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FULL LENGTH ARTICLE

Comprehensive Survey of Driver Drowsiness Systems

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ABSTRACT

Driver monitoring systems have been improved over time as artificial intelligence and computer technology have advanced. Several experimental studies have collected real-world driver drowsiness data and used various artificial intelligence algorithms and feature combinations to dramatically improve the real-time effectiveness of these systems. This study presents an updated assessment of driver sleepiness detection systems implemented over the last decade. In modern automobiles, assessing the driver's cognitive condition is an important aspect of passenger safety. The term cognitive state refers to a driver's mental and emotional state, which has a substantial impact on their ability to drive safely. Drivers' cognitive states may be altered by factors such as fatigue, distraction, stress, or disability. Intelligent automotive technology may be able to adapt and aid the driver by identifying varied conditions in real time, reducing the frequency of accidents. The face, being an integral component of the body, communicates a significant quantity of information. Facial expressions, such as blinking and yawning patterns, exhibit changes in a driver when they are experiencing fatigue.

Keywords: Passenger Safety ▪ Driver Fatigue ▪ Vehicle-Based Detection ▪ Drowsiness Detection using AI

1. INTRODUCTION

In the past few years, there has been a significant increase in the demand for modern transportation, leading to rapid development in this field. Nowadays, vehicles have become the primary mode of mobility for people. While vehicles have undoubtedly revolutionized our lifestyles and made daily tasks more convenient, they are also associated with certain negative consequences, such as traffic accidents. One major risk factor in traffic accidents is fatigued driving, which poses a significant and often unnoticed danger. As a result, the development of fatigue-driving-detection systems has emerged as a prominent area of research in recent years.

These fatigue-driving-detection systems have become a popular subject of investigation. The detection methods can be broadly classified as either subjective or objective. The subjective method requires active participation from the driver, who evaluates their own level of fatigue through processes such as self-questioning. The data collected from these evaluations can then be used to estimate the number of tired drivers on the road, enabling better scheduling and organization. On the other hand, the objective detection approach does not rely on driver feedback. Instead, it analyses the driver's health state and driving behaviour parameters in real time to determine their level of fatigue. These statistics are then used to estimate the number of vehicles operated by fatigued drivers, enabling the drivers to plan their schedules accordingly. Moreover, objective detection can be categorized into two types: contact detection and non-contact detection. Non-contact detection is more affordable and convenient than contact detection because it allows the device to be used in a larger number of vehicles without requiring computer vision technology or advanced cameras. The non-contact approach has been widely adopted for detecting fatigue-related driving due to its easy installation process and low cost.

Overall, with the increasing reliance on vehicles for transportation, it is crucial to address the issue of fatigued driving. The development of fatigue-driving-detection systems offers promising solutions to identify and prevent potential accidents caused by driver fatigue. By implementing these systems, road safety can be enhanced and a smoother and more secure transportation experience can be ensured for everyone.

2. RELATED WORKS

Deng and Wu [1] proposed the DriCare system, which utilizes a combination of different methods to detect driver drowsiness in real time. These methods include analyzing yawning, assessing blinking patterns, tracking eye movements, and using a convolutional neural network. The DriCare system achieved an accuracy rate of 93%, which can greatly enhance road safety. However, despite its success, the system has limitations related to visible facial features and individual variability in how drowsiness is expressed. To improve accuracy, the system may require a larger and more diverse training dataset. The system is also still in early development and lacks widespread deployment, requiring further validation in real-world driving conditions.

Hashemi et al. [2] presented an innovative method for detecting driver drowsiness based on convolutional neural networks. The proposed approach focuses on real-time driver safety development and demonstrates that deep learning can effectively classify drowsiness-related facial cues. However, practical implementation remains sensitive to dataset quality, lighting, camera placement, and differences in driver appearance.

Savaş and Becerikli [3] developed a real-time driver fatigue detection system using a multi-task convolutional neural network to simultaneously extract facial features and classify drowsiness. The system deals with complexity, prevents overfitting, and tackles data imbalance, improving reliability in practical settings. Nevertheless, its accuracy is not perfect and it may generate false alarms or miss detections, especially under low light or poor visibility. It was also trained on a specific dataset, so generalization to other populations and driving conditions requires further investigation.

Mehta et al. [4] presented a real-time drowsiness detection system focused on two indicators: eye aspect ratio (EAR) and eye closure ratio (ECR). By using a random forest classifier, the system achieved an accuracy rate of 84%. The study highlights the potential of non-intrusive facial landmark detection and EAR/ECR analysis for road safety applications. However, environmental factors such as lighting, shadows, and glare can affect reliability, and false positives may distract drivers or reduce confidence in warning systems.

Varun Chand and Karthikeyan [5] introduced a system combining convolutional neural networks with emotion analysis to improve drowsiness detection and infer the emotional state of drivers. The proposed model achieved 93% accuracy in controlled settings. The study emphasizes the importance of carefully curated datasets and adaptation for real deployment. Real-world performance may still be affected by lighting variation, road conditions, driver behaviour, and the complexity of practical deployment.

Jabbar et al. [7] introduced a driver drowsiness detection model for Android applications using convolutional neural networks. The model achieved high accuracy, especially when drivers were not wearing glasses or were driving at night without glasses. The study also acknowledges challenges such as computational intensity, power consumption, model size, latency, and long-term maintenance, all of which affect real-world performance and practicality on mobile devices.

Satish et al. [9] proposed a drowsiness detection model using hand pressure sensors to improve accuracy. The method considers driving tactics, steering wheel interaction, hand placement, and fatigue status. However, the approach faces challenges such as false positives, false negatives, hardware demands, and response time. Since it requires additional sensing equipment, deployment cost and system calibration must be considered.

Prasath et al. [10] studied driver drowsiness detection using machine learning algorithms. Machine learning approaches can analyse features extracted from driver behaviour, face images, or vehicle signals and classify the driver state. Their effectiveness depends strongly on feature selection, dataset balance, and robustness under real driving conditions.

Dua et al. [11] described a drowsiness detection and alert system designed to warn drivers when fatigue symptoms are detected. Such alerting systems are important because timely feedback may prevent accidents. However, alert systems must balance sensitivity and specificity; excessive false alarms may reduce driver trust, while missed detections may compromise safety.

Bala and Sarath [12] presented an Internet-of-Things-based intelligent drowsiness alert system. IoT integration allows fatigue warnings to be connected with broader vehicle and transportation platforms. This can support remote monitoring and safety analytics, but it also introduces requirements related to connectivity, reliability, privacy, and system security.

Jabbar et al. [13] discussed real-time driver drowsiness detection for Android applications using deep neural network techniques. The work demonstrates the feasibility of deploying deep learning on consumer mobile platforms. However, embedded and mobile implementations must consider computational efficiency, battery consumption, and the diversity of real-world vehicle cabins.

Hossain and George [14] proposed an IoT-based real-time drowsy driving detection system for the prevention of road accidents. By integrating sensors with alert mechanisms, the system aims to identify fatigue and respond quickly. The limitations include sensor reliability, robustness to driver variability, and the need to minimize both false positives and false negatives.

Khan et al. [15] proposed an IoT-based non-intrusive automated driver drowsiness monitoring framework for logistics and public transport applications. Non-intrusive monitoring is particularly important in commercial transport, where safety and operational continuity are critical. Challenges include scalability, privacy, cost, and ensuring robust operation under diverse vehicle and route conditions.

Hu et al. [16] proposed driver drowsiness recognition using a 3D conditional GAN and two-level attention Bi-LSTM. This method uses advanced temporal modelling to capture fatigue patterns over time. Although such approaches can improve recognition performance, they usually require more computational resources, larger datasets, and careful model design.

Muhammad et al. [17] surveyed deep learning for safe autonomous driving and discussed current challenges and future directions. Driver drowsiness detection is part of the broader safe-driving ecosystem, where perception, decision making, and human-state monitoring must work together. The main challenges include robustness, explainability, privacy, and integration with autonomous driving functions.

Altameem et al. [18] investigated early identification and detection of driver drowsiness using hybrid machine learning. Hybrid methods can combine complementary data sources and algorithms to improve accuracy. However, they need careful feature fusion and validation to ensure that performance remains stable in real traffic environments.

Nakai et al. [20] proposed a comprehensive drowsiness-level detection model combining multimodal information. Multimodal systems may use visual, biometric, steering, and behavioural data to improve reliability. Their main limitation is increased system complexity, including sensor synchronization, cost, and calibration.

Soman et al. [21] introduced an Internet-of-Things-assisted artificial-intelligence-enabled drowsiness detection framework. Such systems combine edge sensing and AI analysis to support real-time warning. They can be useful for fleet management, but must handle network constraints, privacy risks, and real-time inference requirements.

Zhang et al. [22] proposed privacy-preserving federated transfer learning for driver drowsiness detection. Transfer learning, including TCL and PFTL-DDD, can outperform traditional centralized and federated learning methods and can be applied to different network architectures. However, privacy preservation, non-IID datasets, communication efficiency, gradient optimization, hardware requirements, and scalability remain important challenges for deployment in vehicles.

3. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

Figure 1 compares the accuracy of different classification methods. The accuracy of a classification method measures how well it correctly predicts the class of a given data point. The comparison shows that FD-NN achieved the highest accuracy (98.15%), followed by Mamdani fuzzy inference system (95.5%), TL-VGG16 (95.45%), TL-VGG19 (95%), circular Hough transform (94%), and DriCare (92%). Other methods such as SVM achieved 90%, while traditional methods such as cold voxel and hot voxel achieved 71% and 87%, respectively.

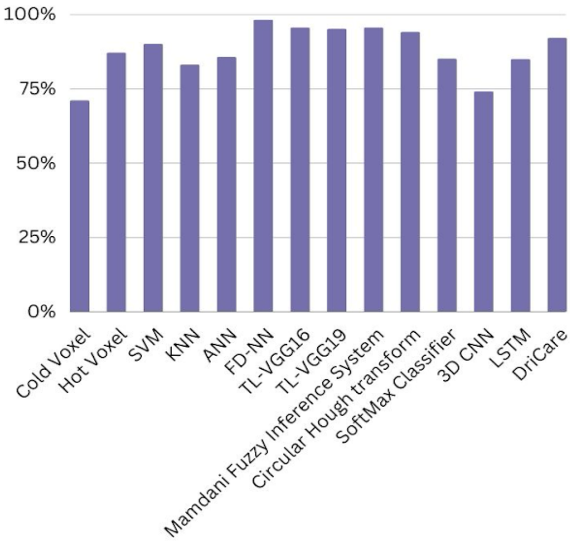
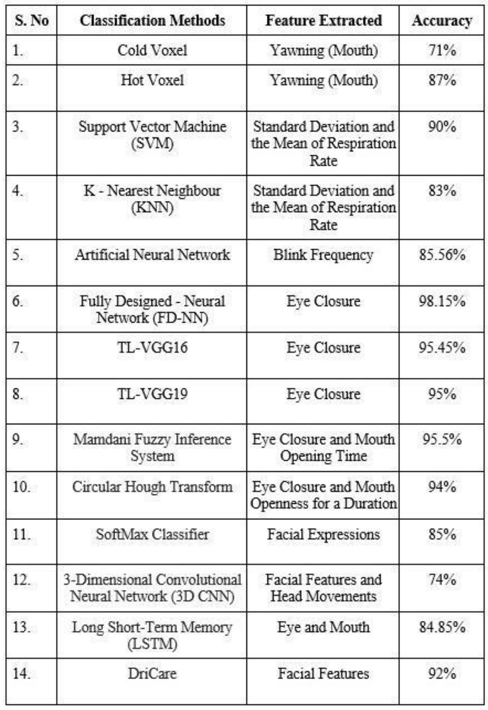


Figure 1. Graphical comparison of accuracy of classification methods.

Table 1 tabulates the features extracted and accuracy values for fourteen classification methods used in driver drowsiness detection. Figure 2 preserves the original table image extracted from the uploaded paper.



S. No	Classification Methods	Feature Extracted	Accuracy
1.	Cold Voxel	Yawning (Mouth)	71%
2.	Hot Voxel	Yawning (Mouth)	87%
3.	Support Vector Machine (SVM)	Standard Deviation and the Mean of Respiration Rate	90%
4.	K - Nearest Neighbour (KNN)	Standard Deviation and the Mean of Respiration Rate	83%
5.	Artificial Neural Network	Blink Frequency	85.56%
6.	Fully Designed - Neural Network (FD-NN)	Eye Closure	98.15%
7.	TL-VGG16	Eye Closure	95.45%
8.	TL-VGG19	Eye Closure	95%
9.	Mamdani Fuzzy Inference System	Eye Closure and Mouth Opening Time	95.5%
10.	Circular Hough Transform	Eye Closure and Mouth Openness for a Duration	94%
11.	SoftMax Classifier	Facial Expressions	85%
12.	3-Dimensional Convolutional Neural Network (3D CNN)	Facial Features and Head Movements	74%
13.	Long Short-Term Memory (LSTM)	Eye and Mouth	84.85%
14.	DriCare	Facial Features	92%

Figure 2. Feature extracted and accuracy of classification methods, reproduced from the source paper.

4. CONCLUSION

Fatigue detection devices installed on drivers significantly improve road safety. These devices are essential in helping drivers recognize symptoms of exhaustion or drowsiness by continuously monitoring their behavior and physiological signals. Such systems are capable of recognizing important

Table 1. Feature extracted and accuracy of classification methods.

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4	K-Nearest Neighbour (KNN)	Standard deviation and mean of respiration rate	83%
5	Artificial Neural Network	Blink frequency	85.56%
6	Fully Designed Neural Network (FD-NN)	Eye closure	98.15%
7	TL-VGG16	Eye closure	95.45%
8	TL-VGG19	Eye closure	95%
9	Mamdani Fuzzy Inference System	Eye closure and mouth opening time	95.5%
10	Circular Hough Transform	Eye closure and mouth openness duration	94%
11	SoftMax Classifier	Facial expressions	85%
12	3-Dimensional Convolutional Neural Network	Facial features and head movements	74%
13	Long Short-Term Memory (LSTM)	Eye and mouth	84.85%
14	DriCare	Facial features	92%

cues, such as eye closure and head nodding, that indicate driver impairment through the use of a variety of sensors and algorithms. The risk caused by tired drivers can be greatly reduced by installing driver drowsiness detection systems in cars, which can lower the number of accidents. These technologies provide a practical way to stop collisions and save lives by warning drivers or turning on autonomous safety features.

While drowsiness-related incidents have decreased thanks to driver tiredness monitoring devices, there are still issues associated with them. These systems use a variety of sensors to detect physiological changes, eye and mouth movements, and other indicators of weariness. However, there is a chance that these sensors will not always correctly detect how tired or sleepy the driver is, which could result in false positives or false negatives. Since every person displays unique signs of weariness, developing a universal fatigue detection system that is reliable for all users is challenging.

The accuracy of these systems can also be impacted by external variables including road condition, lighting, and weather. For instance, the system may have more difficulty accurately detecting facial motions in poorly lit areas. Driver drowsiness detection systems can be significantly improved with enhanced sensor fusion techniques. These systems can be made more accurate and reliable by combining data from multiple sensors, including biometric, steering, and camera sensors. The capacity of driver sleepiness detection systems is further enhanced by the ongoing development of AI and machine learning algorithms. These technologies can identify fatigue symptoms more accurately and analyse intricate data patterns more successfully. Drivers may be able to personalize the alerts they receive when fatigue is identified in the future. To provide additional safety measures, semi-autonomous vehicle technology can integrate driver fatigue detection systems. If tiredness is detected, the vehicle can either initiate autonomous driving mode or provide additional assistance to the driver.

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