International Journal of Innovative Research in Computer Science & Technology (IJIRCST)
ISSN (online): 2347-5552, Volume-11, Issue-3, May 2023
https://doi.org/10.55524/ijircst.2023.11.3.2
Article ID IRP1378, Pages 7-11
www.ijircst.org

Real Time Prevention of Driver Fatigue Using Deep Learning and MediaPipe

Swapnil Dalve[1], Ishwar Ramdasi[2], Ganesh Kothawade[3], Yash Khadke[4] and Manasi Wete[5]

[1,2,3,4] Student, Department Computer Engineering, NBNSSOE, Pune, India
[5] Professor, Computer Engineering of Computer Engineering, NBNSSOE, Pune, India

Correspondence should be addressed to Swapnil Dalve: swapnildalve.nbnssoe.comp@gmail.com

ABSTRACT- This paper describes the development of a system for detecting driver drowsiness whose goal is to alert drivers of their sleepy state to prevent traffic accidents. It is essential that drowsiness detection in a driving environment be conducted in a non-intrusive manner and that the driver not be troubled by alerts when they are not sleepy. We make use of the MediaPipe Facemesh framework to extract facial features and the Binary Classification Neural Network to precisely detect drowsy states in our solution to this open problem. The solution that minimize false positives is created to determine whether or not the driver exhibits sleepiness symptoms. The approach extracts numerical features from images using deep learning techniques, which are then added to a fuzzy logic-based system. This system typically achieve 91% accuracy on training data and 92% accuracy on test data. The fuzzy logic-based approach, however, stands out because it doesn't raise erroneous alerts (percentage of correctly identified footage where the driver is not tired). Although the findings are not particularly satisfying, the recommendations offered in this study are promising and may be used as a strong platform for future work.

KEYWORDS- Deep Learning, Drowsiness Detection, MediaPipe, Real time.

I. INTRODUCTION

Driving while fatigued is a severe problem that is frequently disregarded yet can have fatal effects. These mishaps can occur at any time of day, although they seem to happen more frequently in the late at night and early in the morning when drivers are generally more drowsy. Lack of sleep, untreated sleep problems, drowsy-inducing drugs, and long drives without breaks are just a few of the things that might make a driver drowsy. The reaction times, judgement, and situational awareness of drivers who are weary are all slowed. They could endanger themselves and other people by drifting out of their lane, failing to see traffic signals, or even falling asleep behind the wheel.

Driver drowsiness may be detected and prevented using computer vision and machine learning approaches. To detect indicators of driver weariness, these technologies can analyse face and eye movements. Large datasets of driving behaviour may be used to train machine learning algorithms to spot patterns that point to tiredness. The system, for instance, can learn to recognize slow eyelid movements or adjustments in head posture that indicate a driver is beginning to nod asleep. Current methodologies for using computer vision and machine learning to prevent drowsy driving include the use of driver-facing cameras and sensors in vehicles. These cameras and sensors monitor the driver's facial and eye movements and can alert the driver if signs of drowsiness are detected. Some systems also provide feedback to the driver, such as vibrating the steering wheel or sounding an alarm, to wake them up and keep them alert. Another strategy involves using machine learning to analyse data from many sources, including GPS, vehicle speed, and driver behaviour, in order to forecast when a driver is most likely to start to feel sleepy. By advising drivers to take a break or offering alternate routes to avoid high-risk locations, this strategy can help reduce sleepy driving incidents before they happen. The use of these technologies on a greater scale is not without its difficulties. The requirement for precise and dependable driver fatigue monitoring is one problem. False positives and false negatives may result in pointless notifications or fail to stop accidents. Driver-facing cameras may raise privacy issues, which might be viewed as being obtrusive or unwelcome.

Despite these difficulties, using computer vision and machine learning to stop driver sleepiness has the potential to increase traffic safety. As these technologies develop, they may be installed in more cars and contribute to a decrease in the frequency of accidents brought on by driver weariness.

II. MOTIVATION

Defining criteria for detecting crucial moments of fascination while permitting input information is another essential challenge. For vehicle-based estimations, for example, these occurrences can include steering movement with little to no assistance and subsequent major changes (both of which might indicate tiredness). Identified muscle growth in the mouth region, eye region, or overall facial structure are examples of circumstances that may indicate tiredness in conduct estimates. Finding the optimal time window to illustrate the driver's tiredness when quickly recognising primary occasions is another genuine test connected to characterising input characteristics. The speed and accuracy of the conjecture inexorably trade off. According to one point of view, if the time window is small, the framework could recognise "clamour" and, as a result, create a lot of false positives. However, if the duration is too long, the structure could be too gentle to be effective. Another lethargic detection method is presented in this study, which tackles a number of problems through the integration of sensors, parameter enhancement, choice, and demonstration. One of the main causes of automobile accidents is drowsy driving. Human eyes are essential for determining whether a driver is getting tired while behind the wheel. A method for detecting tiredness may be developed with the help of continuous eye monitoring and recording of the pattern of eye closing and opening. The simplest way to tell whether a driver is getting fatigued while behind the wheel is to look at their eyes. The fundamental difficulty in identifying eyes is that it is difficult to find eyeballs in a dynamic environment when the object is continually moving. Therefore, before using our algorithm, we must first identify the full face and then separate the eyes from it.

III. RELATED WORK

A system based on video analysis is proposed for identifying driver sleepiness or exhaustion. The method of extracting driver yawning is the main topic of this study. The driver's facial area is located using a real-time face detector. The Kalman filter is then used to track the facial region. Additionally, to identify driver yawning in video, the mouth window is targeted within the region of the face, and the degree of mouth openness is retrieved based on mouth features. When obstruction or miss-detection occur, the system will reset. To determine the viability of the suggested approach, experiments are carried out [1]. The technology suggested in this research uses a camera to monitor the driver's eyes and develops an algorithm to detect indications of driver fatigue early enough to avoid an accident. As a result, our technology detects driver drowsiness in advance and provides warning output in the form of sound and seat belt vibration with frequencies ranging from 100 to 300 Hz. Furthermore, rather of being deactivated automatically, the warning will be deactivated manually [2]. The method uses a video series of a driver's frontal face to first detect the face, then locate the eye from the extracted face, to identify tired drivers. Second, the system determines whether the eye pupil is present in the detected eye and simultaneously measures the blink rate. By examining these characteristics, the system determines the loss of awareness before the driver loses all concentration [3]. The suggested study uses facial expressions to create an emotion recognition algorithm based on Support Vector Machines (SVM). The algorithm performed more accurately than recent research when evaluated under settings of varying brightness. They have successfully detected changes in facial expression at an 83.25% rate [4]. A Sleepiness Detection System that sounds an alarm if a driver's eyes are closed for a brief period of time. This study uses deep learning to propose a new frame that categorises the driver's eye condition as either open or closed. The suggested device emits a beep when a driver is deemed to be drowsy once the sleepiness measure reaches a certain saturation point. The suggested work is tested using 48000 images from a significant portion of the MRL eye dataset, and it exhibits accuracy of 86.05% when utilising the CNN model [5]. Method to this open challenge employs 60 s long image sequences that are recorded in a way that makes the subject's face visible. Two different approaches are created to determine whether the driver exhibits sleepiness symptoms or not, concentrating on minimising false positives. The following option uses deep learning to extract numerical information from pictures, which are then added to a fuzzy logic-based system, whereas the prior method uses a recurrent and convolutional neural network. Both systems achieve similar levels of accuracy: about 65% accuracy over training data and 60% accuracy over test data [6]. In the process of analysing and detecting the driver's facial feature points, the issue of mistaken identification brought on by the differentiation of each driver's individual facial features is particularly noticeable, especially for those with small eyes. This research develops a perception-free calibration method to determine individualised eye opening and shutting thresholds in conjunction with head postures in order to address this issue. It does this by using the Mediapipe Facemesh module to detect facial feature points.A useful technique for determining driver fatigue is to identify the facial feature points on the driver's face and analyse the opening and closing states of their eyes and mouths[7].

IV. SYSTEM ARCHITECTURE

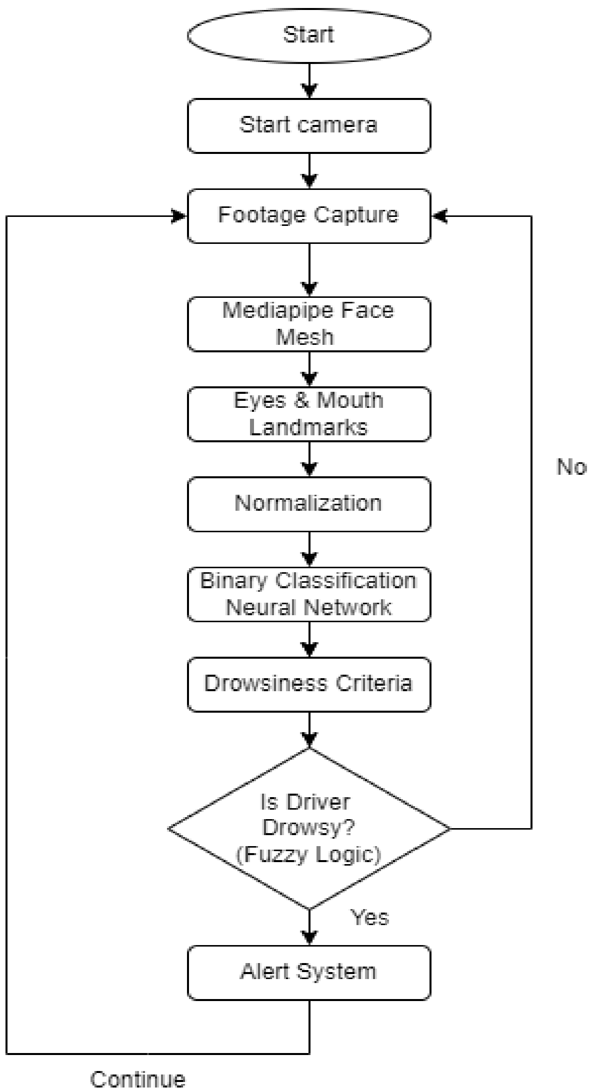

Figure. 1: System Flowchart

The main objective of this study is to create a system for real-time driver sleepiness detection utilising deep learning and the MediaPipe framework. Figure 1 depicts the suggested system flowchart. The system begins by receiving inputs from a camera situated in front of the driver, as indicated in the figure. The camera continuously feeds a stream of frames of face of the driver. Then the footage is analysed using MediaPipe's Facemesh. MediaPipe examines the footage and generates 478 datapoints of eyes and mouth landmarks. These features are then given to Binary Classification Neural Network which identifies the state of driver whether drowsy or not. Further fuzzy logic is used to analyse frames generated per second and are compared with the set threshold and finally the driver is alerted.

V. PROPOSED METHODOLOGY

A. Dataset

To train deep learning model we have used following two datasets.

CEW (Closed Eyes in the Wild)

A total of 2423 subjects make up this dataset, of which 1231 subjects with open eyes were chosen from the Labelled Face in the Wild (LFW) database and 1192 subjects with both eyes closed were obtained directly from the Internet. Eye patches are obtained automatically based on the coarse face region and eye location, which are estimated by the face detector and eye localization, respectively. It first extracts eye patches that are 24x24 in size and are centred at the localised eye position from coarse faces that have been cropped to a size of 100x100 (pixels).

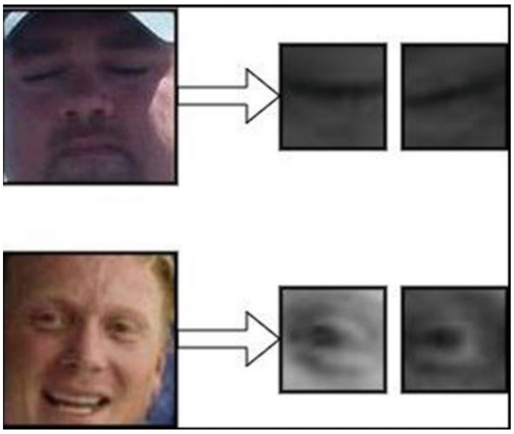

Figure. 2: CEW Dataset [8]

Drowsiness Dataset

Images of different subjects are captured using front faced dash cam and are labelled. This dataset contain 726 pictures with closed eyes, 726 pictures with open eyes, 725 pictures with yawn and 723 pictures with no yawn.

B. Face Detection and feature extraction

Google has made available Mediapipe. This study makes use of the Face Mesh module, which is one of its comprehensive frameworks and directly callable solution modules. The Face Mesh module is built on Blazeface, which has been enhanced and optimised for mobile GPU reasoning on the foundation of MobilenetV2 and SSD detector. The Facemesh module in this study identifies a total of 478 feature points. The details of the mouths and eyes are marked.

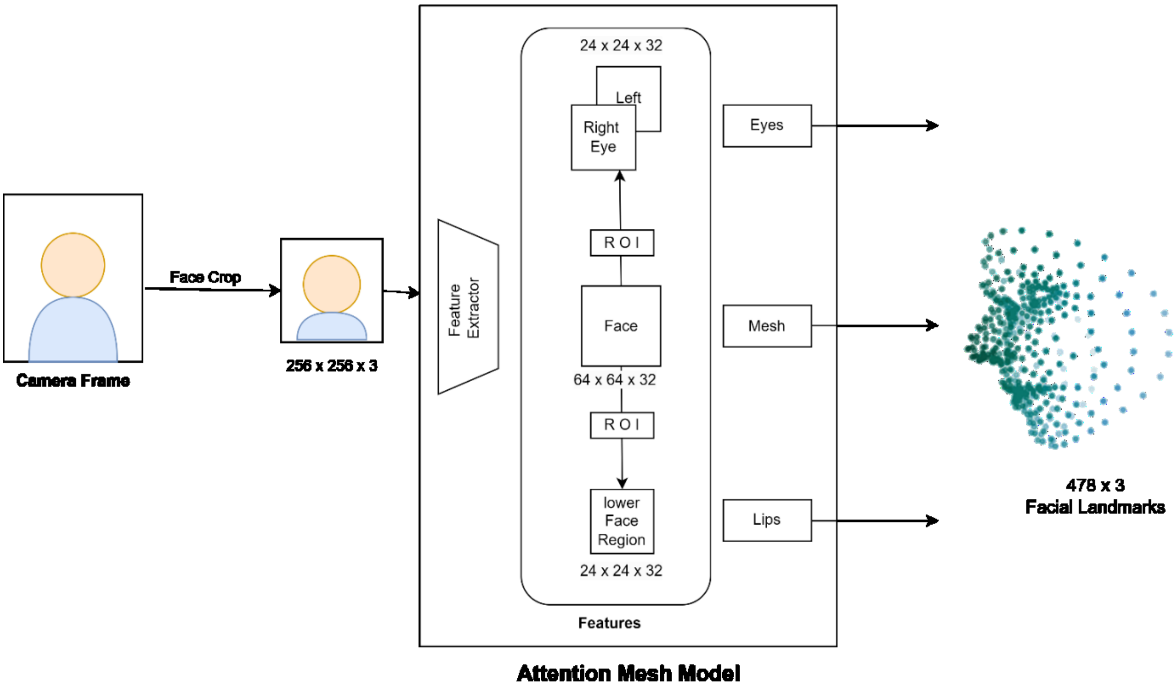

Figure. 3: Feature extraction using MediaPipe

As given in Figure 3, MediaPipe take 256 x 256 cropped facial frame. The feature extractor examines Region of Interests (here are eyes and mouth) to generate 478 Landmarks. These are then analysed using Binary classification Neural Network. Parameters of MediaPipe can be given as-

Max_num_faces = 1
Refine_landmarks = True
Min_detection_confidence = 0.6
Min_tracking_confidence = 0.6

It is essential to set refine_landmarks so that it can generate eyes landmarks.

C. *Drowsiness Detection*

Binary classification Neural Network is used in this study. It takes landmarks extracted by the MediaPipe. Flattening is performed on the landmarks which are mapped to long continuous vector of size 64 which then passed to Dense layer which is using Rectified Linear Unit as an activation function. This layer is connected to another Dense layer which is also using ReLU. In the output layer we are using Sigmoid function as an activation so that it can generate binary outputs(figure 4).

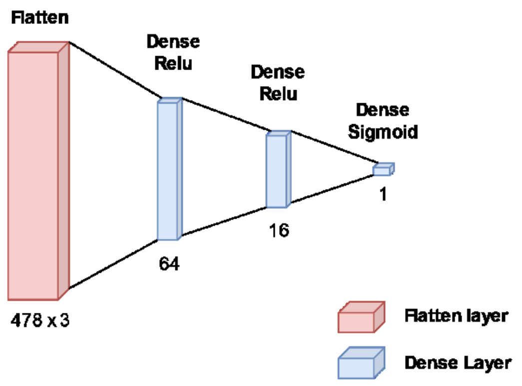

Figure. 4: Model Layers

Table 1: Model Summary

S.No.	Layer (type)	Output shape	Parameters
1	Flatten	(None, 1434)	0
2	Dense Relu	(None, 64)	91840
3	Dense Relu	(None, 16)	1040
4	Dense Sigmoid	(None, 1)	17

D. *Alert*

User is alerted by producing some sound depending upon the level of drowsiness. To avoid alert during conditions like eye blink or speaking, Fuzzy logic is implemented on the predictions to accurately detect the state of the driver in the given frame. Results generatied in each frames per second is compared with a set threshold (Th). This can be given as-

Th = Frames_with_drowsy_state / Total_frames_in_second

VI. RESULTS

A. *Model Performance evaluation*

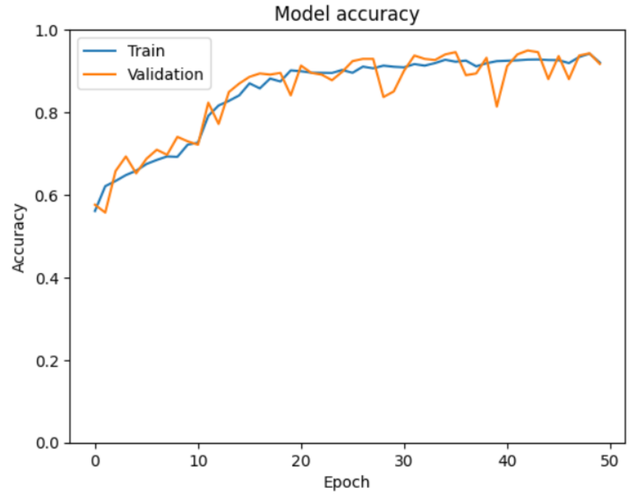

Figure. 5: Model accuracy

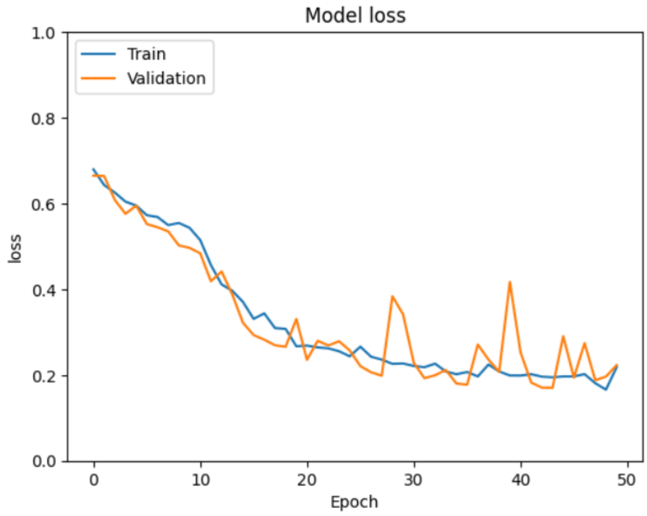

Figure. 6: Model loss

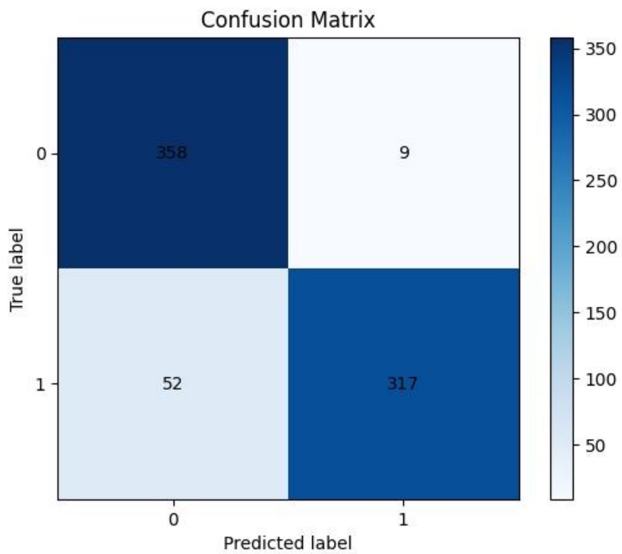

Figure. 7: Confusion Matrix

Adam's optimisation approach, which is superior to the stochastic gradient descent process, was utilised to train the suggested model, which consists of two features—eyes and yawns. After a few attempts, a model with two layers was chosen since it provided the best accuracy. The losses for training and validation for closed eyes in the wild dataset are shown in Figure 6. The graph accuracy values for epochs 1, 10, 20, 30, 40, and 50 are shown in Figure 5. The accuracy of the model was 92.05% for the test, and 91.71% for the validation, according to the results.

VII. CONCLUSION

In this research, a deep learning-based system using MediaPipe as feature extractor for detecting driver drowsiness is introduced. This system makes use of the latest technologies to analyse and continuously track the condition of the driver's eyes and face. The suggested algorithm for face tracking, eye identification, and eye tracking is reliable and precise in the presence of changing lighting conditions, interference from external illuminations, vibrations, and variations in the background and facial orientations. It also performs well on the small eyes. The technology is still being developed and tested, though. It can only be used as a driving companion at this time. Additionally, it occasionally provides erroneous decisions (which can happen in rare cases). A positive outcome can be anticipated from further system developments that include other physical signs of sleepiness (such as skin tone analysis, grip pressure measurement, etc.).

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] Tiesheng Wang, Pendeli Shi, “YAWNING DETECTION FOR DETERMINING DRIVER DROWSINESS”, IEEE, 2005

[2] Hardeep Singh, Mr. J.S Bhatia, Mrs. Jasbir Kaur, ”Eye, Tracking based Driver Fatigue Monitoring and Warning System”, IEEE, 2011.

[3] Manash Chakraborty, Ahamed Nasif Hossain Aoyon, “Implementation of Computer Vision to Detect Driver Fatigue or Drowsiness to Reduce the Chances of Vehicle Accident”, IEEE, 2014.

[4] Ayman Altameem , Ankit Kumar , Ramesh Chandra Poonia , Sandeep Kumar , And Abdul Khader Jilani Saudagar, “Early Identification and Detection of Driver Drowsiness by Hybrid Machine Learning”, IEEE, 2021.

[5] Yeresime Suresh, Rashi Khandelwal, Matam Nikitha, Mohammed Fayaz and Vinaya Soudhri, “Driver Drowsiness Detection using Deep Learning”, IEEE, 2021.

[6] Elena Magán , M. Paz Sesmero , Juan Manuel Alonso-Weber and Araceli Sanchis, “Driver Drowsiness Detection by Applying Deep Learning Techniques to Sequences of Images”, MDPI, 2022

[7] CHENG MING, AND YAN YUNBING, “Perception-Free Calibration of Eye Opening and Closing Threshold for Driver Fatigue Monitoring”, IEEE, 2022.

[8] Song, F., Tan, X., Liu, X., Chen, “Eyes closeness detection from still images with multi-scale histograms of principal oriented gradients”, Elsevier, 2014.