Drowsy Driver Detection Using Eye Aspect Ratio (EAR)

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***Abstract*— nowadays, road accidents are widespread. Driver's tiredness or poor concentration is a cause of such mishaps. Drowsiness is defined as a lethargic feeling or the inability to keep one's eyes open or focused when driving. Unfocused driving is a contributing factor in traffic accidents that must be addressed. This paper presents an approach for implementing an alert system for the unfocussed drivers. This system detects and monitors the yawning and tiredness of the driver while driving. A Histogram Oriented Gradient feature descriptor is used for face recognition. The support vector machine evaluates whether or not the discovered object is a human face. It also tells the driver's Eye Aspect Ratio and Mouth Aspect Ratio up to a certain number of frames to check yawning. Since the loss of the focus of the driver is also based on the number of hours they have been driving, an additional feature is included. It improves the system's sensitivity to detect close eyes or yawning. The outcomes of our experiment show that the methodology we suggested is effective.**

***Index Terms*— HOG, facial features, Drowsiness detection facial landmark, LBPH.**

I. Introduction

In the past few years, there was very little improvement in the area of preventing road accidents because of driver's fatigue or drowsiness. Drowsiness is a state when the driver is unable to control his/her sleep which includes- frequent blinking of an eye, day-dreaming, difficulty in focusing the road, missing traffic signals, constant yawning, etc.

Drivers who are short of more than 4/5 hours of sleep are more likely to be involved in a mishap. There are various ways to develop a system to handle situations where the driver in not focused while driving that may be intrusive or non-intrusive.

The intrusive approach considers biological parameters like an electroencephalogram and electrocardiogram, but it requires electrodes to be attached to the driver's body so it is rarely preferred by drivers

Non-intrusive methods can be vehicle-based, such as the position of the automobile on the road, movement of the steering wheel, or based on the activity/behavior, such as blinking, yawning, and so on. However, it is difficult to set universal guidelines for car-based techniques because they are based on the driver's driving skills and the type of road on which the car is traveling.

As a result, this paper utilizes facial expression analysis, which is believed to be the most suitable way. This requires the installation of a camera inside the automobile to capture the image of the driver. Histogram Oriented Gradient is used to further analyze the collected image, extracting feature descriptors to detect faces in each frame. To differentiate both facial and non-facial zones, a SVM is used. As a result, we use Local Binary Patterns Histograms to identify whether the driver is the same or different in each frame, and then update the time accordingly. For texture categorization, LBP is the most realistic feature. To measure driver tiredness and yawning, we first draw some markers on the face, and then calculate the Eye Aspect Ratio and Mouth Aspect Ratio.

The status of the automobile driver is next evaluated using a thresholding value. Uber initiated a campaign restricting drivers in the United States to a ceiling of 12 hours of driving time. A prompt pop-up appears after the 12-hour shift, requesting that they take a 6-hour break by going off-line. Also, by making their duties less stressful, they will have more flexibility in their jobs. We use this principle in our methodology by establishing a dynamic frame threshold that declines after 3 hours and notifying the user to stop driving after 12 hours.

II. RELATED WORK

This field of inquiry, notably the identification of driver drowsiness, has already gotten a lot of attention. Only the most essential and noteworthy literary works will be highlighted here. The system collects data from a variety of sources and uses a mixture of them as parameters. Physical input includes dizziness, yawning, and blinking, as well as a combination of body temperature and heart rate.

The 'Square-based Fusion Model a Limited Part of the Sleep Typical Squares' was described by Hong Su in 2008. They presented a new driver drowsiness model based on partial minimum squares regression (PLSR) approaches, which would address the issue of substantial collinear correlation between eyelid movement data, thus predicting sleepy tendencies. The predicted accuracy and durability of the model developed thus are guaranteed, indicating that it offers a new way of combining multiple factors to improve our ability to detect and predict drowsiness.

In June, 2010, Bin Yang described the 'Sleep-Based Camera Reference for Driver Region Divide under Real Driving Conditions'. They suggested that the driver's eye movements could detect sleepiness under the hood or test conditions. The latest eye tracking performance based on measures of car fatigue is being tested. These steps are calculated mathematically and categorically based on a large 90-hour database of real road driving. The results show that sleep detection works well for some drivers as long as blink vision is effective. Despite the proposed improvements, however, there are still problems with poor lighting conditions and with people wearing glasses. In short, camera-based sleep measurements provide an important contribution to the sleep indicator, but they are not reliable enough to be the only indicator.

In 2011, M.J. Flores explained the 'driver sleep detection system under the infrared light of a smart car'. They suggested that in order to reduce the number of such accidents, a modified driver assistance program module should be introduced, which addresses automatic driver sleep deprivation and driver disturbance. Artificial intelligence systems use visual information to recognize, track, and analyses both the driver's face and eyes in order to compute signs of exhaustion and disruption. This real-time system also operates at night thanks to the established infrared illumination technology. Finally, samples of various driver images taken in a real car at night are given to validate the suggested procedures. In June of 2012, A. Cheng explained 'Driver Sleep Recognition Based on Computer Visual Technology.' To produce a non-disruptive sleep apnea, researchers used eye tracking and image processing. A reliable eye-tracking algorithm was implemented to overcome the challenges caused by changes in light and the driver's position. Six stages were calculated using the average opening rate of the eyes, the opening speed of the eyes, and the closing speed of the eyes: the percentage of closed eyelids, the duration of the closure, the most frequent blinking, the average opening rate, the opening speed, and the closing speed of the eyes are all factors to consider. Fisher's linear discrimination activities, which use a step-by-step mitigating method and extract independent indicators, are used to combine these metrics. The results of the six drivers who took part in the competition are the collection of drowsiness detection techniques with an accuracy of 86 percent. The term 'Visual Analysis of the Situation and Position of the Head of Driver Monitoring' was coined by G. Kong in 2013. They used visual analysis of the driver's eye state and head posture to keep track of him. To identify the driver's tiredness or level of disturbance, several of the known methods of visual detection of reckless driving behaviors rely on head angles. To extract critical information from the driver's neglect, the suggested approach uses visual elements such as optical indicators, student performance, and head attitude. The vector support machine (SVM) splits the sequence of video segments into driving events that are either warning or non-warning. In real-world driving circumstances, test study reveals that the suggested approach provides high-level precision with acceptable low errors and false alarms for persons of various races and genders.

III. PROPOSED WORK

We proposed a system working in real time which would observe the status of the driver whether the driver is feeling sleepy or if the driver is yawning. In this system, a RGB camera is placed on the front windows constantly watching the driver's face. There are two alarms in this system. First, when the driver sleeps or feels drowsy for more than 4 seconds, it would give an alert to the driver. Second one is that, Once the driver drives ceaselessly for 12 hours, it would deliver an alert to the driver to stop driving and take a few rest.

First Step involved in our system is to check whether the driver is the same or not, by continuously detecting and recognizing the face of the driver from all angles.

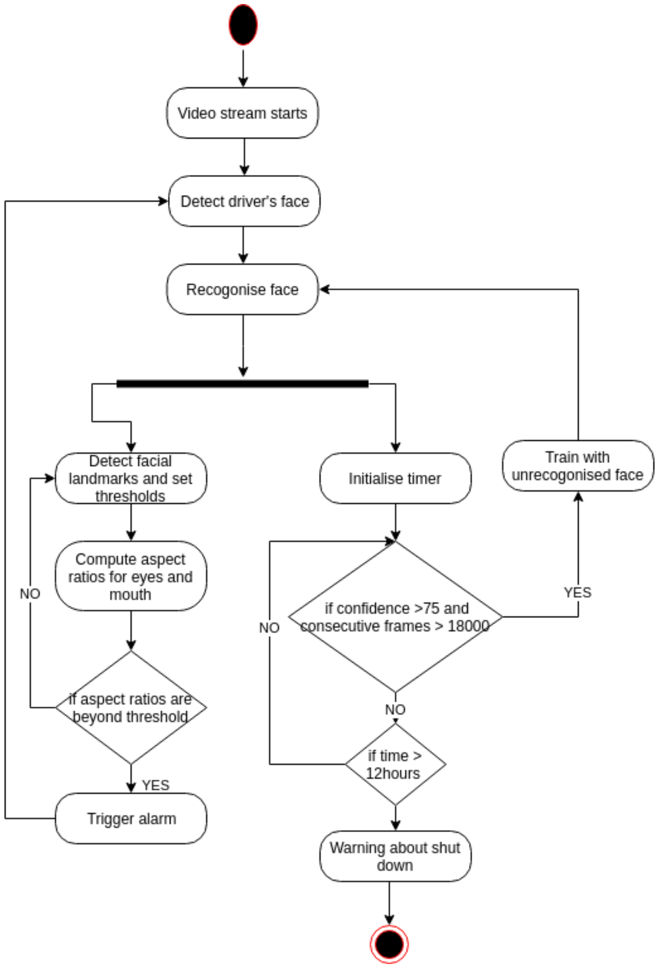
If the driver is the same, we constantly monitor the degree of closeness of his eye and at the same time increase the timer. If the driver is different, a separate timer is commenced and the monitoring of the status of the new driver is started. In order to calculate the degree of yawning and the eye closeness, first we calculate the aspect ratio of eye and mouth and locate facial landmarks. Our mechanism alerts the driver when the aspect ratio reaches a predetermined level.

Input Data: The live feed of the face is recorded using the RGB camera.

Face Detection: HOG, or Histogram Oriented Gradients, are utilized to start the face recognition process. Object detection is aided by this characteristic, which is based on an intensity gradient distribution or edge directions for detection functions. A detection window of identified pixels is swept over the image so that gradients are calculated using Equation 1 for each pixel within the cell. Pixel orientation and magnitude are included in Gradient

$$\begin{aligned}\text{gradient magnitude:}\quad & gm = \sqrt{gm_x^2 + gm_y^2} \\ \text{gradient direction:}\quad & \theta = arctan\frac{gm_y}{gm_x}\end{aligned} \qquad (1)$$

The collection of HOG is performed on the detection window by calculating the overlap of blocks (combined cells) and at last is stored in a feature vector. HOG is an algorithmic program integrated within the dlib library that uses a certain dimension block size counting on the image size with 50% overlap. Depending on the direction of the gradient and the amount of the gradient, the gradient histogram is separated into B containers. The Support Vector Machine recognizes both faces and non-faces. SVM stands for supervised learning model, and it is used to help in data analysis. In this application, Facial features are classified from non-facial features using linear classification in SVM.



Face Recognition: The Local Binary Pattern (LBP) histogram was used to identify the faces. It works parallel with face detection. They are illumination invariant and work by dividing the image into specific pixel cells as follows:

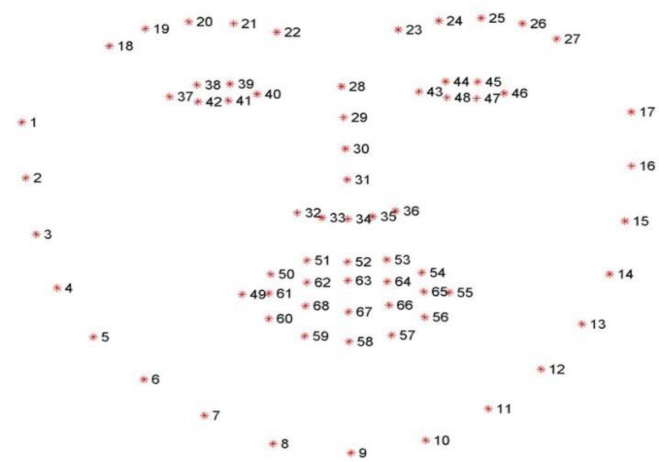
•At a time, 9 pixels are examined by LBP. LBP is mainly interested in the central pixel and compares it to each of its 8 neighbors. If the center pixel's value is bigger than its neighbor's, assign 0. Otherwise, assign 1. Hence an 8-digit binary number (taken clockwise) is generated using this.

• Histograms are calculated at the same time for every cell then joined to give a feature vector of the complete window.

We have trained our system in such a way that it calculates the histogram of different people one by one and compute the difference between the histograms, by comparing it to the histogram of the input image; this is referred to as confidence. The lowest confidence value is selected from the various histograms, which means that the input image is more likely to be similar to that particular person under the following conditions:

$$Face = \begin{cases} Recognized\ \ if\ \ confidence < 75 \\ Unrecognized\ if\ confidence > 75\&CF = 18000. \end{cases} \quad (2)$$

Dlib facial landmarks: The next step is to get face landmarks. This method is used to locate 68 precise locations on the face,



including the corners of the mouth, brows, eyes, and so on. This feature was trained on a dataset named iBUG 300-W [22].

Fig 2: Showing all 68 specific points on the face.

EAR and MAR calculation: The eye aspect ratio can be computed using this equation (EAR)

$$EAR = \frac{\| p_2 - p_6 \| + \| p_3 - p_5 \|}{2 \times \| p_1 - p_4 \|} \quad (3)$$

Where p1, p2, ..., p6 are 6 eye landmarks.
Similarly, the aspect ratio of the mouth (MAR) is calculated using this equation.

$$MAR = \frac{\| q_2 - q_8 \| + \| q_4 - q_6 \|}{2 \times \| q_1 - q_5 \|} \quad (4)$$

Where, q1, q2, ..., q8 are 8 mouth landmarks.
Driver’s Drowsiness Detection: Then Drowsiness is detected by calculating the EAR and MAR based on their facial landmarks. The threshold for the eye is 0.15 and is denoted by symbol (θ) and threshold for mouth is 0.1 and is denoted by the symbol (θ1) . If EAR is less than 0.15 or if MAR is greater than 0.1 over a specified number of frames, then drowsiness alert is triggered.

$$\text{Eyeclosed} = \begin{cases} True & \text{if } EAR \leq \vartheta \\ False, & \text{otherwise.} \end{cases} \quad (5)$$

$$\text{Yawn} = \begin{cases} True & \text{if } MAR \geq \vartheta_1 \\ False, & \text{otherwise.} \end{cases} \quad (6)$$

Drowsiness alert using dynamic timer: For eyes closed, consecutive eye (CE) is the non-stop frame threshold and for yawning, consecutive mouth. (CM) is the non-stop frame threshold. CE and CM, respectively, have 50 and 90 points. Initialization of threshold depends upon the distance of the driver from the camera which is being used to take the feed.

Consecutive eye values and consecutive mouth values are calculated using these Equations.

$$
\begin{aligned}
CM &= 90 - 2.72 \times (TIME)/3600 \\
CE &= 50 - 1.81 \times (TIME)/3600
\end{aligned}
\tag{7}
$$

Where, 2.72 and 1.81 are the slope values of the linear equation. TIME = 9×60×60 = 32400, since the threshold starts decreasing after 3 hours, thus we take a total of 9 hours or 32400 secs to complete the work.

The driving time of a driver and sensitivity of the program is inversely proportional to thresholds of continuous frames of eyes and mouth. A healthy person has an average yawning time of 4 to 6 seconds as per studies.

The values are reduced after 3 hours of uninterrupted driving, as the driver is usually active up to this point.

Our system usually waits for 6 seconds for the yawning and about 4 seconds for the closed eyes before the alarm is activated. But after 3 hours of driving by the same person, the waiting time is reduced by approx. 4.5 seconds when yawning and 2 seconds when the eyes are closed.

When approaching 12 hours of continuous driving, the system has become very sensitive and would tend to alert in a very small interval of blinking or yawning, since at this point the driver will reach a state of complete fatigue and further driving can even cause a deadly accident. When the timer strikes 12 hours of driving, it repeatedly sends a warning to the driver to stop the car and not drive any further and to take some rest/sleep.

Fig. 5: shows 68 landmark co-ordinates of facial region

IV. EXPERIMENTAL ANALYSIS

Our tests are performed on Windows 11 OS running with 8 GB of RAM. We presented a technique for monitoring driving tiredness and warning the driver to remain alert. We implemented HOG to learn features and SVM that determines whether the detected area was face or non-face. The face of the identified motorist is returned by our system. As seen in Figure 4, a square is formed around the identified face.

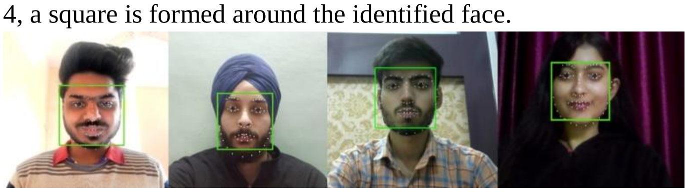


Fig. 4: shows face detection in bounding box region.

A pre-trained facial landmark detector contained in the dlib package is used to identify and recognise the 68 face points, as illustrated in Figure 2, such as the exact proportions of the eyebrows, lips, nostrils, ears, and jawbone. The findings are shown in Figure 5.Since the drivers may swap within a certain duration of travelling, a fresh timer for each new driver must be initiated. This also necessitates the use of a face recognition algorithm, which is accomplished via the LBPH approach. This approach compares the recognized face to a pre-trained dataset of distinct drivers according to the confidence score. The statistical mismatch between the recorded face and the input face is used to determine a confidence score. If the confidence rating is more than 75, the individual is unknown. As illustrated in Figure 6, the driver is unrecognized when the confidence score is more than 75 for consecutive frames of 18000, i.e. 20 minutes.

The driver's samples are then taken for training, and if they match (confidence score less than 75), a different label is

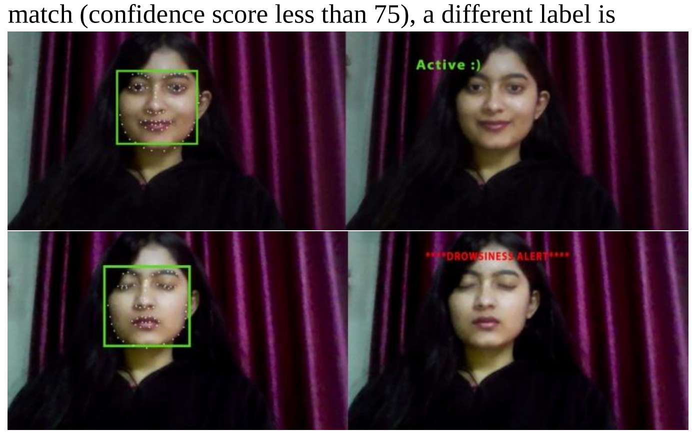


Fig. 6: It displays the motorists' confidence levels as 81, 83, 86, and 88, accordingly.

That means the facial expression is unrecognized by the recognition system and must be taught before the timer can be started.

Assigned to the driver, as illustrated in Figure 7. It displays the label that has previously been applied to that matching dataset for the present driver.

The concepts of Eye Aspect Ratio (EAR) Equation 3 and Mouth Aspect Ratio (MAR) Equation 4 are used to identify

Fig. 7: After dynamic training, the drivers are given specific labels of 2,3,4,5, and the confidence score is decreased to 61, 60, 58, and 62, respectively.

For sleepiness alert, the retrieved facial points are used to compute the EAR and MAR of the scanned and recognized face. There will be two phases for accounting for input parameters.

- Phase 1 (Timer up to 3 hours of driving) - Initial eye and mouth thresholds are 0.15 and 0.1, respectively, with subsequent frame thresholds of 95 and 55 for lips and eyes, respectively. This phase, as illustrated in Figure 8, has a static threshold, which means that the threshold values do not fluctuate over time.

CE: continuous frames for eyes closed, CF: continuous frames for unrecognized person.

- Phase 2 (between 3 and 12 hours of driving) - Using the linear Equation 7, both the threshold values of consecutive frames for lips are gradually decreased and compared to the computed EAR and MAR for drowsiness alert, as illustrated in Figure 9. As a result, the system will notify the driver significantly sooner than in phase 1.

According to our research, an average eye blink lasts 400 milliseconds, and any duration longer than this for closed eyes is considered non-natural. With the equation provided, the consecutive frames threshold for closed eyes is dropped from 50 frames (about 3.5 seconds) to 30 frames (about 2 seconds). This decrease occurs after 3 hours of continuous travelling, because the driver is normally engaged for that long time. When the timer hits 11 hours, the algorithm is very sensitive enough to detect a yawn and shutting of eyes, and it waits for too shorter period of time to warn the driver, since at that point, the driver is completely exhausted, and continuing to drive might result in a deadly accident. In addition, when the timer hits 12 hours of uninterrupted driving, the driver is prompted to stop the vehicle and not go any further.

A. Accuracy and time analysis

Our suggested approach has a 90 percent real-time accuracy. Because it correctly recognized sleepiness, the alert was generally activated. This is self-evident; the camera is positioned in the front, and when the driver looks to the left, right, or bends, the designed system detects it as non-face, and processing is terminated. We used the sensitivity formula from Equation 8 to compute the accuracy. The sensitivity formula is used to assess whether or not there is sleepiness. As a consequence, our developed technique has a 90% accuracy for 100 samples.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{8}$$

N = 100	Positve	Negative
True	TP/83	TN/0
False	FP/10	FN/7

Fig. 8: Precision recall table of proposed approach. We tested 100 samples and found that it accurately categorized 83 of them and misclassified 10 of them.

The frame rate of our developed technology is 15 cycles per second.

V. CONCLUSION AND FUTURE WORK

Despite the fact that no universal definition of drowsiness exists, the various definitions and explanations for them were discussed. This paper also discusses the various ways in which weariness can be adjusted in a virtual setting. Subjective, vehicle-based, physiological, and behavioural measures can all be used to detect drowsiness. The benefits and drawbacks of each strategy were thoroughly studied. Physiological tests have a high accuracy rate for detecting drowsiness, although they might be inconvenient. This intrusive nature can be removed, however, by using contactless electrode implantation. As a result, combining physiological markers like ECG with behavioural and vehicle-based metrics to create an effective drowsiness detection system would be advantageous. In order to achieve optimal results, it's also crucial to consider the driving environment.

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