodding are approximately 84% and 83%, respectively.

Thus, the accuracy of recognition of the driver's state is increased by about 3% compared to existing models. Accuracy can be increased by increasing the number of ANN training samples. It should also be taken into account that the training sample of drivers in a sleepy state was partially formed from staged videos.

Conclusions

All the tasks set in the study, were successfully resolved. A thorough review of studies of domestic and foreign work in the field of automation of driver condition control systems was carried out. It was found, based on the review, that the current developments, despite all the advantages, have several disadvantages, the main issues being high cost and the inability to transfer to another vehicle.

A method and algorithm for monitoring the driver's condition based on ANN has also been developed. In this study, significant indicators were selected for the formation of an ANN, which includes, in addition to common ones, such indicators as head nodding angle, time factors, and time of day.

It has been proven that the developed ANN-based assessment model is able to reliably assess driver fatigue. Also, the developed model can assess driver fatigue on an individual basis since it is trained on individual PERCLOS and changes in the head angle in a state of drowsiness. With these advantages, our fatigue model can be applied to real driving.

An automated system for monitoring the state of a person at work associated with increased danger has been created, which confirms the receipt two certificates on data registration in the state register of copyrighted objects of the Republic of Kazakhstan No. 18410, June 04, 2021 and No. 38413, August 15, 2023.

However, more research and some refinements are required:

1) Expanding the database of ANN samples to increase the accuracy of recognition of the driver's state in spite of existing samples from Internet resources
2) Additional testing under real conditions.

Also, in future studies, factors such as sleeping with open eyes, difficulties in determining the state of a driver wearing glasses or a headdress, and make-up can be taken into account.

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References

[1] Global status report on road safety, World Health Organization, https://www.itf-oecd.org/sites/ default/files /docs/ irtad-road-safety-annual-report-2021.pdf –2021 – accessed 11.06.2022

[2] Fatality Analysis Reporting System (FARS), NHTSA, https://www-fars.nhtsa. dot.gov /Main/index. aspx – accessed 11.06.2022

[3] Treat N. J., John R., Tumbas, N. S., McDonald, Stephen T., Shinar, David Hume R. D., Mayer R. E., Stansifer R. L., Castellan: Tri-level study of the causes of traffic accidents: final report, Executive summary, 1979-05

[4] Otte D., Pund B., Jänsch M.: A new approach of accident causation analysis by seven steps access, German In-Depth Accident Study, Medical University Hannover, Germany, Paper Number 09-0245

[5] He Qichang, Li Wei, Fan Xiumin, Fei Zhimin.: Evaluation of driver fatigue with multiindicators based on artificial neural network, IET Intelligent Transport Systems, 2016, Vol. 10, Iss. 8, pp. 555-561, doi: 10.1049/iet-its.2015.0021www.ietdl.org

[6] Li Y., Zhang J., Lu Y., Jiang Y.: Exploring the effect of nudge approach on driver's willingness to use driver tracking, Transportation Research Part F: Traffic Psychology and Behaviour, Volume 101, 2024, pp. 15-32, ISSN 1369-8478, https://doi.org/10.1016/j.trf.2023.12.016

[7] Orlovska J., Novakazi F., Lars-Ola B., Karlsson M., Wickman C., Söderberg R.: Effects of the driving context on the usage of automated driver assistance systems (ADAS) - naturalistic driving study for ADAS evaluation// Transportation Research Interdisciplinary Perspectives, 2020, №4, p.

100093, doi:10.1016/j.trip.2020.100093http:// www.sciencedirect.com /science /article /pii/S259019822030004X

[8] Wierwille W., Wreggit S., Kirn C. L., Ellsworth L. A., Fairbanks R.: Research on Vehicle-Based Driver Status/Performance Monitoring: Development, Validation, and Refinement of Algorithms for Detection of Driver Drowsiness, Technical Report DOT- HS-808-247, National Highway Traffic Safety Administration., 1994, 247 p.

[9] Shvets O., Smakanov B.: Overview of approaches and methods for automated driving support systems development, Proceedings of the XIV International Scientific and Practical Conference, Lisbon, Portugal, 2022, pp. 560-564, https://isg-konf.com/theoretical-and-science-bases-of-actual-tasks/ – doi: 10.46299/ISG.2022.1.14

[10] Picco A., Stuiver A., Winter J., Waard D.: The use of monitoring and feedback devices in driving: An assessment of acceptability and its key determinants, Transportation Research Part F: Traffic Psychology and Behaviour, Volume 92, 2023, pp. 1-14, ISSN 1369-8478, https://doi.org/10.1016/j.trf.2022.10.021

[11] Karrouchi M., Nasri I,, Rhiat M,, Atmane I., Hirech K., Messaoudi A., Melhaoui M., Kassmi K.: Driving behavior assessment: A practical study and technique for detecting a driver's condition and driving style, Transportation Engineering, Vol. 14, 2023, 100217, ISSN 2666-691X, https://doi.org/10.1016/j.treng.2023.100217

[12] Nasri I,, Messaoudi A., Kassmi K., Karrouchi M,, Snoussi H.: Safety Embedded System Integration in Automotive Network CAN Bus to Prevent Road Accidents, International Review of Mechanical Engineering (IREME), 2021, Vol. 15, No. 8, DOI: https://doi.org/10.15866/ireme.v15i8.21175

[13] Thorslund B.: Electrooculogram Analysis and Development of a System for Defining Stages of Drowsiness, Linköping University, Linköping, 2013, 44 p.

[14] Kaushish V., Singh N., Maggo K., Nagrath P., Jain R.: Driver Drowsiness Detection System with OpenCV and Keras, Proceedings of the International Conference on Innovative Computing & Communication (ICICC), 2021

[15] C. B. S. Maior, M. J. das C. Moura, J. M. M. Santana, and I. D. Lins, Real-time classification for autonomous drowsiness detection using eye aspect ratio, Expert Systems with Applications, Vol. 158, p. 113505, Nov. 2020, https://doi.org/10.1016/j.eswa.2020.113505

[16] Abtahi S., Hariri B., Shirmohammadi S.: Driver Drowsiness Monitoring Based on Yawning Detection, Proc. IEEE International Instrumentation and Measurement Technology Conference, Binjiang, Hangzhou, China, May 2011, 4 p.

[17] Verma H., Kumar A., Gouri Sh. M., Gouri, Deep U., Pradeep K. M., Nand P. Driver drowsiness detection. Shu Ju Cai Ji Yu Chu Li/Journal of Data Acquisition and Processing, 2023, 38, 1527, DOI 10.5281/zenodo.776772

[18] Eskandarian A., Sayed R., Delaigue P., Mortazavi A., Blum J.: Advanced Driver Fatigue Research: Tech. Rep. FMCSA-RRR-07-001, U.S. Department of Transportation, April 2007, 210 p.

[19] Zhu X. G. S. H. X.: Real-time driver drowsiness detection based on machine learning techniques, IEEE Transactions on Intelligent Transportation Systems, Volume 21, No. 4, pp. 1524-1533, 2020

[20] Anon A.: Proximity array sensing system: head position monitor/metric, Advanced Safety Concepts, Inc., Sante Fe., NM87504, 1998

[21] Klauer S. G., Dingus T. A., Neale V. L., Sudweeks J.D., Ramsey, D.J.: The Impact of Driver Inattention on Near-Crash/Crash Risk: An Analysis Using the 100-Car Naturalistic Driving Study Data., DC: National Highway Traffic Safety Administration Report No. DOT HS 810 594, Washington, 2006, 226 p.

[22] Bylykbashi K., Qafzezi E., Ikeda M., Matsuo K., Barolli L.: Fuzzy-based Driver Monitoring System (FDMS): Implementation of two intelligent FDMSs and a testbed for safe driving in VANETs, Future Generation Computer Systems, Vol. 105, 2020, pp. 665-674, ISSN 0167-739X, https://doi.org/10.1016/j.future.2019.12.030

[23] Lisper O., Eriksson B.: Effect of the length of a rest break and food intake on subsidiary reaction-time performance in an 8-hour driving task., J. Appl. Psychol., 1980, 65:117 – 122 p.

[24] Singh H., Kathuria A.: Analyzing driver behavior under naturalistic driving conditions: a review, Accident Anal. Prevent., 150, 2021, Article 05908, 10.1016/j.aap.2020.105908

[25] Shvets O., Smakanov B., Bakatbayeva Zh.: Monitoring Of The State Of A Person At Hazardous Work., Proceedings 16th International Symposium on Applied Informatics and Related Areas., November 2021, ISBN 978-963-449-263-4, pp. 88-91