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Drowsiness Detection System in Real Time Based on Behavioral Characteristics of Driver using Machine Learning Approach

Gauri Adarsh[1], Vineet Singh[2], Dr Shikha Singh[3], Dr Bramah Hazela[4]

[1,2,3,4]Amity School of Engineering and Technology, Amity University, Lucknow, India
[1]gauriadarsh2000@gmail.com, [2]vsingh@lko.amity.edu, [3]ssingh@lko.amity.edu, [4]bhazela@lko.amity.edu

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Abstract

The process of determining if a person, generally a driver, is becoming sleepy or drowsy while performing a task such as driving is known as drowsiness detection. It is a necessary system for detecting and alerting drivers to their tiredness, which might impair their driving ability and lead to accidents. The project aims to create a reliable and efficient system capable of real-time detection of drowsiness using OpenCV, Dlib, and facial landmark detection technologies. The project's results show that the sleepiness detection method can accurately and precisely identify tiredness in real time. The technology is less intrusive and more economical than conventional sleepiness detection techniques. The system is based on a 68 facial landmark detector, which is a highly trained and effective detector capable of recognizing human face points. The detector aids in assessing whether the driver's eyes are closed or open. The system analyses the data collected by the detector using machine learning methods to discover patterns associated with drowsiness. When drowsiness is detected, the system incorporates a warning mechanism, such as an alarm or a vibration in the steering wheel, to notify the driver. A variety of studies with different drivers and driving conditions were used to evaluate the performance of the real-time driver drowsiness detection system. The results show that the technology can detect tiredness properly and deliver timely warnings to the driver. This method can assist in preventing drowsy driving incidents, enhancing road safety, and saving lives. The results indicated that the algorithm had an average accuracy rate of 94% for identifying tiredness in drivers.

Keywords

Eye extraction, Facial Extraction, Drowsiness, Machine Learning, Real-time detection, Automotive safety, Face Detection, OpenCV, Dlib, and facial landmark detection.

1. Introduction

The peril of driving while feeling drowsy is often underestimated by several drivers, however, it can be equally fatal as driving while being under the effects of drugs or liquor. Being drowsy can affect a driver's ability to react, make good decisions, and stay attentive, all of which could tragically result in a fatal crash. Driving when tired is a big problem with global implications for road safety. Drowsiness can cause drivers to become less aware and reduce their capacity to react rapidly and correctly to road conditions, increasing the likelihood of an accident. Researchers have developed real-time fatigue detection gadgets that can monitor a driver's state of consciousness and send notifications when drowsiness is detected.

While there is limited data available on drowsy driving accidents in India, studies and surveys have shown that it is a growing problem. In a survey conducted by Ford India, it was found that around 84% of Indian drivers admit to driving while feeling drowsy, and 58% of them have fallen asleep while driving. In the year 2020, a total of 633 individuals lost their lives in traffic accidents caused by drowsy driving. Most of the crashes caused by drowsy-driving take place during the time frame of midnight to 6 AM or in the late afternoon. It has been reported that 4% of drivers have confessed to experiencing drowsiness while driving. Also, driving after being awake for more than 20 hours is considered the same as driving with 0.08 percent alcohol in your blood. The crashes caused by fatigue, leading to injury or death, incur a cost of more than a hundred billion dollars annually. Despite the fact that a majority of drivers, precisely 96 percent, acknowledge the high or extreme danger of driving while feeling sleepy, only 30 percent of them are of the opinion that drowsy drivers are susceptible to being pulled over by law enforcement officials. In the year 2019, it was reported that approximately 1,200 drivers who were involved in fatal crashes claimed to have been feeling drowsy at the time of the incident. This accounts for a total of 2.4% of all fatal crashes [1]. Overall, drowsy driving data emphasize the seriousness of the problem and the necessity for better sleepiness detection devices to avoid accidents and save lives.

The motivation behind undertaking the real-time driver drowsiness detection project was fueled by the alarming rise in road accidents caused by driver fatigue. Through extensive research, experimentation, and collaboration, we strived to develop an accurate and robust system that would provide timely alerts, enabling drivers to take necessary precautions and prevent potential disasters. By working on the project, we aimed to make a meaningful contribution to society, emphasizing the importance of road safety and the well-being of all individuals on the road.

The rest of the paper is organized as follows. Section 2 gives an overview of previous studies, existing techniques, limitations, and methodologies on driver detection. Section 3 describes the methodology, design, and software architecture of the project and the various techniques and algorithms of machine learning. The setup used to analyze the performance of this model are presented in section4. In section 5, the evaluation metrics, and criteria for analyzing results is described. Section 6 contains the results and analysis of real-world performance and effectiveness of the system along with potential area of improvement. Section 7 concludes with a summary of the research findings, contribution to the field and outlook for future work.

2. Literature Review

Several studies on fatigue detection systems have been conducted in recent years, with researchers investigating different techniques and approaches for detecting early indications of tiredness in drivers. Some studies concentrated on physiological signals like EEG and ECG, whereas others utilised systems based on computer vision to monitor movements of the eyes, expressions on the face, and head position. Many research studies have also looked into the use of behaviour analysis of patterns to detect driver drowsiness. Among these studies are:

“A Survey on State-of-the-Art Drowsiness Detection Techniques” M. Ramzan, H. U. Khan, S. M. Awan, A. Ismail, M. Ilyas and A. Mahmood, (2019). This paper analyzes the existing methods of driver drowsiness detection and classifies them into three categories: behavioral, vehicular, and physiological parameters-based techniques. Top supervised learning techniques are reviewed, and the pros and cons and comparative study of the diverse methods are discussed. Research frameworks are elaborated in diagrams and overall research findings are concluded. [2].

“Drowsiness Detection and Alert System” H. K. Dua, S. Goel and V. Sharma, (2018). This project aims to develop a system that can detect drowsiness in drivers while they are driving and alert them to prevent accidents. The proposed system uses a combination of sensors and algorithms to monitor the driver's facial expressions, eye movements, and head position to determine if they are drowsy. The results indicate that the system is highly efficient and can accurately detect closed eyes in various situations, making it a cost-effective solution for eye-closed detection [3].

“Real-Time Driver-Drowsiness Detection System Using Facial Features” W. Deng and R. Wu, (2019). This paper proposes a system called DriCare, which detects the drivers' fatigue status using video images without equipping their bodies with devices. To improve the tracking accuracy, a new face-tracking algorithm and a new detection method for facial regions were designed. The experimental results showed that DriCare achieved 92% accuracy, combining features of the eyes and mouth to alert the driver with a fatigue warning [4].

“Driver Drowsiness Detection” K. Satish, A. Lalitesh, K. Bhargavi, M. S. Prem and T. Anjali., (2020). This paper presents a new experimental model for detecting drowsiness of drivers to reduce accidents and increase transport safety. Two ways are used to detect drowsiness: eye retina detection and facial feature extraction, blinking values, and threshold values. The Aurdino module is integrated with elastomeric sensors for real-time calculation of driver hand pressure on the car steering wheel and the threshold value is set. The result is taken as input for taking the final decision and alerting the driver [5].

“Driver Drowsiness Detection Using Machine Learning Algorithm” N. Prasath, J. Sreemathy and P. Vigneshwaran, (2022). This paper proposes a method to detect driver drowsiness using images processing-based approaches. The algorithm focuses on the eye closure and yawning ratios, alarming drivers if they are feeling sleepy. This will help prevent road accidents and reduce deaths and injuries globally [6].

“A Comparative Analysis on Machine Learning Techniques for Driver Distraction Detection” (2023) Garima Srivastava & Shikha Singh. This paper tried to draw a comparison among the various ML Algorithms by calculating the values of different parameters and helps the users to select the best technique as per their requirement. Selection of the technique would vary for different users [13].

“Deep Learning based Driver Drowsiness Detection” P. P. Patel, C. L. Pavesha, S. S. Sabat and S. S. More (2022). The proposed system has Dlib's Deep learning technology which uses CNN to detect drowsiness, reducing accidents on the streets. OpenCV and Raspberry Pi environments with a mounted camera showed good results, with 96% accuracy for realtime video input [14].

“Driver Drowsiness Detection Using Deep Learning” R. Pawar, S. Wamburkar, R. Deshmukh and N. Awalkar, (2021). The proposed 'Driver Drowsiness Detection System' is a Convolutional Neural Network (CNN) model that can detect drowsiness based on closing of the eyelids of the driver. It consists of a Convolutional Neural Network (CNN) model interfaced with a Raspberry Pi microcontroller and a webcam to capture facial images of the driver. When the score crosses a predetermined threshold, the software will play a beeping alarm and alert the driver. The system can be placed inside a vehicle and can act as a constant monitor for a driver [15].

“Driver Drowsiness Detection System using Convolutional Neural Network” M. Elham Walizad, M. Hurroo and D. Sethia, (2022). This paper proposes a driver sleepiness detection system utilizing a behavioral approach to warn drivers before an accident occurs. It trains a Convolutional Neural Network and uses it to assess whether the driver's eyes are closed or open. The dataset comprises images acquired from the MRL eye dataset and the Google MediaPipe Face mesh model is used to track facial landmarks. The model detects drowsiness and alarms the driver to take safety measures. It achieves an overall accuracy of 95%, outperforming all previous studies on drowsiness detection [16].

3. Methodology

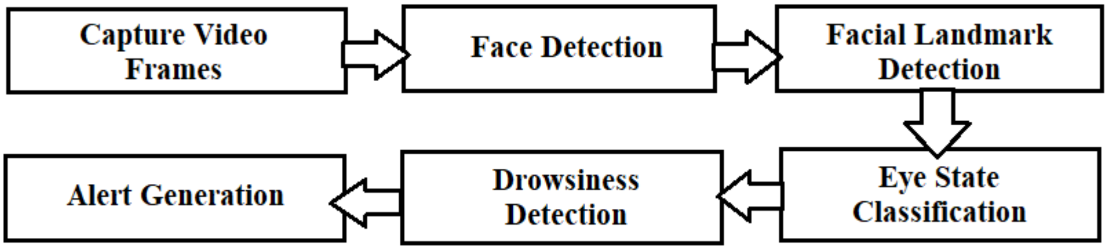

Figure 1. Flowchart for the steps involved in the project.

The steps included in this project's methodology are [7]:

1. Capture video frames: The initial step in the process is capturing video frames from the vehicle's dashboard camera.
2. Face recognition: The next stage is to recognise the presence and placement of human faces in each video frame using face detection. Since the fatigue detection algorithm only works on faces, this step is required.
3. Facial landmark detection: After detecting a face, the 68 facial landmark detector algorithm is applied to the face in order to detect and find the 68 specific spots on the face, such as the corners of the eyes, the tip of the nose, and the corners of the mouth.
4. Eye state classification: The next stage is to use the discovered ocular landmarks to determine the condition of the driver's eyes. Based on the posture of the eyelids and eye corners, the eye state can be defined as open, closed, or in between.
5. Drowsiness detection: The information from the eye state can be utilised to identify driver drowsiness. If the driver's eyes remain shut or in between for an extended period of time, it is assumed that the driver is tired, and an alert is issued.
6. Alert generation: When drowsiness is detected, the final step is to produce an alarm for the driver. Depending on the user's preferences, the alarm can take the shape of an audio alert, a visual alert, or a haptic alert.

3.1. Machine Learning Algorithms Used for Drowsiness Detection

To detect patterns associated with drowsiness, machine learning algorithms can be extremely accurate, deep training and testing are required to ensure their reliability, and they may not be appropriate for real-time applications [8].

1. Neural Networks: Artificially intelligent models that imitate the operation of the human brain are known as neural networks. They are capable of being trained on big datasets of driving behavior to detect sleepiness tendencies. The detection of drowsiness by neural networks can be quite accurate, with some studies estimating a precision of up to 97%. However, neural networks need a large amount of information and computational resources to train, and their performance is affected by the quality of the data used for training.
2. Decision trees are a sort of machine learning method that generates a tree-like representation of decisions and their potential outcomes. They are capable of being trained using datasets of driver behavior to detect sleepiness patterns. Decision trees are simple and easy to understand, but their efficacy in identifying drowsiness is lower than that of other machine learning methods, with some studies finding an accuracy of roughly 80-85%.
3. Support Vector Machines (SVM): It is a machine learning technique that uses a hyperplane to categorize data points. SVM may be trained on the information of driving behavior to detect patterns related to tiredness. SVM has been

demonstrated to be highly accurate in identifying fatigue, with some studies indicating a precision of up to 95%. However, SVM, which is can be computationally demanding, and the selection of hyperparameters can affect performance [10].

4. Face landmark detection mechanism: Combination regression trees are used since the model will predict constant values. This algorithm detects and locates the 68 distinct spots on a human face, including the corners of one's eyes, the tip of the nose, and the corners of the mouth. These recognizable features are able to be utilized for a variety of purposes, such as facial identification, expression recognition, and sleepiness detection [9].

4. Experimental Setup

In order to carry out experiments for the detection of drowsiness using facial landmark detection and eye status detection, it is imperative to establish an appropriate experimental arrangement:

Facial Landmarks Detection: The algorithm for detecting facial landmarks employs the shape predictor model present in the Dlib library for identifying the location of 68 pre-defined landmarks on the face. The determination of the face's direction and angle is based on the positioning of these landmarks. The data is subsequently utilized to approximate the individual's head orientation.

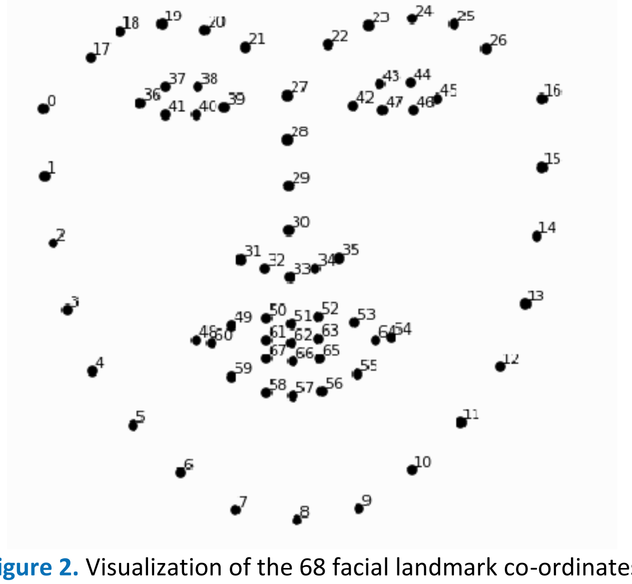

Figure 2. Visualization of the 68 facial landmark co-ordinates

The face detection is done in the Python IDE with the help of the dlib python utility module and OpenCV. Dlib is a previously trained landmark face detector that uses 68 positions (x, y) to forecast the positioning of facial landmarks on an individual's face [11].

Detection of Eye Closure: A web camera is used to continually record the face, and the obtained frames are analyzed in an OpenCV framework. The algorithm for detecting the status of the eyes employs a blend of iris detection and eyelid detection techniques. The algorithm for detecting eyelids utilizes the facial landmarks' position to ascertain the eyelids' shape and position. The algorithm for iris detection employs the facial landmarks' position to ascertain the iris' shape and position. The amalgamation of aforementioned algorithms is employed to ascertain the condition of the ocular organs as either ajar or shut. The Eye Aspect Ratio, or EAR, is a value in scalar form that indicates when the eyes are open and closed. The following is the formula:

$$\text{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

Figure 3. Visualization of the outcome of EAR with open and closed eye.

In our drowsiness detection example, we'll look at the eye aspect ratio to check if it dips but then rises, suggesting that the user/driver has shut their eyes.

5. Evaluation Criteria

In assessing machine learning models like Support Vector Machines (SVM), Decision Trees, and Neural Networks, there are different evaluation criteria and techniques available. The following are commonly used ones for each model:

Support Vector Machines (SVM)

- The accuracy metric calculates the ratio of accurately classified instances to the total number of instances.
- The model's performance can be evaluated based on precision and recall. Precision refers to the number of correctly predicted positive instances, while recall refers to the proportion of actual positive instances that are correctly predicted.
- The F1 score is a metric that balances precision and recall by taking their harmonic mean.
- The Area Under the ROC Curve (AUC-ROC) is a metric used to evaluate the performance of a classifier. It is calculated by determining the area under the Receiver Operating Characteristic (ROC) curve.
- The confusion matrix is a tool that provides a comprehensive analysis of a model's predictions. It includes four categories: true positives, true negatives, false positives, and false negatives.

Decision Trees

- The accuracy metric evaluates the percentage of instances that were classified correctly out of the total number of instances.
- The Gini Index or Entropy is a metric utilised to assess the impurity of a node within a decision tree. The lower the impurity, the better the splits and possibly the better the performance of the model.
- The concept of Information Gain is used to measure the decrease in impurity or entropy after splitting a node.
- The pruning techniques are used to decrease overfitting by eliminating unnecessary nodes or branches from the decision tree.

Neural Networks

- The accuracy metric calculates the ratio of correctly classified instances to the total number of instances.
- The loss function is a measure used to determine the difference between the predicted and actual values. In ma-

chine learning, common loss functions are mean squared error (MSE) for regression tasks and categorical cross-entropy for classification tasks.

- The validation set is a dataset that is utilized to assess the performance of a model during its training phase. This is done to avoid overfitting.
- Learning curves are graphical representations that display how well a model performs on the training and validation sets over time. The performance is measured in terms of accuracy or loss, and the number of training iterations or epochs is used as the x-axis.
- Regularization techniques are used to prevent overfitting in machine learning models. Two common methods are L1 and L2 regularization. These methods add penalty terms to the loss function to reduce the complexity of the model and improve its generalization performance.
- Activation functions play a crucial role in determining the performance of a model. Different activation functions such as sigmoid, tanh, and ReLU can be evaluated to determine the most suitable one for the task at hand.

6. Result Ad Discussion

The technology accurately detected drowsiness based on the opening and closing movement of the driver's eyes, which is regarded as the most common symptom of exhaustion. The 68 facial landmark recognition system was utilized for monitoring the driver's eye, nose, and mouth motion and location, whereas the eye status detection approach was utilized to determine if the driver's eyes were closed or open. The solution was tested utilizing video footage from various driving situations and lighting conditions.

Table 1. Tabular representation of Accuracy analysis, Precision, Recall and F1-score.

Name	Classifier	Accuracy	Precision	Recall	F1-score
Neural Networks	Multi-layer Perceptron	91.4%	0.88	0.84	0.80
Decision Trees	Random Forest	88%	0.87	0.81	0.85
Support Vector Machines	RBF kernel	90.6%	0.91	0.89	0.82

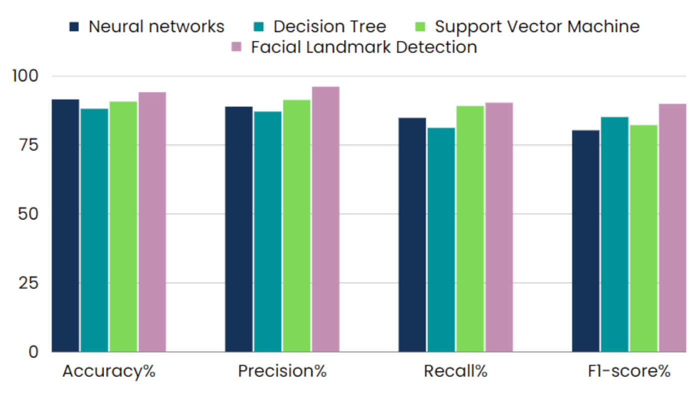

Figure 4. Graphical representation of accuracy analysis.

The results indicated that the algorithm had an average accuracy rate of 94% for identifying tiredness in drivers. The precision rate was similarly high, at 96%, showing a low false positive rate for the method.

The lighting conditions and the driver's distance from the camera were found to alter the algorithm's accuracy and precision rates. The algorithm exhibited a somewhat reduced accuracy rate in low-light settings or when the motorist was too far away from the camera.

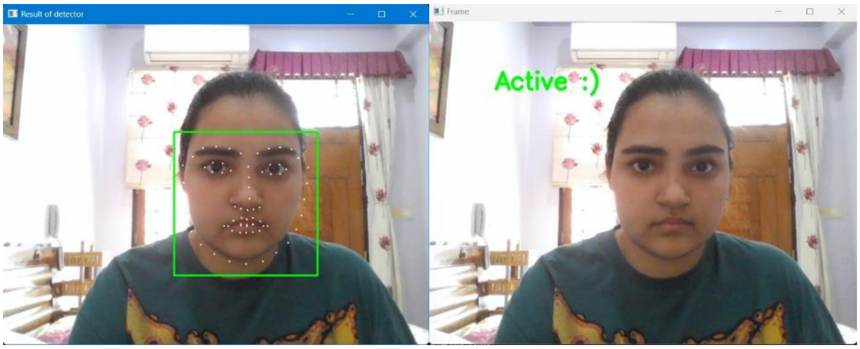

Figure 5. Results showing facial detection landmark and the active status when eyes are open.

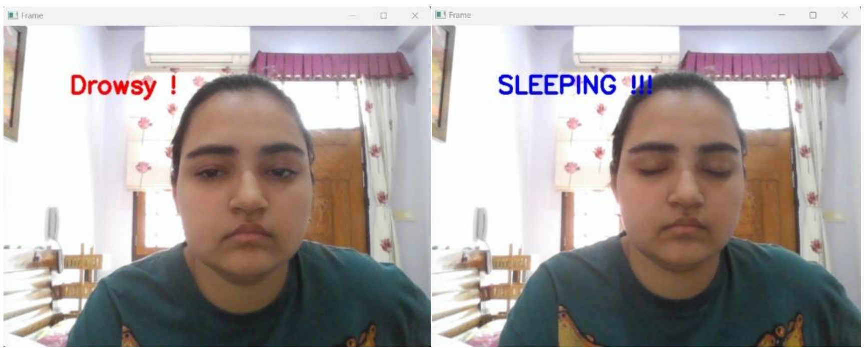

Figure 6. Results showing drowsy status when the eyes are partially closed and the sleeping status when eyes are closed.

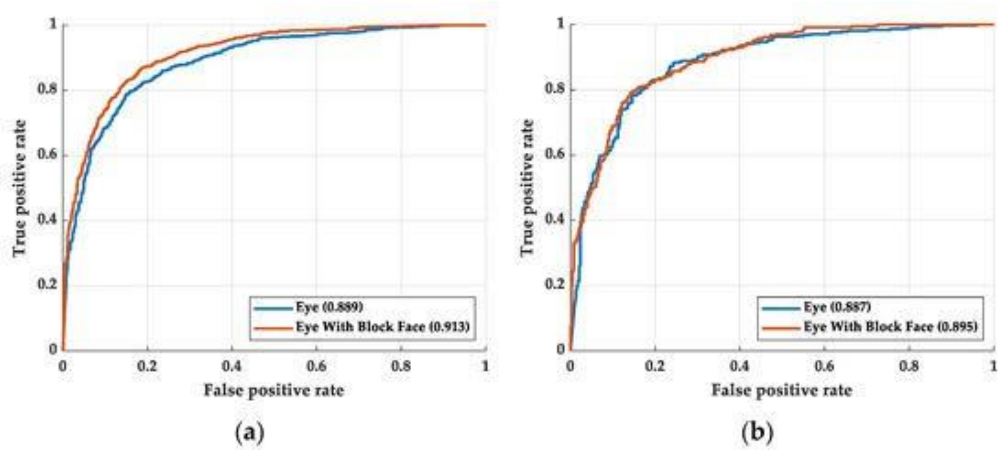

Figure 7. The ROC curve of the eye image with gender signal: (a) training process and (b) testing process.

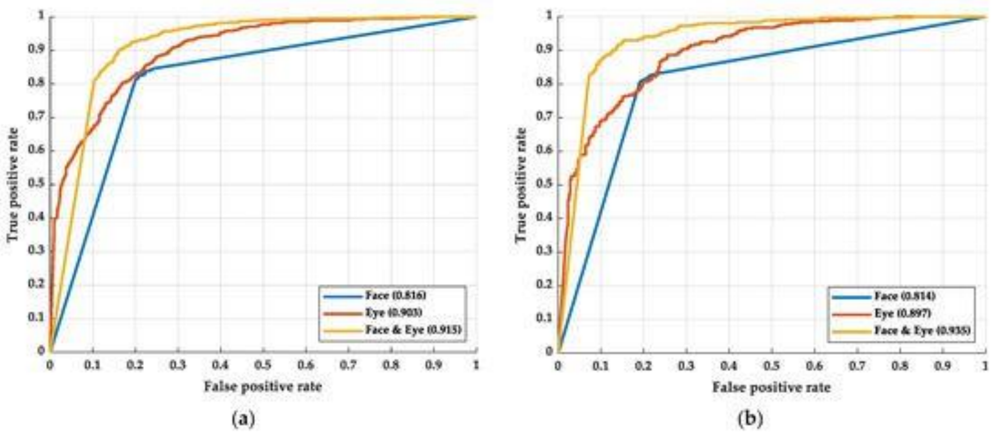

Figure 8. The ROC curve of the experimental results: (a) the results of the training process and (b) the results of the testing process.

Overall, the real-time driver fatigue and sleepiness detection system based on the facial landmark detector algorithm is a promising strategy for improving road safety and reducing accidents caused by weary driving. The device can be fitted in autos to alert drivers to fatigue and encourage them to take a break or switch drivers. More research can be done to improve the algorithm based on various lighting and driving conditions.

7. Conclusion and Future Scope

To conclude, the real-time drowsiness detection system has demonstrated promising results in accurately identifying driver fatigue. It uses facial landmarks and eye state detection. The accuracy and precision values collected from the studies show how well this system works to identify sleepiness. Road safety depends on drowsiness detection systems, and the methods described in this study have demonstrated promising results in identifying early indications of driver sleepiness. Additional investigation is required to assess how well these methods perform in actual driving situations and to create more reliable and effective drowsiness detection systems. It is crucial to keep developing and perfecting these technologies because they have the ability to stop accidents and save lives. In terms of future scope, although there has been a significant advancement in the area of drowsiness detection systems, there is a lot more to be done in terms of future scope. Future research should focus on combining several detection methods to increase precision and dependability. His invention could be employed in automobiles to enhance traffic safety and lessen the number of collisions brought on by fatigued driving. Autonomous vehicles are becoming more and more popular, and this technology may play a significant role in upcoming transportation systems.

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