# Driver Drowsiness Detection

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***Abstract*—** The primary cause of the hundreds of fatalities caused by car accidents each year in the world is driver inattention. A device that detects tiredness would help to lessen accidents like these and save countless lives globally. Convolutional Neural Networks (CNN)-based methodology that uses sleepiness detection as a task to detect an item is what we suggest as a solution to this problem. Based on the drivers' real-time video stream, it will be able to recognise and pinpoint whether the eyes are open or closed. This object detection challenge is carried out using the MobileNet CNN Architecture with Single Shot Multibox Detector. Based on the output provided by the SSD MobileNet v1 architecture, a different algorithm is employed. To train the SSD MobileNet v1 Network, a dataset of roughly 4500 photos was tagged with the object's face yawn, no-yawn, open eye, and closed eye. Using the PASCAL VOC metric, around 600 randomly chosen images are utilised to test the trained model. The suggested strategy will guarantee improved computing efficiency and accuracy. Because it does not require any expensive hardware support and can process incoming video feeds in real-time, it is also reasonably priced. The Raspberry Pi 3 or other inexpensive devices can be used in cars to build a standalone camera.

***Keywords—Deep learning; drowsiness detection; object detection; MobileNets; Single Shot Multibox Detector***

## I. INTRODUCTION

Driving while fatigued increases the risk of collisions and accidents. Every year, many people lose their lives in car accidents as a result of drowsy driving brought on by lack of sleep, intoxication, drug and alcohol misuse, heat exposure, or drinking. Several technologies for driving assistance are available from automakers like Tesla, Mercedes-Benz, and others, including lane departure warning, emergency braking systems, variable cruise control, and steering assistance.

These developments have helped drivers reduce the likelihood of crashes. By scanning facial features and patterns, Samsung has examined how attentive a driver is. Yet, the majority of these technologies are exclusive and only available in expensive vehicles.

These mechanisms for identifying drowsiness can be further broken down based on many criteria, including as the context of the vehicle, behavioural patterns, and physiological factors. Drowsiness can be detected using a variety of techniques that have been established in the past. Based on vehicle-based sleepiness identification methods, lane changes, steering wheel rotation, speed, and pedal compressions are observed. Measurement of a driver's physiological signals, performance evaluation using a vehicle, and behaviour recording are some of these methods. The methodology that exclusively depends on the driver's state, the bio-signal measurement method, outperformed the other two in terms of its capacity to identify driver drowsiness. Drowsiness identification procedures require a camera since they rely on behaviours such precise eye closure, yawns, and head posture. Another phase in the physiological drowsiness diagnosis procedure involves keeping track of how fatigue affects physiological markers like the electrocardiogram and electrooculogram (EOG). The physiological approach of sleepiness identification has the drawback of requiring the diver to wear sensors on their bodies. A significant restriction is based on vehicle-based sleepiness identification, such as their susceptibility to forces associated with drivers and cars, as well as road conditions. There are numerous methods that have been described in various works of literature, each with its own limitations and advantages.

The purpose of this study is to suggest a practical method for detecting fatigue among drivers who are divers. We used a CNN architecture to build the drowsiness detecting application. Based on the main contribution, this work may be separated into two sections: (a) Convolutional neural networks to find the best sleepiness identification methods based on object detection, and (b) drowsy datasets to aid the researchers in finding the best drowsiness identification method.

## II. LITERATUE REVIEW

Eyelid closure has proven to be a significantly more accurate indicator of sleepiness. Despite the fact that other behaviours, including as faster blinking times, sneezing, a slow movement of the eyelid, repeated blinking, set eyes, and sagging posture are also predictors of driver drowsiness, many of the systems currently in use should rely on eyelid closure. The use of standard cameras, Infrared (IR) cameras, and stereo cameras to forecast drowsiness has been advocated in numerous works of literature in this topic. To list the various sleepiness detection systems and technologies, a literature review has been done. A model to detect sleepiness was developed by Dwivedi et al. using CNN.This method used CNN-based representation feature learning, which had a 78% accuracy rate.

Alshaqaqi et al. suggested the Specialized Driver Support System to lessen the number of accidents caused by sleepy drivers. It was suggested that an algorithm be used to find, map, and assess the face and eyes in order to test PERCLOS and identify drowsy driving. An eye-tracking-based driver drowsiness system was proposed by Said et al. The method alerts drivers when a motorist is drowsy during this task by sounding an alarm. The region of the face and eye were detected in this work using Viola Jones' model. It offered 82% accuracy in tests conducted indoors and 72.8% accuracy in testing conducted outdoors.

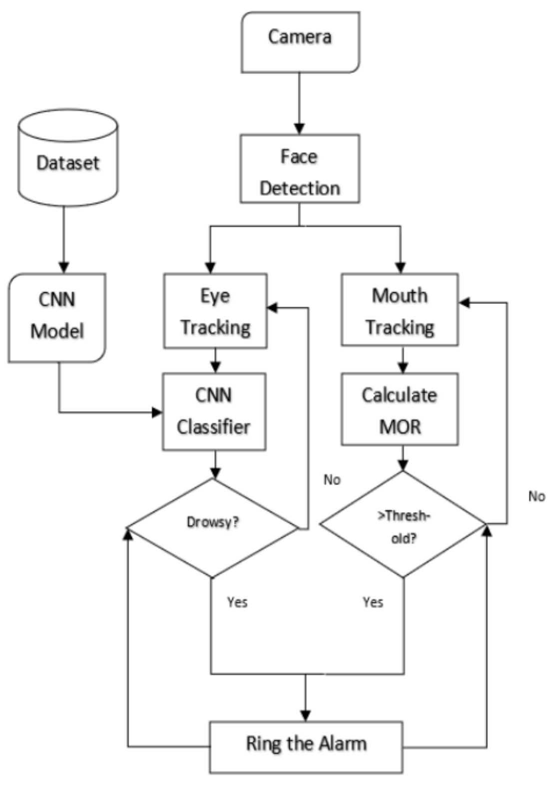
With an accuracy of 84% based on machine learning models, Mehta et al. have developed a smartphone app that can recognise facial landmarks and compute the Eye Aspect Ratio (EAR) and Eye Closure Ratio (ECR) to predict driver drowsiness. A start-up called Ellcie-Healthy has developed smart glass that uses blink detection, eye recording, and control of vital signs to combine somnolence monitoring technologies. The smart glass tracks these inputs and provides somnolence interference by beeping, advising the driver to take a break. In order to achieve exceptional performance, combination tactics combine various sensors, including infrared, cameras, and heart rate monitors, on a single device.These tools are quite expensive and call for the implementation of proprietary solutions.

A vision-based technique for identifying driver weariness has been presented by Mandal et al. for monitoring bus drivers. In this study, driver and headshoulder detection are accomplished using AHOG and SVM, respectively. For face detection and eye detection, they made use of the OpenCV face detector and eye detector, respectively. Spectral Regression Embedding was utilised to learn the eye structure, and a novel method of determining eye openness was developed. The features produced by two I2R-ED and CV-ED eye detectors were combined via fusion. Perclos was selected to identify sleepiness. Using transfer learning and sequential learning from yawning video clips, Xie et al. were able to detect yawning in the YawDD and NTHUDDD datasets.

Deep learning-focused Android apps now have a concept for detecting driver drowsiness, thanks to Jabbar et al. Here, a model that focuses on locating face landmark points was built. Here, the first images are created from video frames, and landmark coordinates were then extracted using the Dlib package. The multi-layer perceptron classifier receives the landmark coordinate points as input. These points are categorised as either drowsy or not drowsy by the classifier. 350 pictures were trained for a unique dataset using the MobileNet-SSD architecture by Shakeel et al. The model was able to reach a mean average precision of 0.84. The method was successful and affordable since the algorithm could be used on an Android device and the camera stream could be classified in real-time.

## III THE PROPOSED SYSTEM

The suggested driver sleepiness detection system has been shown in block diagram form. The real-time video is initially captured with a webcam. To get a frontal facial shot, the camera will be placed in front of the driver. To create 2-D pictures, video frames are extracted. The frames' faces are identified using the Haar-Adaboost face identification algorithm. Face detection is followed by the marking of facial landmarks on the photos, such as the locations of the eyes, nose, and mouth. The position of the eyes and mouth are measured using the facial landmarks. The sleepiness of the driver is determined using these extracted features and machine learning techniques. Convolution neural network is used to classify eyes and identify driver drowsiness by taking into account eye blinking.



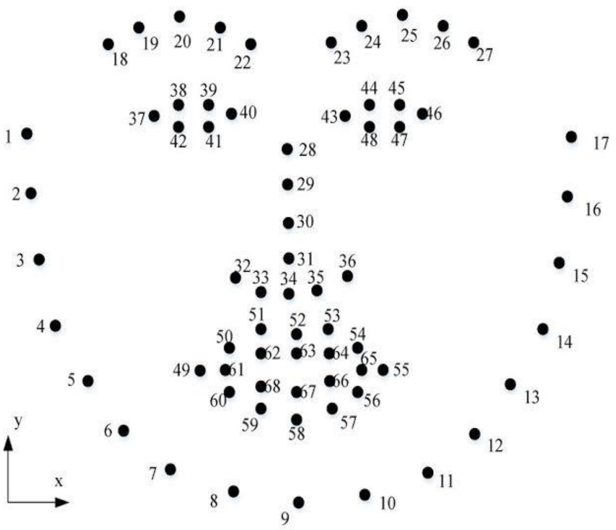

The mouth opening ratio is calculated using the feature extraction approach as an additional attribute to the system, which also aids in determining whether the driver is simple. An alarm will be sent to the driver to warn him or her if drowsiness is found. Each block's specifics are covered in later sections.

A dataset of eyes from Media Research Lab is used to train the algorithm to recognise open or closed eyes.

The collection includes pictures of male and female eyes, as well as closed and open eyes, eyes with and without spectacles, and eyes with low, high, and no reflection.

### 3a.Face Detection and Facial Landmark Marking

The suggested system uses a face detection method based on the Haar-Adaboost algorithm. The face detector is trained using OpenCV functions. For training, different brightness, brightness angles, and face photographs of people wearing and not wearing glasses are fed. Following training, the created face classifier is capable of detecting faces with sizes ranging from 240x240 to 320x320 pixels. The real-time detection is incorporated using dlib library functions. For real-time face detection, the functions shape predictor and get frontal face detection are used. We imported the OpenCV 4.2.0 and Dlib 19.19 libraries using Python 3.8.2. Moreover, these libraries may be used for face morphing or swapping operations. The OpenCV library offers a detector as well as a classifier for the face or the eyes that has been previously trained.




Finding the locations of various facial features, such as the corners of the mouth and eyes, the tip of the nose, and so forth, comes next after the face has been detected. In order to lessen the impact of distance from the camera, uneven lighting, and changing image resolution, the facial photos should first be normalised. With the use of gradient boosting learning, the sum of square error loss is optimised. The boundary points for the eyes and mouth are marked using this technique, and the number of points for each is provided in Table

| Parts | Landmark Points |
|---|---|
| Mouth | [13-24] |
| Right Eye | [1-6] |
| Left Eye | [7-12] |

Table I : Facial landmark points

### 3b.Yawning Detection

Unconscious behaviours like yawning are signs of fatigue and sleepiness. Examining a driver's yawning pattern is one way to spot minor weariness. In the action unit of the Facial Action Coding System, yawning is defined as the mouth extending as a sign of exhaustion. Since yawning is distinguished by a leisurely, wide mouth opening, it is required to detect the sides of the mouth and gauge the size and shape of the mouth in order to recognise a yawn.

Mouth opening ratio (MOR): Mouth opening ratio detects yawning during drowsiness. It is calculated as:

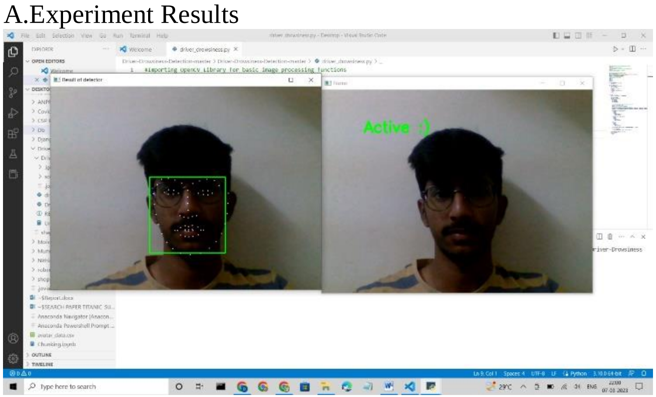
$$MOR=\frac{(P15-P23)+(P16-P22)+(P17-P21)}{3(P19-P13)}$$

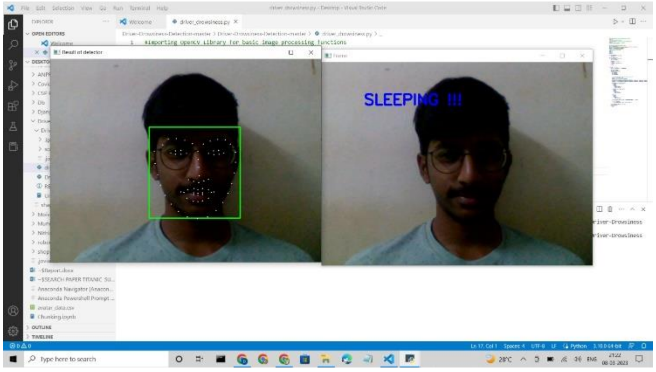
As stated, it climbs quickly when the mouth opens as a result of yawning, stays at a high value for a time as a result of yawning, and then rapidly lowers back to zero. Yawns are one of the signs of tiredness, hence MOR provides a measurement of driver drowsiness. Together with the convolutional neural network, this functionality is used as an additional functionality in the suggested system.

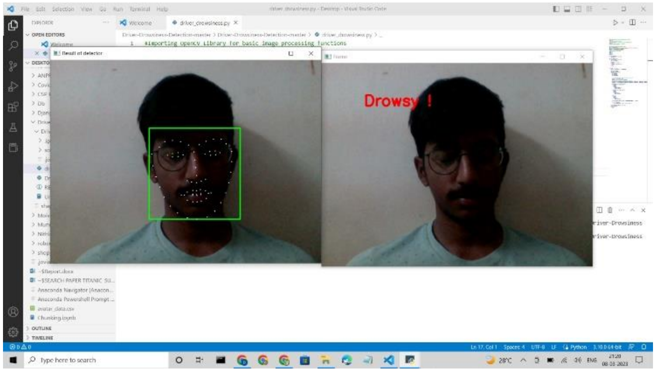
## IV RESULT AND DISCUSSION

In this section, the experiment results and associate outcomes have been explained in details.

A.Experiment Results






The approach occasionally claimed that the result was open when the eye was closed, and vice versa. This outcome may have been influenced by light and its reflection. The system's performance metrics are displayed in Table II. Precision, Recall value, and F1-Score are listed in Table II. The classification accuracy for the training and test datasets is reported in Table III. Table IV lists the confusion matrix for analysis and investigation.

| **State** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| closed | 0.95 | 0.95 | 0.95 |
| Open | 0.93 | o.93 | 0.93 |

TABLE II: Result of applying the system to the dataset.

| **Method of Evaluation** | **Accuracy** |
|---|---|
| Trainig Accuracy | 98.1 |
| Test Accuracy | 94 |

TABLE III: Classification accuracy on training and test dataset.

| State | Predicted Closed | Predicted Open |
|---|---|---|
| Actual Closed | 410 | 22 |
| Actual Open | 21 | 411 |

TABLE IV: Confusion matrix

B. Discussion

Manual feature extraction was formerly performed using machine learning algorithms, however deep learning architectures today eliminate this step. Automatic learning is performed. Deep learning architectures now automate the process of extracting its feature. So, a significant amount of time is saved here as opposed to when we would have to spend time figuring out the feature needs to enhance the categorization result.

## CONCLUSION

Facial characteristics, eyes, and lips were recognised on the video of a person driving in order to determine whether or not that person was drowsy.

It was decided to use a convolutional neural network to categorise eyes as open or closed. Using the frequency of closed eyes, drowsiness was assessed. We looked at yawning frequency using Python, OpenCV, and Dlib. After the detection, an alarm was programmed to sound to notify the driver. Due to circumstances including darkness, light reflection, obstructions caused by drivers' hands, and the wearing of sunglasses, it will be more difficult to discern drivers' situations and facial expressions. As an additional drowsiness detection strategy that is frequently employed with other facial extraction methods, convolutional neural delivers higher performance and facial extraction method accompanies it.

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