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Driver Drowsiness Detection using Deep Learning

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Abstract- *According to the National Highway Traffic Safety Administration (NHTSA), drowsiness is a leading cause of road accidents. To address this problem, various methods based on monitoring driver behavior and vehicle dynamics have been suggested and implemented. Traditional vehicle-based methods typically rely on fixed parameters, such as variations in steering wheel angle or lane departure, to detect drowsiness. However, these parameters may not always accurately indicate a driver's alertness level. Consequently, it is crucial to develop a more effective method for detecting driver drowsiness.*

Deep learning techniques, particularly convolutional neural networks (CNN), offer a robust solution for identifying drowsiness by analyzing drivers' facial features. The proposed CNN-based approach focuses on the eye and mouth regions, using the nose as a reference point. Utilizing the rectified linear activation function (ReLU), this CNN method achieves an accuracy of 94.95%, outperforming existing methods even under challenging conditions such as low light, different head angles, and drivers wearing transparent glasses.

Keywords- *Convolutional Neural Network (CNN), Electrooculography (EOG), and Rectified linear activation function (ReLU).*

1 INTRODUCTION

Driver drowsiness is a major cause of road accidents . Prolonged periods of driving can lead to significant fatigue, causing drivers to become tired and sleepy. Research across various countries consistently shows that drowsiness is a leading factor in road accidents. For instance, a report from the Ministry of Road Transport and Highways highlighted that India experienced 16,231accidents in 2022 due to driver fatigue. The rising number of vehicles on the road correlates with an increasing number of accidents, especially at night when many heavy trucks are in operation. Continuous driving of such vehicles for long durations increases the likelihood of fatigue-related accidents.

Over the past two decades, several methods have been developed to detect driver drowsiness. These include GPS systems that alert when a vehicle drifts out of its lane due to driver inattention, and electrocardiographic equipment that monitors heart rate to gauge sleepiness. Intelligent transportation systems (ITS) aim to enhance road safety and reduce accidents by addressing driver fatigue, which is a major cause of accidents, particularly on congested roads. Drowsiness impairs a driver's decision-making ability and awareness, especially in the early afternoon and late at night when fatigue levels are high. Additionally, alcohol and hypnotic substances can further diminish driver alertness. Other countries report different statistics, but driver distraction remains a common factor in many accidents. Studies indicate that implementing drowsiness detection systems can reduce accidents by at least 20% .

To detect driver drowsiness, facial images are analyzed to monitor eye blinks and head movements. This area of research, known as facial pattern exploration, has applications in facial recognition, security systems, and virtual tools. The proposed approach focuses on identifying the driver's eyes and mouth by capturing comprehensive facial representations from a dataset of 1,400 images sourced from Kaggle. Using a convolutional neural network (CNN), the system detects the positions of the eyes and mouth to determine drowsiness based on their movements.

The CNN-based system is designed to accurately detect driver drowsiness using the dataset, identifying common signs such as heavy eyelids, yawning, and nodding off. The system must function effectively under various lighting conditions and be robust enough to handle variations in head movements and facial expressions. The paper is organized into sections covering previous research, current system limitations, methodology, and experimental results.

2 Previous Works

This section reviews recent advancements in drowsiness detection.

Sukrit et al. [2] utilized the Eye Aspect Ratio (EAR) and Eye Closure Ratio (ECR), which are widely used techniques. They found similar accuracy for individuals wearing glasses and for long-distance drivers. However, adaptive thresholding varies significantly among individuals. In another study [3], Deng and Wu employed video images to detect blinking, yawning, and eye closure duration. They developed a facial region identification technique based on the Golden Ratio of 68 key points, achieving up to 95% accuracy with a Euclidean distance within 20 pixels and an average accuracy of around 92% regardless of environmental conditions. However, this method requires high-performance machines with substantial processing power and memory.

An Artificial Neural Network was used by researchers in [4], focusing on EEG (Electroencephalography) and EOG (Electrooculography) signal measurements and image classification. Although effective in adverse conditions, the complexity of handling signaling devices poses a significant challenge. Another study [5] employed an ensemble machine learning approach based on hybrid sensing, observing driving performance through simulation and driver monitoring systems, achieving an accuracy of 82.4%. However, the study's sample size was limited, comprising only young male participants.

Anchan and Saritha [6] used image processing algorithms to detect facial features, head position, and eye blinking. This method is available as an Android application, making it cost-effective but unreliable with a low accuracy of 81%. Yan et al. [7] utilized face detection systems to assess fatigue using the percentage of eye closure, eyelid separation, and eye shutdown rate, offering more comprehensive fatigue and distraction detection. However, this method cannot measure dizziness and fatigue directly.

Kuo and Fan-Lin used PERCLOS (Percentage of Eye Closure) and grayscale image processing for drowsiness detection, which requires less memory compared to RGB images and achieves over 90% accuracy when the driver's eyes are open more than 50% of the time. However, additional computational steps are necessary. Another publication [8] suggested using blink patterns and horizontally symmetrical eye features for sleepiness detection, achieving over 90% accuracy and only 1% false positives. This system is advantageous as it does not depend on head position changes but only detects blinks without a common database for comparison.

Parisa et al. [9] proposed using electrooculography to detect eye blinks and horizontal symmetry features of the eyes. Their algorithm achieves a false drowsy rate of less than 5% and a true positive rate of over 80%, outperforming the median filter by at least 20%. However, 3-means clustering is needed to avoid confusion with other eye movements.

In [10], various sensors, including heart rate, breathing, and visual signals, were used to detect distractions with 93% accuracy, focusing on four types of distractions but without alerting the driver. Schwarz et al. [11] utilized the National Advanced Driving Simulator (NADS) to detect low levels of drowsiness, predictive of microsleeps. Another study [12] used image processing to sense driver operations, physiological factors, and vehicle responses, handling various conditions like light changes and reflections. However, sensor performance can degrade with water vapor buildup.

Finally, in [13], an Eye Aspect Ratio method was proposed to detect drowsiness from various angles, performing well in rainy weather, with transparent glasses, and under different lighting conditions. However, it fails to detect drowsiness when the driver wears sunglasses or drives at night.

Table 1. Comparative analysis of various techniques

Ref	Problem	Need	Technique Used	Parameters	Solution	Environment	Future Direction
[3]	Purposed a DriCare System that detects the yawning, eye closure duration and blinking with the help of the video images.	To detect the driver drowsiness with more tracking accuracy.	Optimizes the algorithm KCF with the help of purposed Multi convolutional Neural Network.	Detect the eyes and mouth movements with the help of the Dlib Library	Developed a facial region detection technique based on 68 essential components with92%accuracy.	Data Set is generated with the help of the different team members to collect the dataset from the vehicle camera in same conditions.	Data set should be based on different public in different conditions.
[2]	Develop a system(application) install on the driver car to track the eyes movement for driver drowsiness.	To provide the more accuracy in different conditions.	Eye Closure Ratio and Eye Aspect Ratio is used detect the driver drowsiness.	Detection of the face with the help of linear SVM and histogram	System works with almost same accuracy with spectacles and useful in conditions when drivers drive for long distances.	Method based on the real-time detection of the driver's face with the help of the application installed on the system.	Adaptive thresholding varies greatly from person to person. Thresholding based on the other criteria rather than sleep count
[5]	Detection system based on the factors: vehicle, physiological indicators and behavioural using hybrid sensing.	Classified the driver's alert state mainly slightly drowsy state for early drowsy detection.	For the Physiological signals: electroencephalogram and electrocardiogram, driving simulators for behavioural indices.	Combination of the three techniques: ECG and EEG for the physiological signals, simulators for driver behaviour and vehicle classification using sensors.	System works on every field using combination of the technologies with accuracy of 82.4%.	Driver is covered with sensors on body and surrounding.	System is expensive using these methods. System must be adaptable for everyone.
[4]	Three types of methods introduced for driver drowsiness: EEG, EOG and image analyzation. Artificial Neutral networks used	Detection of driver drowsiness using different methods for better results.	Sensors of EEG and EOG fixed for the brain and eyes activity. ANN is used for analysis of the images.	Detection of brain, eyes activity done using sensors fixed. Images analyse using ANN.	Work efficiency of system is good in bad conditions.	Sensors and camera used for physiological signals and driver's images.	Collecting data and handling EEG and EOG signaling devices is difficult.

	to analyse the eyes state.						
[14]	Driver's eyes and mouth location find using their geometric features which helps in drowsiness detection.	Detection of drowsy using state of eyes and mouth for better accuracy.	Two methods are introduced: Percentage and Time That Mouth is Open (PTMIO), Percentage and Time that Eyelids cover the Pupils (PATECP).	Detect eyes and mouth location.	AdaBoost algorithm used for face detection including edge and line features which leads to 84% accuracy.	Image is captured using camera and carrying out for further process.	Accuracy of method is less in bad conditions and different people.
[11]	Detection of driver drowsiness using sensors for monitoring driver movements.	For analysing level of drowsiness from low level to high level.	NADS (National Advanced Driving simulator) and signals from the vehicle's sensors integrated with the driver monitoring system.	Detection of vehicle-based activities like handle movement, phone use and distractions.	Models performed well in identifying mild tiredness from moderate to severe drowsiness.	Sensors fixed in different locations of vehicle.	Blinks have been shown to be predictive of microsleeps.

Shen et al. [14] assessed user sleepiness by analyzing multiple facial features, including the percentage and duration of eyelid coverage over the pupils and the visibility of the mouth to the camera. This method detects sleepiness through eye and mouth movements but struggles with target extraction in some cases and may fail to detect certain behaviors. Khosro et al. [15] proposed calculating operator drowsiness using Haar-like features and AdaBoost classifiers, employing Local Binary Pattern to extract eye feature characteristics. Mohit Dua et al. [16] combined different deep learning models, such as ResNet and AlexNet, using RGB videos to detect drowsiness. This model leverages GPUs for improved accuracy in detecting facial expressions and hand gestures, with each deep learning model performing specific functions.

Current driver drowsiness detection systems have several drawbacks, including high false alarm rates, difficulty in detecting microsleeps, and the need for calibration or individual customization. Some systems can be intrusive or uncomfortable for drivers, and their effectiveness can be influenced by environmental factors. Many of these systems use complex and expensive equipment, like Electrooculogram (EOG) devices that monitor eye muscle movements. Face detection methods utilizing 68 facial points often store coordinates in dynamic storage, but they struggle to accurately identify target regions if the entire face is not visible in the frame, as all coordinates are interrelated.

In recent years, convolutional neural networks (CNNs) have been widely adopted due to their higher accuracy. However, they still face challenges in different conditions, such as varying angles, low light, and transparent glasses. The primary reason for these failures is that CNNs require different angles (0, +20°, -20°) to analyze the object effectively. This angle issue persists across all driver-based techniques because they tend to focus on increasing the number of hidden layers, leading to significant data loss.

3 Methodology

The primary goal of this paper is to present a method that offers higher accuracy under various conditions. To achieve this, the method is divided into subparts that function efficiently. The proposed approach is applied to a dataset comprising 1,400 images sourced from Kaggle, encompassing different conditions. The following steps, illustrated in Figure 1, are used to address the issues of driver drowsiness.

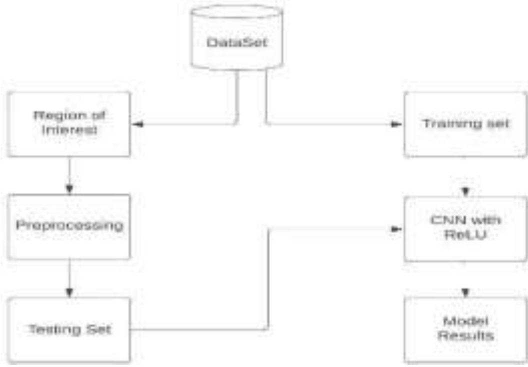


Fig. 1. Steps of Methodology.

Step1:
The first step in the methodology, after loading the dataset into the machine, is to split it into training and testing sets. For datasets with over 1,000 images, the most common split ratio is 80% for training and 20% for testing. However, this approach has a high risk of overfitting in pursuit of higher accuracy. To mitigate this risk, the k-fold cross-validation method is employed, resulting in 1,078 images for training and 302 images for testing. This method helps to eliminate the chances of overfitting.

Step 2:
Next Step of methodology to detect eyes and mouth region for further process. As earlier mention in paper, driver looked at different angle so concerned regions sometimes lost. To overcome this problem, detection of eyes and mouth region done based on nose coordinates. Some of sample figures are mentioned below for reference how interested region is detected.

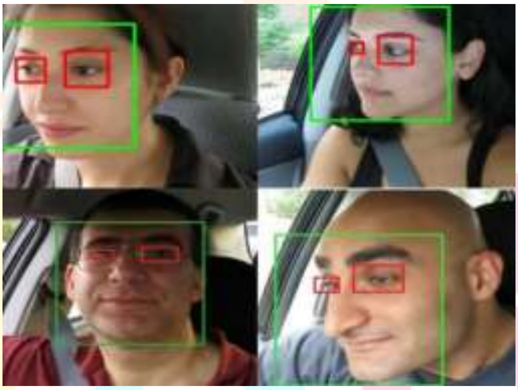


Fig. 2. Detection of Eyes Region

The region is segmented using a Convolutional Neural Network (CNN) model based on a pre-trained model of human eyes, mouth, and face. The trained CNN model processes images using the TensorFlow library. This method utilizes CNN Python libraries to detect the eyes and mouth regions without manual image processing. The trained model can be applied to various images with different features and attributes. TensorFlow's class feature is used to distinguish between closed, open, and other facial expressions. We employ an open-source library called OpenCV for training and analyzing the images.

Step 3:

The model uses a trained Convolutional Neural Network (CNN) and converts the weights into simple and max-pooling layers. The Sequential model, a high-level neural network architecture, is employed to implement sequence learning. It processes a sequence of zero or more random inputs and predicts a single output, which can then be fed into subsequent layers of the network. The model is trained over 30 epochs using a training set, with validation data generated based on the model's output. Validation steps data generated based on the model's output.

Validation steps are optimized to achieve the best training accuracy while minimizing time and memory usage. Finally, the model is flattened, undergoes dropout, and is trained on the provided dataset.

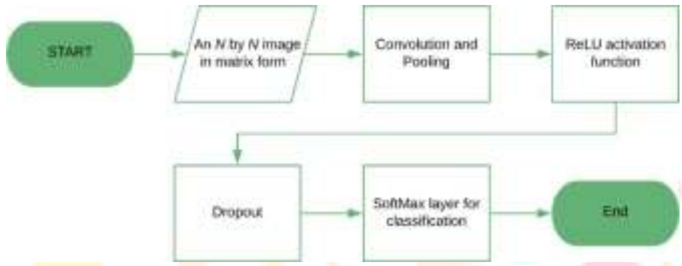


Fig. 3. Working of CNN with ReLU

This model consists of 3 convolutional layers, 4 max-pooling layers, and 1 flatten layer on top of the previous layers. The final output is a dense vector with 64 dimensions per class. In a CNN, the ReLU activation function is typically applied after the convolutional and pooling layers. The output from the convolutional layer is processed through the ReLU function, which sets all negative values to zero while retaining positive values. This process helps to remove negative values that might degrade the network's performance. Utilizing ReLU in conjunction with CNNs has been shown to enhance accuracy, particularly in image recognition tasks.

4 Experimental Results

This study aimed to develop a new CNN-based driver drowsiness detection system using a dataset containing 1,400 frontal face images, evenly balanced between normal and drowsy states. The images were resized to 145x145 pixels and their pixel values were normalized during preprocessing.

The proposed CNN model, implemented using Keras with TensorFlow backend, comprised three convolutional layers followed by max pooling layers, and two fully connected (dense) layers. ReLU activation function was applied to the convolutional layers, while the SoftMax activation function was used for the output layer.

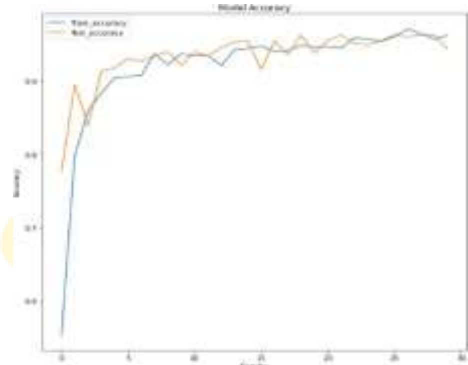
Training the model involved using a batch size of 39 and running it for 30 epochs. The Adam optimizer and categorical cross-entropy loss function were employed during training. The CNN model achieved an accuracy of 94.95%, surpassing the performance of existing techniques for driver drowsiness detection.

Table 2. Different Models Comparison

Model	Technique	Accuracy (%)
Proposed Approach	Eyes and Mouth Region	94.95
CNN-based	Eyes Tracking	92.3
SVM-based	EEG	88.9
Random Forest	Heart Rate Variability	91.2
LSTM-based	Driving Behavior Analysis	87.5
Rule-Based	Steering Wheel Movements	82.1

The findings reveal that the model achieved an impressive accuracy of 94.95%, surpassing the performance of other methods for detecting driver drowsiness. This high accuracy underscores the effectiveness of the enhanced CNN model in identifying signs of driver drowsiness.

Figure 4 illustrates the accuracy of the CNN model across 30 epochs, with two distinct labels: train accuracy and test accuracy. Train accuracy indicates the model's performance on the training dataset, initially starting low as the model learns and gradually improving as it becomes more adept. Test accuracy, on the other hand, gauges the model's performance on a separate dataset that it hasn't encountered previously. This metric is crucial as it reflects how well



the model can generalize to new, unseen data. Initially, test accuracy is low due to the model's limited ability to generalize, but it increases steadily alongside train accuracy as the number of epochs progresses.

Ideally, the train accuracy and test accuracy should follow a similar trend, with both increasing as the model is trained on more data.

The graph in figure 5 shows the model’s loss over 30 epochs, with two labels: train loss and test loss. It indicateshow well the model is fitting the data, with a lower loss indicatingbetter performance. Overall, both graphs provide valuable insight into the performance of the CNN model over time, allowing for adjustments to be madeto improve its accuracy and generalization capabilities.

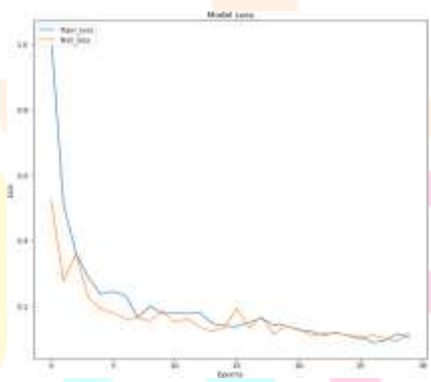


Fig. 5. Model Loss

In Figure 6, the experimental results of our Proposed Model demonstrate that our CNN-based driver drowsiness detection system achieved an impressive accuracy of 94.95% in detecting driver drowsiness. Moreover, the precision varied from 80% to 99%, and recall ranged from 82% to 98% for different factors present in the dataset. Additionally, the system attained an F1 score ranging from 88% to 97% and an AUC of 0.95.

However, it's worth noting that as the number of epochs increases, there is an elevated risk of model overfitting. Despite this, the overall performance of the model remains consistent after 30 epochs. These results indicate that our model performs well across various conditions, highlighting its robustness and effectiveness in detecting driver drowsiness.

	precision	recall	f1-score	support
yawn	0.95	0.82	0.88	45
no_yawn	0.80	0.98	0.88	45
Closed	0.99	0.94	0.96	216
Open	0.95	0.98	0.97	229
accuracy			0.95	535
macro avg	0.92	0.93	0.92	535
weighted avg	0.95	0.95	0.95	535

Fig. 6. Model Performance Summary

5 Conclusion

To address the issue of road accidents caused by driver drowsiness, the proposed model concentrates on identifying closed and open eyes, along with instances of yawning, which are significant indicators of drowsiness. The primary objective is to detect drowsiness accurately under various conditions. In essence, the experimental findings illustrate the promise of employing CNN for driver drowsiness detection, emphasizing the potential for further enhancements through larger datasets and advanced CNN architectures. These results underscore the importance of creating dependable and resilient driver drowsiness

References

[1] K. Kumari, "Review on Drowsy Driving: Becoming Dangerous Problem," International Journal of Science and Research,
a. (2014).
[2] S. Mehta, S. Dadhich, S. Gumber, and A. J. Bhatt, "Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio Fatigue Detection Non-Intrusive Methods Driver monitoring system," (2019).
[3] W. Deng and R. Wu, "Real-Time Driver-Drowsiness Detection System Using Facial Features," IEEE Access, vol. 7, pp.
a. 118727–118738, (2019).
[4] T. Vesselenyi, S. Moca, A. Rus, T. Mitran, and B. Tătaru, "Driver drowsiness detection using ANN image processing," in IOP Conference Series: Materials Science and Engineering, vol. 252, no. 1, (2017).

[5] J. Gwak, A. Hirao, and M. Shino, "An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing," Applied Sciences, vol. 10, no. 8, (2020).
[6] S. L.R. and S. Anchan, "Human Drowsiness Detection System," International Journal of Engineering and Advanced
[7] Technology, vol. 8, no. , pp. 316–319, Apr. (2019).
[8] J. J. Yan, H. H. Kuo, Y. F. Lin, and T. L. Liao, "Real-time driver drowsiness detection system based on PERCLOS and grayscale image processing," IEEE International Symposium on Computer, Consumer and Control, IS3C ,pp. 243– 246,(2016).
[9] T. Danisman, I. M. Bilasco, C. Djeraba, and N. Ihaddadene, "Drowsy driver detection system using eye blink patterns,"
[10] in 2010 International Conference on Machine and Web Intelligence, ICMWI 2010 - Proceedings, pp. 230–233,(2010).
[11] P. Ebrahim, W. Stolzmann, and B. Yang, "Eye movement detection for assessing driver drowsiness by electrooculography," in Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013,pp. 4142–4148,(2013).
[12] M. Gjoreski, M. Z. Gams, M. Luštrek, P. Genc, J. U. Garbas, and T. Hassan, "Machine Learning and End-to-End Deep Learning for Monitoring Driver Distractions from Physiological and Visual Signals," IEEE Access, vol. 8, pp. 70590– 70603, (2020).
[13] C. Schwarz, J. Gaspar, T. Miller, and R. Yousefian, "The detection of drowsiness using a driver monitoring system,"
[14] Traffic Inj Prev, vol. 20, no. sup1, pp. S157–S161, (2019).

[15] S. Himani Parmar, M. Jajal, and Y. Priyanka Brijbhan Electronics, "Drowsy Driver Warning System Using Image Processing | Drowsy Driver Warning System Using Image Processing," IJEDR, (2019).
[16] C. B. S. Maior, M. J. das C. Moura, J. M. M. Santana, and I. D. Lins, "Real-time classification for autonomous drowsiness
[17] detection using eye aspect ratio," Expert Syst Appl, vol. 158, (2020).
[18] P. Wang and L. Shen, "A method of detecting driver drowsiness state based on multi-features of face," in 2012 5th
[19] International Congress on Image and Signal Processing, CISP 2012, pp. 1171–1175,(2012).

[20] J. Gwak, A. Hirao, and M. Shino, "An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing," Applied Sciences, vol. 10, no. 8, (2020).
[21] S. L.R. and S. Anchan, "Human Drowsiness Detection System," International Journal of Engineering and Advanced
[22] Technology, vol. 8, no. , pp. 316–319, Apr. (2019).
[23] J. J. Yan, H. H. Kuo, Y. F. Lin, and T. L. Liao, "Real-time driver drowsiness detection system based on PERCLOS and grayscale image processing," IEEE International Symposium on Computer, Consumer and Control, IS3C ,pp. 243– 246,(2016).
[24] T. Danisman, I. M. Bilasco, C. Djeraba, and N. Ihaddadene, "Drowsy driver detection system using eye blink patterns,"
[25] in 2010 International Conference on Machine and Web Intelligence, ICMWI 2010 - Proceedings, pp. 230–233,(2010).
[26] P. Ebrahim, W. Stolzmann, and B. Yang, "Eye movement detection for assessing driver drowsiness by electrooculography," in Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013,pp. 4142–4148,(2013).
[27] M. Gjoreski, M. Z. Gams, M. Luštrek, P. Genc, J. U. Garbas, and T. Hassan, "Machine Learning and End-to-End Deep Learning for Monitoring Driver Distractions from Physiological and Visual Signals," IEEE Access, vol. 8, pp. 70590– 70603, (2020).
[28] C. Schwarz, J. Gaspar, T. Miller, and R. Yousefian, "The detection of drowsiness using a driver monitoring system,"
[29] Traffic Inj Prev, vol. 20, no. sup1, pp. S157–S161, (2019).
[30] S. Himani Parmar, M. Jajal, and Y. Priyanka Brijbhan Electronics, "Drowsy Driver Warning System Using Image Processing | Drowsy Driver Warning System Using Image Processing," IJEDR, (2019).
[31] C. B. S. Maior, M. J. das C. Moura, J. M. M. Santana, and I. D. Lins, "Real-time classification for autonomous drowsiness
[32] detection using eye aspect ratio," Expert Syst Appl, vol. 158, (2020).
[33] P. Wang and L. Shen, "A method of detecting driver drowsiness state based on multi-features of face," in 2012 5th
[34] International Congress on Image and Signal Processing, CISP 2012, pp. 1171–1175,(2012).