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 the 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. The 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 like 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.

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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, we can enhance road safety and ensure a smoother and more secure transportation experience for everyone.

2.**Related Works**

[1] Wanghua Deng, Ruoxue Wu (2019) system 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 utilizing a Convolutional Neural Network. The DriCare System has been able to achieve an impressive accuracy rate of 93%, which greatly enhances road safety. However, despite its success, the system does have some limitations. These limitations are primarily related to visible facial features and the individual variability in how drowsiness is expressed. This research makes a significant contribution to the field of driver drowsiness detection by highlighting the potential of analyzing facial features alongside advanced algorithms for ensuring real-time safety applications. To improve accuracy, the system may require a larger and more diverse dataset for training. Moreover, it's worth noting that the DriCare System is still in early development and lacks widespread deployment, necessitating further research to validate its effectiveness in real-world driving conditions. While promising, these limitations should be considered before using it.

[2] Maryam Hashemi, Alireza Mirrashid et al. (2020) Presented in this study is an innovative method for detecting driver drowsiness in real-time using Convolutional Neural Networks (CNNs). Specifically, the system utilizes Transfer Learning with VGG16 and VGG19 architectures to achieve accurate estimation of eye closure, a crucial factor in identifying drowsiness. Notably, the system maintains low computational complexity while delivering high accuracy. However, certain challenges arise when deploying this system on devices with limited resources due to its data dependency and real-time processing requirements. Despite these hurdles, this research makes a significant contribution towards improving driver safety by showcasing the potential of CNN-based systems in real-time drowsiness detection. The combination of high accuracy and low computational complexity offered by this approach represents a promising advancement towards implementing practical and effective road safety applications. By addressing the pressing issue of driver drowsiness through advanced technology, we can strive for safer roads and prevent accidents caused by fatigue-induced impairment. The system needs to be able to process video frames in real time in order to provide timely alerts to the driver. This can be challenging on devices with limited resources, such as smartphones or embedded systems. Deployment challenges: The system needs to be deployed in a way that is both practical and effective. This may require additional hardware or software components, which can add to the cost and complexity of the system.

[3] Burcu Kir Savaş and Yaşar Becerikli (2020) proposed a real-time driver fatigue detection system has been developed in a study, which utilizes a Multi-Task Convolutional Neural Network (ConNN) to simultaneously extract facial features and classify drowsiness. The system effectively deals with complexity, prevents overfitting, and tackles issues related to data imbalance, thus improving its reliability in practical settings. The study highlights the challenges associated with complexity and data imbalance, underscoring the need for further research and optimization in these areas. This research makes a valuable contribution to driver safety by showcasing the potential of Multi-Task ConNNs for real-time fatigue detection. The system's ability to handle complexity and overfitting while addressing data imbalance represents a significant advancement towards implementing practical and effective road safety applications. The system's accuracy is still not perfect, and it may generate false alarms or miss detections, especially in challenging conditions such as low light or poor visibility. The system was trained on a specific dataset, and it is not clear how well it would generalize to other populations or driving conditions.

[4] Sukrit Mehta, Sharad Dadhich et al. (2020) presented a new study - a driver drowsiness detection system that operates in real-time. The system focuses on two key indicators of drowsiness: Eye Aspect Ratio (EAR) and Eye Closure Ratio (ECR). By utilizing a random forest classifier, the system achieves an impressive accuracy rate of 84%, proving its effectiveness in detecting driver fatigue. The study acknowledges several challenges associated with individual variability and environmental sensitivity. These challenges highlight the need for further research and customization to enhance the reliability of the system. This research contributes to improving driver safety by highlighting the potential of non-intrusive methods like facial landmark detection and EAR/ECR analysis for real-time drowsiness detection. The achievement of high accuracy, while effectively addressing false positives, represents a significant advancement in practical road safety applications. The system may be affected by environmental factors such as lighting conditions, shadows, and glare. This can make it less reliable in real-world driving conditions. The system may generate false positives, i.e., it may flag a driver as drowsy when they are not actually drowsy. This can be annoying and distracting for drivers, and it could also lead them to ignore legitimate warnings about drowsiness.

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[5] H. Varun Chand and J. Karthikeyan (2021) Introduced a new system for detecting driver drowsiness, the study combines Convolutional Neural Networks (CNN) with emotion analysis to improve accuracy and gain insights into the emotional state of drivers. With an impressive accuracy rate of 93%, the proposed model effectively detects driver drowsiness. The study acknowledges challenges related to data availability, annotation, and real-world variability. It emphasizes the importance of carefully curating datasets and adapting models for practical implementation. This research makes a valuable contribution to driver safety by utilizing CNNs and emotion analysis for comprehensive drowsiness detection, including classifying different driver states. The high level of accuracy achieved is a significant advancement towards practical and effective road safety applications. While achieving 93% accuracy in controlled settings, faces uncertainty in real-world performance due to lighting, road condition, and driver behaviour variability. Challenges in data collection, handling real-world complexity, and practical deployment could limit its effectiveness.

[6] Rateb Jabbar, Mohammed Shinoy et al. (2020) in their research paper introduces a model for detecting driver drowsiness in Android applications using Convolutional Neural Networks (CNN). The model has proven to be highly accurate in detecting drowsiness, especially in situations where drivers are not wearing glasses or driving at night without glasses. However, the study acknowledges several challenges such as computational intensity, power consumption, and long-term maintenance. This research makes a valuable contribution to the field of driver safety by utilizing CNN techniques for real-time drowsiness detection on Android devices while also considering resource optimization and device maintenance. Android devices face challenges such as high computational intensity, power consumption, large model sizes, latency, and potential accuracy and interpretability issues, affecting their real-world performance and practicality.

[7] K. Satish, A. Lalitesh et al. (2020) presented a study that introduces a novel drowsiness detection model that utilizes hand pressure sensors to improve accuracy. Although this approach is an impressive accomplishment, it does come with some challenges including false positives, false negatives, hardware demands, and response time. The model's capability to take into account driving tactics, steering wheel interaction, hand placement, and driver fatigue enhances its potential in combating drowsy driving. To make the model practical and effective in real-life situations, further adjustments and optimizations might be required to address the mentioned limitations. It faces issues with false positives and false negatives, hardware demands, uncertain response time, limited consideration of driving tactics and steering wheel interaction, and sensitivity to hand placement on the wheel, potentially impacting its effectiveness and usability in real-world driving scenarios.

[8] N Prasath, J Sreemathy et al. (2022) in their research paper introduces a system for detecting drowsiness that utilizes Machine Learning algorithms to calculate EAR and detect yawns. The inclusion of an alarm system enhances its usefulness. However, the system's effectiveness is dependent on the quality and quantity of data, as well as individual variations and environmental factors. The emphasis on EAR, yawn detection, and the use of a Haar Cascade Classifier are valuable contributions to the field of driver drowsiness detection. Additional research and improvements may be required to address the identified limitations and ensure that the system remains robust and reliable in real-world driving situations. It faces limitations related to data quality and quantity, individual variations in drowsiness expression, susceptibility to environmental factors, and the potential for false positives, which may affect its accuracy and reliability in real-world driving scenarios.

[9] Hemant Kumar Dua, Sanchit Goel et al. (2018) in their research paper introduces a system for detecting and warning against drowsiness, which employs image processing techniques based on computer vision. The incorporation of an alert system into the driver's smartphone provides practical benefits to this solution. However, there are acknowledged challenges pertaining to response time and implementation cost. The emphasis on tackling accidents caused by sleep deprivation through monitoring with cameras and integration with the driver's smartphone is a commendable contribution towards improving road safety. Additional research and optimization might be necessary in order to address the identified limitations and increase accessibility of the system for a broader range of drivers. It faces challenges related to response time, implementation cost, battery consumption, privacy concerns, and limited generalizability, potentially impacting its suitability for widespread adoption and user acceptance.

[10] U.K Ceerthi Bala, TV Sarath (2020) present a sophisticated system for alerting drowsiness, which is based on the Internet of Things (IoT) technology. The integration of IoT with Controller Area Network (CAN) for communication represents significant progress in enhancing road safety. However, there are acknowledged challenges regarding the system's complexity, maintenance requirements, and implementation costs. This focus on improving road safety through advanced driver information systems and IoT technology is a valuable contribution that addresses the issue of road accidents. It may be necessary to conduct further research and make efforts to simplify the system's complexity and reduce implementation costs in order to make it more accessible to a wider range of drivers. The IoT-based driver drowsiness detection system faces limitations concerning

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complexity in design, maintenance demands, and high implementation costs, which can pose challenges for its widespread adoption, particularly for smaller businesses and individual users.

[11] Md. Yousuf Hossain, Fabian Parsia George (2018) present a real-time detection system for drowsy driving based on the Internet of Things (IoT), where a Raspberry Pi controller acts as the central hub. The integration of IoT devices, specifically the use of a camera module for monitoring drivers, is a noteworthy advancement in improving road safety and preventing accidents caused by driver fatigue. However, it is important to acknowledge concerns regarding data privacy and implementation complexity. These factors could potentially impact how acceptable and affordable the system will be. The research showcases a proactive approach to addressing road safety issues through technology and automation. Further research should focus on refining and optimizing the system for practical use on a larger scale while also considering data privacy and cost-effectiveness aspects. The IoT-based drowsy driving detection system faces limitations regarding data privacy concerns, installation complexity, and cost-effectiveness, which are important considerations for widespread adoption and driver acceptance.

[12] Rateb Jabbara, Khalifa Al-Khalifaa et al. (2018) outlines a driver drowsiness detection system that is specifically designed for Android applications. It utilizes Deep Neural Networks (DNN), with a particular focus on Convolutional Neural Networks (CNN). The system's ability to accurately detect drowsiness, achieving an 88% accuracy rate, is both noteworthy and essential for ensuring the safety of drivers. However, it does acknowledge challenges related to resource usage and model complexity. These challenges may limit the practicality of the system on devices with limited resources. By integrating drowsiness detection into mobile applications, this system contributes significantly to enhancing road safety and preventing accidents caused by drowsy driving. Nevertheless, additional research and optimization efforts are necessary to address the identified drawbacks and improve accessibility and efficiency across a broader range of Android devices. The Android-based driver drowsiness detection system faces limitations tied to resource usage, model complexity, and the potential for generating false positives, which can affect battery life, storage constraints, and driver acceptance, respectively.

[13] M. Adil Khan and Tahir Nawaz (2023) present a specialized framework for monitoring driver drowsiness in logistics and public transport using IoT technology. This framework incorporates various techniques, including thresholding-based, traditional machine learning-based, and deep learning-based approaches. The goal of this comprehensive approach is to enhance road safety by preventing accidents caused by driver drowsiness. The effectiveness of the system is demonstrated through its ability to achieve high precision, recall, and accuracy in identifying alert and attentive driving behavior. However, the paper acknowledges that challenges may arise when dealing with misclassifications related to reflections from drivers' glasses. This research makes a significant contribution to the field of Advanced Driver Assistance Systems (ADAS) and road safety by introducing a non-intrusive monitoring framework. To optimize this system for real-world applications, further refinement is needed along with consideration for potential misclassifications resulting from unique scenarios such as reflections. Overall, this research paper provides valuable insights into how IoT technology can be utilized in driver drowsiness monitoring systems for logistics and public transportation sectors. By addressing challenges specific to these industries and continuously improving the framework's accuracy, road safety can be significantly enhanced. The specialized IoT-based drowsiness monitoring framework encounters limitations including misclassifications due to driver's glasses reflections, generalizability to real-world conditions, cost and complexity of hardware, and potential privacy concerns, which are crucial considerations for its practical deployment in logistics and public transport settings.

[14] Yaocong Hu, Mingqi Lu, Chao Xie et al. (2020) introduce an advanced driver drowsiness recognition framework that is up-to-date and employs a combination of various techniques. These techniques include face detection/tracking, 3D conditional GAN, Two-Level Attention Bi-LSTM, and temporal smoothing. The incorporation of temporal smoothing significantly improves the accuracy of the system by increasing the total accuracy rate by 4%. The paper highlights the effectiveness of this proposed framework through quantitative experiments and comparisons with other state-of-the-art methods. This research makes a valuable contribution to the field of driver safety and drowsiness detection by introducing a robust and sophisticated recognition system. Further exploration and practical application of this framework could have a significant impact on road safety measures and accident prevention efforts. The advanced driver drowsiness recognition framework grapples with limitations involving computational complexity, data requirements, susceptibility to environmental factors, and the potential for generating false positives, which can impact its computational efficiency, data acquisition efforts, real-world reliability, and driver acceptance, respectively.

[15] Muhammad Ramzan, Hikmat Ullah Khan et al. (2019) in their survey document act as a thorough guide for those intrigued by the realm of identifying sleepiness. It organizes current methods, performs a comparative

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examination of classifiers, and assesses existing models. This offers an organized and enlightening depiction of the latest advancements in detecting drowsiness. Professionals and researchers specializing in driver safety systems can gain valuable knowledge and organization from this survey's findings. The limitations of the survey include its reliance on published scientific literature, potentially missing the latest innovations. It also focuses on real-world dataset evaluations, which might not represent all driving conditions. Moreover, the survey doesn't address real-world implementation challenges, crucial for understanding practical system reliability.

[16] Sandeep Kumar, Abdul Khader Jilani Saudagar et al. (2021) discuss how physiological signals, such as EEG, ECG, and EOG, can be used to accurately detect driver drowsiness. These signals provide valuable information about the driver's physical state, which can indicate if they are feeling sleepy. However, it is important to consider certain factors that may affect the accuracy of drowsiness detection when using physiological signals. For example, stress and medication can impact the reliability of these signals. Therefore, in order to develop robust detection systems for real-world scenarios, it is crucial to take into account variations and external influences. In summary, this research paper explores the use of physiological signals and hybrid machine learning algorithms for identifying and detecting driver drowsiness. While there is potential for accurate detection with these signals, challenges related to external factors and cost must be addressed in order to implement them practically. This research contributes innovative approaches towards mitigating the risks associated with drowsy driving and preventing accidents on the roadways. Using physiological signals for drowsiness detection has limitations due to external factors affecting signal accuracy, the cost of sensors, and privacy concerns that may deter drivers from using such systems.

[17] Jaime Lloret, Khan Muhammad at al. (2020) discuss the advancements made in vehicular sensors, highlighting their ability to perform a wide range of tasks, both simple and complex. These tasks include object detection, localization, tracking, and activity recognition. All of these functionalities are crucial for various applications in autonomous driving. Another topic covered in the paper is the use of deep learning approaches within autonomous driving systems. Deep learning has played a significant role in enabling autonomous vehicles to perform tasks such as road detection, lane detection, vehicle detection, pedestrian detection, drowsiness detection, collision avoidance, and traffic sign detection. The limitations in advancements in vehicular sensors, including cost, reliability, and security concerns. Additionally, the use of deep learning in autonomous driving systems faces accuracy challenges in real-world conditions, explainability issues, and significant computational requirements, impacting its practical application in vehicles.

[18] Mika Sunagawa, Shin-ichi Shikii et al. (2020) The research conducted involved the collection of a wide range of data from 49 participants. This data included different physiological and behavioural measurements such as eye movements, heart rate variability, and frequency of speed changes. By utilizing multiple sources of data, the study was able to provide a comprehensive assessment of drowsiness. The main focus of the proposed model was to detect various levels of drowsiness in individuals, ranging from mild to severe. The model achieved an F1-score of 53.6% and a root mean square error value of 0.620. These metrics indicate that the model is capable of accurately identifying different stages or levels o f drowsiness experienced by drivers. However, it should be noted that while the accuracy achieved by the model is reasonable, with an accuracy rate at 53.6%, there may be certain applications where this level might not be sufficient for critical safety purposes. The study and proposed model have limitations, including a small sample size that might not fully represent diverse demographics, potential difficulty in generalizing the model's performance to real-world conditions, and the possibility of an incomplete feature set that could affect detection accuracy.

[19] Sibu Philip Soman, G. Senthil Kumar at al. (2023) in the drowsiness detection framework provides a comprehensive approach by taking into account various behavioural factors. It has achieved a high validation score, indicating its potential for real-time implementation. Real-world testing has confirmed the effectiveness of the framework in practical driving scenarios. The deep learning algorithm demonstrates advanced artificial intelligence techniques in detecting drowsiness. Further research and improvement can be focused on data fusion optimization and sensor details. It is important to note that the framework primarily focuses on detection and does not discuss intervention strategies. Addressing integration challenges is crucial for successful practical deployment of the framework. In conclusion, the "Internet-of-Things-Assisted Artificial Intelligence-Enabled Drowsiness Detection Framework" combines multiple sources of data and utilizes deep learning to accurately detect drowsiness. The limitations to consider include the absence of intervention strategies for drowsiness, integration challenges that need clarification, potential optimization of data fusion, the need for more detailed sensor information, and a desire for greater clarity on the validation process and metrics used to define a "high" validation score, all of which are critical for assessing the framework's practicality and effectiveness.

[20] Linlin Zhang, Hideo Saito, Liang Yang et al. (2020) examines various techniques for detecting driver drowsiness and emphasizes the benefits of PFTL-DDD, which provides improved accuracy and privacy

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safeguards. Transfer learning, specifically TCL and PFTL-DDD, surpasses traditional CL and FL methods in terms of performance. PFTL-DDD can be applied to different network architectures, ensuring consistent convergence rates. Safeguarding privacy is a major concern in federated learning as it has the potential to expose sensitive driver information. Striking a balance between communication efficiency and model performance is a challenge in industrial settings where effective management of communication costs is necessary. "Privacy-Preserving Federated Transfer Learning for Driver Drowsiness Detection" presents an advanced approach to detecting drowsiness using transfer learning and federated techniques. While it offers significant advantages, it also faces challenges related to gradient descent optimization, non-IID datasets, maintaining privacy, and managing communication costs effectively. The limitations include the lack of specific information regarding gradient descent optimization challenges, insufficient elaboration on how non-IID datasets impact model training, a need for more details on privacy preservation techniques, limited discussion on strategies to manage communication costs effectively, and the absence of insights into the real-world applicability of the federated transfer learning approach, encompassing hardware requirements and scalability for practical deployment in vehicles.

3.**Comparative Analysis of Existing Systems**

Fig. 2. tabulates the accuracy of 14 different classification methods and the feature extracted in each case. Fig. 1. compares the accuracy of different classification methods. The accuracy of a classification method is a measure of how well it can correctly predict the class of a given data point. It shows that FD-NNs achieved the highest accuracy (98.15%), followed by DriCare (92%), TL-VGG16 (95.45%), and TL-VGG19 (95%). Other methods that achieved high accuracy include MFIS (95.5%), circular Hough transform (94%), and SVM (90%). Traditional methods such as cold voxel and hot voxel achieved lower accuracy (71% and 87%, respectively).

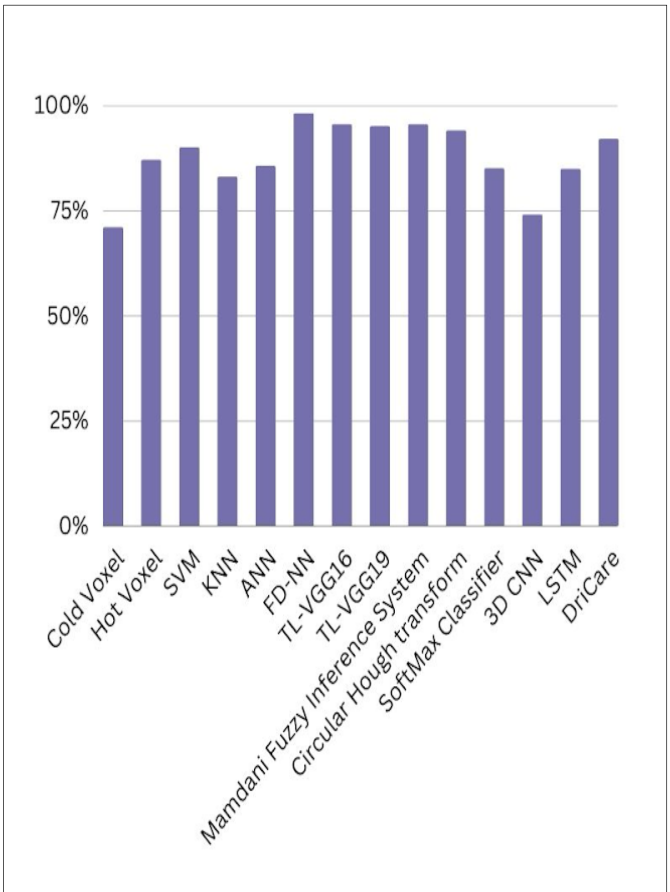

Figure 1: Graphical comparison of accuracy of classification methods

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Table 1: Feature Extracted And Accuracy Of Classification Methods

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

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. These systems are capable of recognizing important cues, like 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 will 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 some issues with them. These systems use a variety of sensors to detect physiological changes, eye and mouth movements, and other indicators of weariness. However, there's a chance that these sensors won't 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 outside variables including the state of the roads, lighting, and weather. For instance, the system may have more difficulty accurately detecting face motions in less lit areas. Driver drowsiness detection systems can be significantly improved with improved 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 analyze intricate data patterns more successfully. Drivers may be able to personalize the alerts they get when fatigue is identified in the future. To provide additional safety measures, semi-autonomous vehicle technology can integrate driver fatigue detection systems. Should the system detect tiredness, it can either initiate autonomous driving mode or provide the driver help.

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