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Original Article

Development of a Software to Drowsiness Detection for Drivers Using Image Processing and Neural Networks

*Ali Askari [1,2], Ali Salehi Sahlabadi [3,4], Maliheh Eshaghzadeh [5], *Mohsen Poursadeghiyan [6,7], *Gebraeil Nasl Saraji [1]*

1. Department of Occupational Health Engineering, School of Public Health, Tehran University of Medical Sciences, Tehran, Iran
2. Department of Occupational Health and Safety, OICO, Azar Oilfield Project, Ilam, Iran
3. Safety Promotion and Injury Prevention Research Center, Research Institute for Health Sciences and Environment, Shahid Beheshti University of Medical Sciences, Tehran, Iran
4. Department of Occupational Health and Safety, School of Public Health and Safety, Shahid Beheshti University of Medical Sciences, Tehran, Iran
5. Department of Nursing, School of Nursing and Midwifery, Torbat Heydariyeh University of Medical Sciences, Torbat Heydariyeh, Iran
6. Social Determinants of Health Research Center, School of Health, Ardabil University of Medical Sciences, Ardabil, Iran
7. Department of Occupational Health Engineering, School of Health, Ardabil University of Medical Sciences, Ardabil, Iran

***Corresponding Authors:** Emails: poursadeghiyan@gmail.com, jnsaraji@tums.ac.ir

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Abstract

Background: During driving, drowsiness may happen for a few moments, but its consequences can be terrible. Drowsiness in the driver can be detected in the early stages. Each method used for detecting drowsiness has its own strengths and weaknesses or benefits and flaws. The main contribution of our research was improving Driver Drowsiness Detection (D.D.D) systems.

Methods: In accordance with the research objective, it is imperative to address the subsequent inquiries (Q) throughout the process of constructing, testing, and delivering the ultimate D.D.D software model: Q1. What is the methodology employed for constructing the initial model of drowsiness detection software? Q2. How is the initial model of drowsiness detection software tested and refined during the development phase? Q3. What is the operational mechanism of the final model of drowsiness detection software?

Results: The results were able to detect different facial conditions (with hair and glasses) with a 92.3 percentage detection rate.

Conclusion: This model could help improve D.D.D systems, and detect drowsiness in different environments and situations.

Keywords: Driver monitoring system; Software drowsiness detection; Neural network; Viola-Jones algorithm; Image processing

Introduction

Drowsiness, characterized by an inappropriate or excessive feeling of sleepiness, can significantly impair daily activities and is particularly dangerous when driving (1). It is classified into three states: awake, Non-Rapid Eye Movement (NREM), and Rapid Eye Movement (REM) sleep. Drowsiness often serves as a precursor to sleep, indicating a transition from wakefulness to sleep stages (2). Many study have been done on survry of drowsinee or sleepiness in worker and nursing (3-9). The dangers of drowsy driving are well documented. According to the National Highway Traffic Safety Administration (NHTSA), approximately 100,000 accidents annually in the U.S. are attributed to drowsy drivers, resulting in over 1,500 fatalities and 71,000 injuries (10). The WHO highlights that a staggering 93% of traffic-related injuries occur in low- and middle-income countries, making road traffic accidents a leading cause of death among individuals aged 5 to 29 (11,12). In Iran, for instance, road traffic accidents are the primary cause of permanent injuries and the second leading cause of death, with fatigue being a significant contributor. Notably, drowsiness linked to sleep deprivation accounts for roughly 20% of these accidents (13,14). Therefore, detecting drowsiness in drivers is crucial for accident prevention.

Early identification can be achieved through various methods, including physiological assessments (e.g., monitoring brain waves), performance-based evaluations (analyzing driving behavior), and appearance-based assessments (noticing changes in facial expressions and posture) (15-17). Each method has its advantages and limitations; for example, physiological assessments may be uncomfortable due to electrode attachments, while performance-based methods can be influenced by external factors like road conditions (18).

Each method for detecting drowsiness has its own strengths and weaknesses. The development of these techniques should prioritize user-friendliness, reliability, precision, and cost efficiency to reduce effectively the significant losses associated with road accidents.

This study specifically aimed to evaluate and enhance a software component of a face-based model for detecting driver drowsiness, ultimately improving the accuracy and reliability of the Driver Drowsiness Detection (D.D.D) System.

Materials and Methods

This study was a fundamental-applied research project with a basic experimental design aimed at developing drowsiness detection software. The conceptual model of study design is shown in Fig. 1.

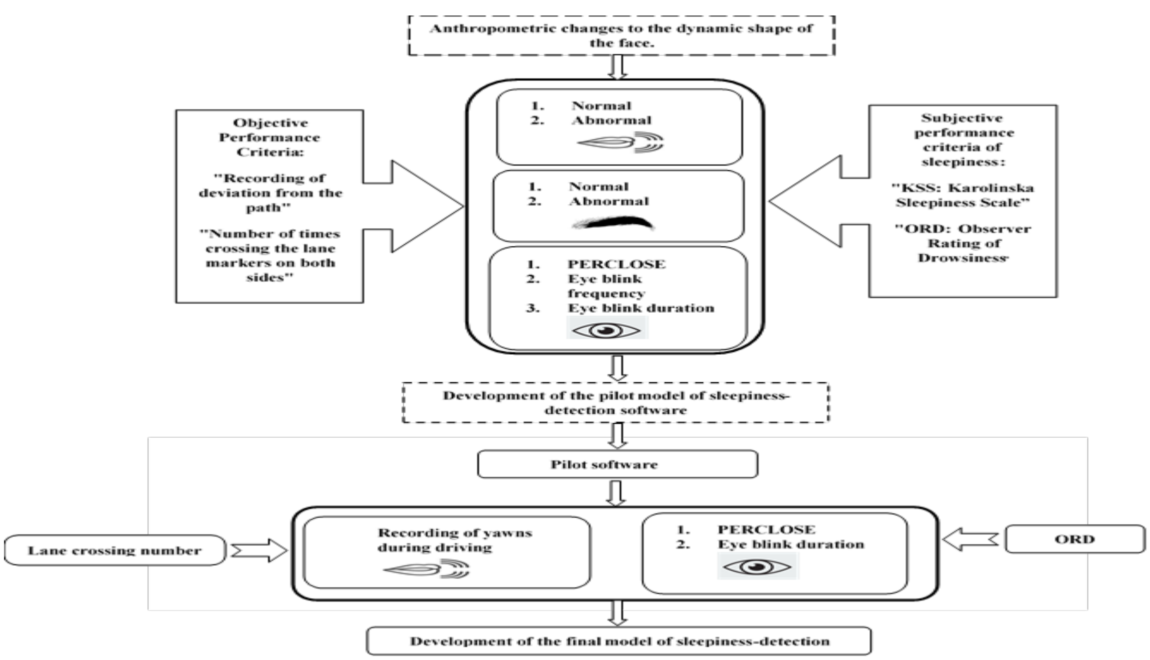


Fig. 1: Conceptual model of study

The initial model involves placing a camera in front of the driver to capture images, which are then processed to assess the driver's level of drowsiness (18).

Face Detection: The software classifies faces as known or unknown by comparing them to stored facial biometrics. This process is challenging due to the similarities among human faces, which complicates accurate recognition. The Viola-Jones algorithm, commonly used for object detection, is employed for face recognition. Although training this algorithm is time-consuming, it allows for quick identification through the Adaboost method, which combines multiple weak classifiers into a stronger version (18,19).

Detection of Facial Features: After locating the face, the software identifies key features such as eyes, mouth, and eyebrows by analyzing specific areas of the face by the Viola-Jones method (19).

Feature Extraction: The analysis of facial features involves converting eye images to binary format to assess the state of eye openness, utilizing metrics such as PERCLOS, blink frequency, and duration. The mouth region is analyzed similarly, where an increased pixel count may indicate yawning. Additionally, changes in pixel values in the eyebrow region are extracted for feature analysis (14, 18-20).

Drowsiness indicators: Sleepiness levels are evaluated through various methods, including the Observer Rating of Drowsiness (ORD), which involves visual assessments of facial expressions from recorded videos. Additionally, the number of lane deviations is monitored and normalized on a scale from zero to ten. The Standard Deviation of Lane Position (SDLP) measures the extent of vehicle deviation from the lane center, with an experiment being halted if the deviation exceeds three meters (14, 18, 20, 21).

Image Processing and Neural Network Role: In this study, a neural network is implemented on a laptop within a driving simulator to monitor driver drowsiness through real-time image processing of the driver's face via a Hikvision DS-2CE1582P-IR camera (21). The system employs appearance-based methods, particularly Principal Component Analysis (PCA), for effective face detection. The camera, capturing HD quality images at 10 frames per second from a distance of one meter, aids in isolating facial features. A Multi-Layer Perceptron (MLP) neural network analyzes inputs such as blink frequency, eye closure, blink duration, and yawns to assess drowsiness levels, trained through backpropagation and gradient descent techniques (22). Additionally, the study utilizes an AI-based clustering method to enhance the neural network's performance and includes backup structures for improved reliability (23).

In this study, sensitivity and specificity were utilized as measures of the neural network's accuracy in detecting and tracking facial features such as the eyes, mouth, and eyebrows. Sensitivity refers to the proportion of actual positive cases identified correctly, while specificity denotes the proportion of actual negative cases identified accurately. The calculations for these metrics were based on equations 1 and 2, respectively.

$$\textbf{Eq.1}\ \text{Sensitivity}= \frac{\textit{Number of true positive}}{\textit{Number of true positive}+\textit{Number of false negatives}}$$

$$\textbf{Eq.2}\ \text{Specificity} = \frac{\textit{Number of true negatives}}{\textit{Number of true negatives}+\textit{Number of false positive}}$$

Driving Simulator Preparation and data integration

A driving simulator model was developed in collaboration with the Mechatronic Group at Khajeh Nasir University, utilizing the SCANIA BI 301 simulator to create a three-lane highway environment that promotes fatigue and drowsiness in drivers (18). Essential requirements for the simulator included a camera positioned one meter from the driver's head with a resolution of at least 800 x 600 pixels and an IR lens for low-light conditions. The setup featured small IR lights for consistent ambient lighting, with drivers selected to ensure typical appearances without unusual hairstyles or reflective glasses. The computer system was required to operate with a minimum of Core i7 specifications and 8GB RAM to prevent lag. Testing involved ten university students with sleep deprivation, along with 25 male inter-city bus drivers who met stringent selection criteria, including no visual impairments, a healthy appearance, at least two years of driving experience, and abstention from caffeinated beverages prior to testing. Those drivers who displayed signs of sleepiness or failed to adhere to traffic regulations during the simulation were excluded from participation. In addition, we utilized information fusion from face detection software along with sleepiness data recorded by researchers (ORD) and self-reported measures (KSS). This data was used to assess driver sleepiness levels and led to the development of a pilot model named DINN (Drowsiness Identify by Neural Network).

Drowsiness detection initial and final model

In the initial phase of testing the drowsiness detection model, a sample of 35 drivers, comprising 25 professional drivers and 10 students, engaged with the simulator. The software's accuracy was assessed by comparing its ORD with the interpretations of the experimenter. This evaluation sought to enhance the software by incorporating insights from both the automated analysis and the drivers' subjective experiences of drowsiness, particularly in relation to their lane-keeping abilities. The final model for drowsiness detection was developed by integrating data from simultaneous software tracking and simulator variables, including deviations from the driving path, alongside sleepiness ratings recorded at two distinct phases and self-reported measures from previous assessments. A multidimensional analysis was conducted across two testing phases to assess the model's efficacy. The study specifically addressed the following subjects: the construction of the initial model, the methods of testing and refinement, and the functionality of the final model in detecting drowsiness. This structured methodology was designed to ensure the model's robustness and effectiveness across different driver profiles, including those with facial hair or glasses.

Results

Preliminaries results

Eyes: The analysis of eye frames focuses on changes in the ratio of white to black pixels in the upper and lower parts of the eyes, along with blink detection (Fig. 2, A). To enhance tracking, a factor of 3 was applied to the upper half of the signal. (Fig. 2, B) Data on pixel changes during eye-opening, closing, and blinking is presented, indicating that the lower half of the eyeball provides a more accurate distinction between open and closed states when the appropriate threshold is applied (Fig. 2, C). Ultimately, using a neural network to process information related to the eye states and blink metrics enables the assessment of fatigue levels (14, 18, 20).

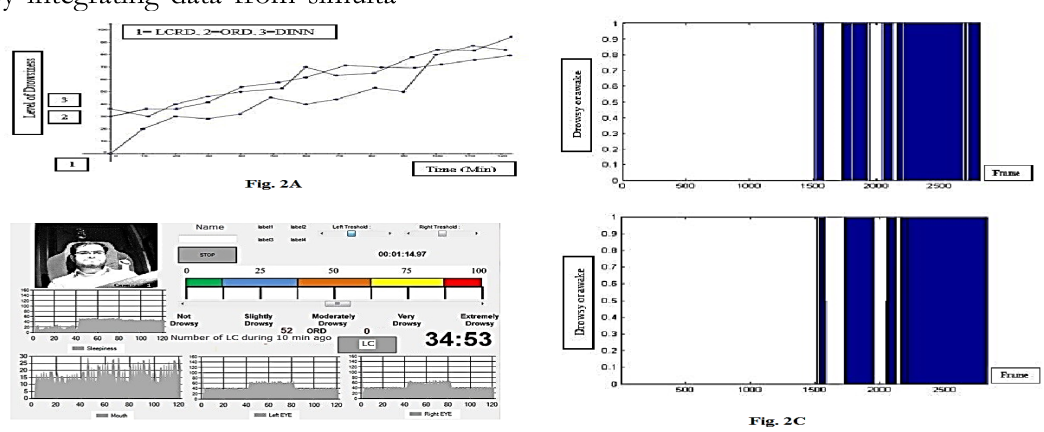


Fig. 2: Eyes detection

- **Mouth:** The results indicate that there is a noticeable difference in the signal level during yawning, allowing for effective monitoring of yawns over time when an appropriate threshold is applied (Fig. 3, A).
- **Eyebrow:** Analysis of eyebrow movements revealed that, despite some positional changes, there were no significant or useful features detected in the signal. Consequently, the analysis of eyebrows was deemed unproductive and removed from the study (Fig. 3, B).

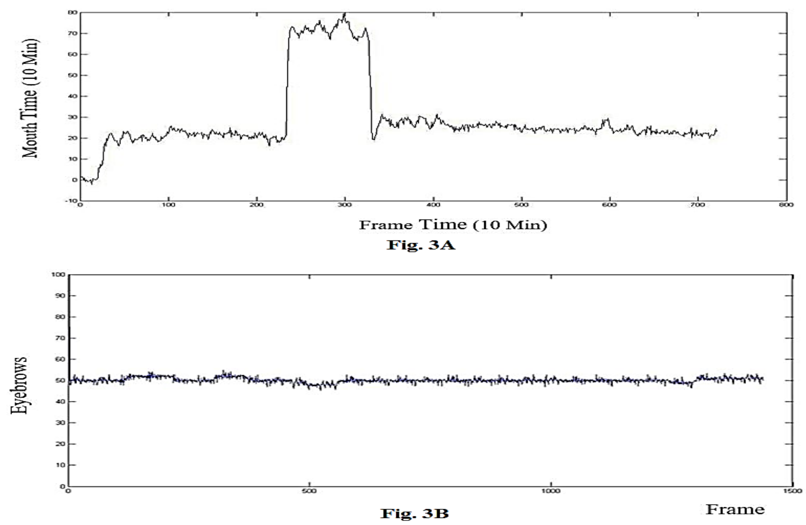


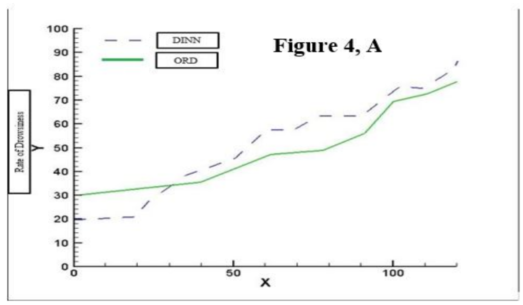
Fig. 3: Mouth and Eyebrow detection

The study on eye, mouth, and eyebrow detection and tracking using neural networks demonstrated high performance, achieving detection rates of 98% and 95% for individual and general cases, respectively. Specifically, the eyes were accurately detected 95% of the time, while mouth detection achieved 96%. On average, mouth detection accuracy was about 94%, eye detection reached 95%, and eyebrow detection was notably lower at 53%. Overall, the mouth and eye detection performance improved to 97%, whereas eyebrow detection accuracy remained at 45%. Results regarding accuracy, precision, sensitivity, and specificity of the facial recognition and tracking model are summarized in Table 1, reflecting outcomes from both training and testing stages.

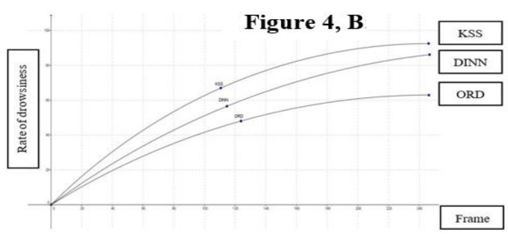
Table 1: Neural networks performance

Model	Identifying a person's image relative to himself (%) [Training]		
	Eye	Mouth	Eyebrows
Precision	96	95	60
Accuracy	98	99	51
Model	Identifying a person's image relative to others (%)[Test]		
	Eye	Mouth	Eyebrows
Precision	94	93	56
Accuracy	96	95	39
Detection (%)	Eye	Mouth	Eyebrows
Sensitivity	98	98	61
Specificity	95	96.5	49

Primary drowsiness detection model: The findings illustrated in Fig. 4, A-B demonstrate the effectiveness of the DINN and ORD for sleepiness detection. Eye tracking accuracy was reported at 91%, with the detection software exhibiting a sensitivity of 79.5% and a feature detection capability of 77%. The integration of facial anthropometric changes with both the KSS and ORD data achieved an average correctness rate of 82% and an accuracy rate of 81%. The neural network's accuracy for sleepiness detection, when incorporating both KSS and ORD data, stood at 78%. Training on individual data improved accuracy to 82%, although testing on different individuals resulted in a reduced accuracy of 76.3%. The average sum of square errors for the training and testing datasets was 0.04369 and 0.0503, respectively, culminating in an overall output accuracy rate of 78%. These results highlight the model's capability for effectively identifying driver drowsiness through facial analysis.



Average sleepiness detection and tracking based on DINN and ORD



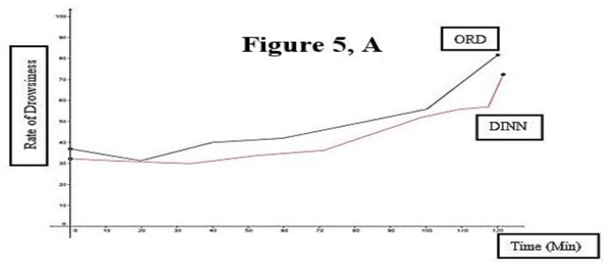
Output comparison of the DINN, KSS, and ORD in a 250-frame dataset

Fig. 4 A-B: Primary drowsiness detection model results

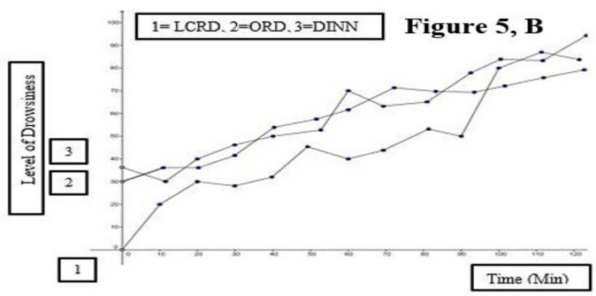
Model test and developing steps

In this phase, the accuracy of the drowsiness detection software was evaluated by comparing sleepiness levels identified by the researcher ORD with those detected by the software. The analysis incorporated data from 25 professional drivers and 10 students, focusing on their crossing of longitudinal lines due to sleepiness to enhance the software's performance. During testing, the DINN achieved an accuracy of 83.3% and a precision of 86.7% among student participants. Improved results were attributed to better camera installation, increased resolution, optimal lighting conditions, and the removal of additional equipment like EEG devices. Fig. 5, A illustrates the changes and comparisons between ORD and DINN variables throughout the driving sessions. The results from 25 professional drivers revealed that seven drivers fully fell asleep, while 13 showed signs of approaching sleepiness, evidenced by multiple deviations from their lane. Only five drivers remained alert without exhibiting sleepiness symptoms. This data, along with film analysis and deviations linked to Lane Crossing Resulted Drowsiness (LCRD), contributed to refining the sleepiness detection model, as shown in Fig. 5, B. A total of 99,643 frames of sleepiness data were collected from the drivers, with

30% used for training the neural network and 70% for testing. The average squared errors for training and testing datasets were 0.02684 and 0.0463, respectively. Ultimately, the output accuracy rate was assessed at 92.3%. The equations (Eq.3-6) governing the neural networks for determining sleepiness levels and developing the initial model are included in the appendix.



Mean variations and comparison test of ORD, DINN variables



Variations of LCRD, ORD, and DINN

Fig. 5 A-B: Model test and developing steps

Final model

The testing results for the drowsiness detection software revealed an accuracy of 92.3% during training with the same individuals and 90.8% during testing with different individuals, leading to an overall final accuracy of 92.1% and a detection feature accuracy of 91%. Under optimal conditions, the software reached detection and identification accuracies of 96.5% and 91%, respectively, for faces without issues. Further details on the neural network regression diagrams for the final model can be found in Fig. 6, with a summary of drowsiness inference and tool accuracy across various face types presented in Table 2.

Table 2: Drowsiness inference and tool accuracy with different types of faces

Faces types	Drowsiness statues	Detected drowsy (%)	Detected non-drowsy (%)
With facial hair	Drowsy	81	19
	Non-drowsy	6	94
With glasses	Drowsy	71	29
	Non-drowsy	17	83
Without facial hair and glasses	Drowsy	89	11
	Non-drowsy	7	93

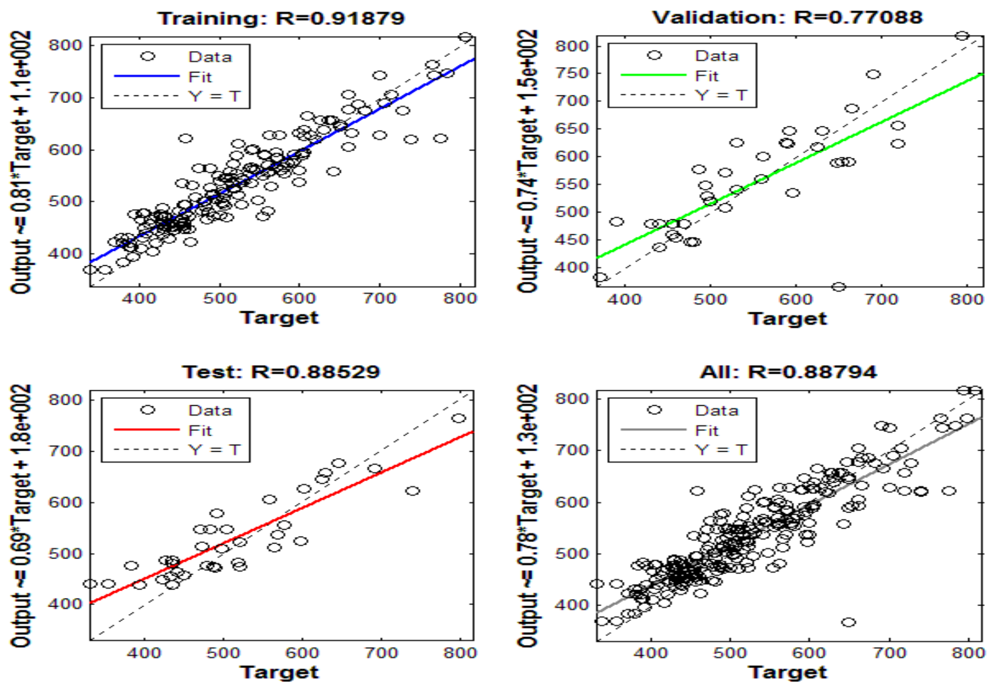


Fig. 6: Neural network regression diagrams

Discussion

This study highlighted key findings from its final step, emphasizing the limitations of existing behavioral approaches to detect driver drowsiness, which primarily focus on tracking eye movements and rapid blinking. While methods like PERCLOS and eyelid blinks have shown high success rates—close to 100% and 98%, respectively—these techniques require considerable time for accurate identification. Additionally, participants must not wear glasses during testing, as glasses can obstruct eye movements and hinder detection accuracy (24, 25).

The study emphasizes that while prior simulations demonstrated high effectiveness in detecting driver drowsiness, these results decline markedly in real-world scenarios, pointing to the limitations of existing methods (2). Golz et al assessed various commercial drowsiness detection solutions and found them inadequate for accurately evaluating driver condition. Their findings indicate that current behavioral metrics do not significantly enhance driver performance, highlighting the necessity for more comprehensive strategies beyond mere behavioral indicators (26).

Recent research highlights that the accuracy and reliability of drowsiness detection through physiological signals exceed those of alternative methods, though concerns about the invasiveness of these measurements persist. To alleviate these concerns, scientists have engineered wireless devices for less invasive data collection. By employing technologies such as Bluetooth and near-field communication, data can be collected without direct electrode attachment to the body, thereby increasing convenience. Additionally, non-invasive methods have advanced with the strategic placement of electrodes on surfaces like the steering wheel or driver's seat, thus enhancing the practicality of monitoring physiological signals for drowsiness detection (27-29).

The signals produced are processed using Android-enabled mobile devices to alert drivers at optimal times. Non-intrusive methods face challenges such as movement artifacts and misalignment of electrodes, which can impair accuracy. Nevertheless, researchers are committed to promoting the use of these devices. Methods for assessment typically utilize the vehicle's Steering Wheel Movement (SWM) and SDLP scale; however, the SWM method is applied by manufacturers only in specific conditions due to its reliance on specialized environments and vehicle geometric characteristics (30).

Detecting driver drowsiness involves various methods, each with distinct advantages and drawbacks. Automotive scales are particularly effective for identifying drowsiness when it results in loss of vehicle control or deviation from the intended path. However, in certain instances, the driver's drowsiness may not affect vehicle parameters, potentially undermining the reliability of detection systems. Ultimately, the accuracy and effectiveness of these detection methods depend on several factors, including sensor types, drowsiness measurement metrics, detection techniques, and the extraction and classification of relevant information (12, 21).

In a study by George et al.(31), various methods were employed for detecting drowsiness, including sensor types and classification techniques such as Convolutional Neural Networks (CNN) and the Viola-Jones algorithm, achieving a detection rate of 98.32%. Conversely, Manu et al utilized a 15fps, 40M pixels camera alongside features like eye closure and yawning detection, applying Dual Support Vector Machines (SVM) with a linear core, resulting in a detection rate of 94.58% (32).

Various studies have explored driver-monitoring systems employing different methodologies to detect driver drowsiness. Reddy et al achieved a detection rate of 91.6% utilizing multi-task cascaded convolutional networks and a driver drowsiness detection network (33). Tipprasert et al reported a remarkable detection rate of 99.47% by implementing infrared cameras and employing support vector machines alongside the histogram of oriented gradients for detecting eye closure and yawning (34). Similarly, Lahoti et al reached the same detection rate of 99.47% using infrared cameras, focusing on aspect ratios and support vector machines (35). In contrast, the present study employed an infrared camera alongside the Viola-Jones algorithm and convolutional neural networks to detect facial features such as eye and mouth closure, resulting in a detection rate of 92.3%.

The proposed model for detecting driver drowsiness achieves a detection rate of at least 90% by utilizing a histogram of facial features, specifically tracking eye position, blink rate, and mouth opening. This comprehensive method examines a continuous sequence of images to analyze various facial expressions, which enhances accuracy compared to existing techniques, yielding detection rates of 92.1% and 91%. Although this study's identification rate is lower than some previous research (Table 2), the approach signifies a notable advancement in driver drowsiness detection systems. It successfully addresses a range of facial conditions, including obstructions from hair and glasses, indicating its potential for real-time applications in various environments. This model could significantly improve D.D.D systems and enhance drowsiness identification across different conditions.

Conclusion

The proposed method offers an innovative and effective strategy for monitoring driver behavior and detecting drowsiness. Moving forward, the research aimed to implement a surveillance system that logs driver activity to assess drowsiness levels, potentially reducing accidents related to driver fatigue. The developed model demonstrates a robust capability to identify drivers' faces under various conditions, including the presence of hair and glasses, achieving a detection accuracy exceeding 90%. This is a great achievement in comparison with previous studies primarily focused on subjects without such obstructions.

Ethical Approval

The approval of Ardabil University of Medical Sciences was obtained for conducting the study.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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Conflict of Interest

The authors declare that there is no conflict of interests.

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