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Bindu Verma
Jawaharlal Nehru University

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Real-Time Driver's Drowsiness Monitoring Based on Dynamically Varying Threshold

Isha Gupta, Novesh Garg, Apoorva Aggarwal, Nitin Nepalia and Bindu Verma*
Department of Computer Science Engineering
Jaypee Institute of Information Technology, Noida, India
*Email: bindu.verma@jiit.ac.in

***Abstract*—One of the most prevailing problems across the globe nowadays is the booming number of road accidents. Improper and inattentive driving is one of the major cause of road accidents. Driver's drowsiness or lack of concentration is considered as a dominant reason for such mishaps. Research in the field of driver drowsiness monitoring may help to reduce the accidents. This paper therefore proposes a non-intrusive approach for implementing a driver's drowsiness alert system which would detect and monitor the yawning and sleepiness of the driver. The system uses Histogram Oriented Gradient (HOG) feature descriptor for face detection and facial points recognition. Then SVM is used to check whether detected object is face or non-face. It further monitors the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) of the driver up to a fixed number of frames to check the sleepiness and yawning. Since the drowsiness or tiredness of the driver is also based on the number of hours he or she has been driving, an additional feature of varying the threshold frames for eyes and mouth is included. This makes the system more sensitive towards drowsiness detection. Also, this requires the inclusion of face recognition implementation so that monitoring can be done individually for every driver. Our experimental results shows that our proposed framework perform well.**

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

I. Introduction

In the recent years, not much improvement has been seen in the reduction of road accidents. Amongst the various reasons, the major one is the driver's fatigue and drowsy state. This reduces driver's decision-making ability to control the car. Symptoms of being drowsy or sleepy include-difficulty in focusing, frequent eye blinking, day-dreaming, missing traffic signs, yawning repeatedly etc. Further, in [1] show that the driver's who are deprived of more than 4 hours of sleep are 10.2 times more likely to indulge in accidents. According to the statistics [2] [8] it has been estimated that driver's drowsiness kills $1,500$ people and leaves $71,000$ people injured in US road accidents every year. Considering the Australian survey, about 20% of severe road accidents and 30% of fatal crashes involve drivers mistake. Further, a survey [3] in Norway found that 3.9% of the accidents were sleep related and almost 20% of night-time accidents involved driver's drowsiness.

Therefore, it is necessary that the next set of cars coming out in the market should have an additional safety feature to alert sleepy driver's and handling auxiliary task using hand gesture [6]. Such a system can be created using various approaches which may be intrusive or non-intrusive. The intrusive one takes into consideration biological parameters such as electroencephalogram (EEG), electrocardiogram (ECG) but this method requires electrodes to be connected to the body of the driver. Since it is usually expensive and would create disturbance annoyance to the driver, so it is not much preferred by the drivers. Non-intrusive approach may be vehicle based such as the position of car on roads, movement of steering wheel or behaviour based such as the blink of the eye, yawning etc. But since the vehicle-based methods are dependent on the driving skills of the driver and the type of the road on which the vehicle is running therefore it is difficult to create standardized rules for it.

Hence, analysis of facial expressions which is considered to be the most appropriate method is used in this paper. This requires a camera to be placed inside the car for capturing driver's image. Further processing of the captured image is achieved by Histogram Oriented Gradient in which we extract feature descriptor to detect the faces in each frame. Support Vector Machine (SVM) is trained to classify the face and non-face region. Face recognition feature is included in starting to keep a separate timer for every new driver. Thus, first we use Local Binary Patterns Histograms (LBPH) to recognize face in each frame to check whether same driver or different, accordingly update/set the time. LBP is the most convincing feature for texture classification and when combined with Histogram Oriented Gradient (HOG) descriptor, it improves the detection performance. To monitor the sleepiness, yawning of driver's, we first draw 68 *landmarks on facial region, then calculate the Eye Aspect Ration (EAR) and Mouth Aspect Ration (MAR). Then used thresholding value to check driver's state.*

In our research our main focus is not only to alert the driver but also to keep track of their driving schedule. Uber [4] led a campaign in which they restricted U.S. drivers to a maximum 12 hours of driving time. Immediately after the 12 hours shift, a prompt pop-up acquiring them to take a 6-hour break by going off-line. This leads to declination of accidents to a great extent. Also, providing more flexibility in their jobs by making them less exhausting. In our methodology we are applying this concept by introducing dynamic frame threshold that will start decreasing after 3 hours and would prompt the driver to stop driving after 12 hours.

Rest of the paper is organized at follows: In Section II literature survey has been discussed. We discuss proposed approach in Section III. Experimental analysis has been done in Section IV. Finally, we conclude in Section V with future directions.

II. Literature Survey

As of now there has been an extensive amount of work done on drowsiness detection. But here we specify only a few important and relevant literature works. Chellappa et al. [5] uses physiological and physical signs for drowsiness detection. System takes input from both the factors and uses a combination of these as a parameter. Physiological inputs include body temperature and pulse rate, physical inputs comprises of yawning and blinking. Eventually they result in annoyance to the driver thus not reliable as compared to non-intrusive approaches. One of the non-intrusive approaches include the HOG descriptor algorithm which was introduced by Dalal et al. [7] for face detection. Also, Comparative analysis of performance of HOG descriptors against generalized haar wavelets, PCA-SIFT descriptors and shape context descriptors commenced on different dataset. Linear SVM is then trained on HOG features to classify the facial expression. Ngxande et al. [9] give a meta-analysis on three machine learning techniques i.e. Support Vector Machines(SVM), Convolutional Neural Networks (CNN) and Hidden Markov Models (HMM) to figure out the behaviour aspects. It then concludes that out of the three techniques the SVM technique is most commonly used but the convolutional neural networks gives finer results than the other two. Wang et al. [10] proposed framework for driver drowsiness detection where the method PATECP (Percentage and Time that Eyelids Cover the Pupils) and PATMIO (Percentage and Time that Mouth Is Open) is used to decide whether the driver is drowsy by setting a particular threshold. Zhao et al. [11] proposed a schema for recognizing drowsy expressions which is based on facial dynamic fusion information and a deep belief network (DBN). To make the system more robust in different light conditions in [12] uses various visual cues along with remotely located camera with infrared illuminators. Assari et al. [13] also proposes a system that used infrared camera, to capture the video stream of the driver, in order to resolve the issues imposed by lightning conditions, presence of glasses, beard etc. Further face region is detected and facial components are extracted from the stream and then compared with that of a drowsy person using template matching. Many other theories were also implemented for the same. Daza et al. [14] build an efficient non-intrusive approach which uses the combination of Percentage of Eye Closure (PERCLOS) and the driving information (the steering wheel angle, lateral position, heading error provided by the CAN bus) which is studied in the time and frequency domain. Lyu et al. [15] build a system taking into consideration the temporal dependencies with variable length e.g. eye blink and eye closure, speaking and yawning. Their work uses two main integrals, one is Multi-granularity Convolutional Neural Network (MCNN), and second a deep Long Short Term Memory network. Littlewort et al. [16] proposes a software i.e. Computer Expression Recognition Toolbox (CERT) which can code the intensity of the facial expressions automatically and can process 320×240 video images at 10 frames per seconds in real-time. Chen et al. [17] together describe a system based on the color space transformation of YCbCr for achieving face location. Further, processing of the face region is done on the binary image and the eye close open ratio is used to detect drowsiness. Khunpisuth et al. [18] uses Raspberry Pi 3 module and Raspberry Pi Camera to calculate drowsiness level taking into consideration the blinking of the eyes and the head tilting frequency of face. Catalbas et al. [19] give an implementation based on saccadic eye movements. Infrared led camera device is used to get the eye data and the analysis is done on two driving scenarios with low and high traffic density. Chakraborty et al. [20] describe a system to extract face from video sequence of a driver and detect the eye region. Further system analyses the existence of eye pupil using Hough transform to calculate the blink rate. This parameter is then used to identify the drowsy state of the driver. Singh et al. [21] proposed a system that monitors the time span of eye blinking. On an average eye blink duration is less than 400ms and a minimum of 75ms.

III. Proposed Work

We proposed a real time system to monitor driver's state such as sleepiness, yawning and if drivers fall sleep or yawn more than 4sec, our systems alert the driver to be in normal driving state. A RGB camera is mounted at front windows and constantly looking at drivers face. We also set a timer for each driver such that if driver is driving constantly till 12 hours, our proposed system triggers an alarm to switch off from driving. First step of our proposed approach is to detect the face from each frame and recognize the face to check whether it is same driver or different driver. If it is the same driver we constantly monitoring eye closeness and yawning and simultaneously timer is also increases. If it is different driver, a separate timer is initialized and start monitoring the driver state. To find the eye closeness and yawning, we first find the facial landmarks and compute the aspect ratio of mouth and eye. If aspect ratio is beyond certain threshold our proposed system triggers an alarm to warn the driver. The working module of our flowchart is given in Figure 1.

Input Data: We used RGB camera to capture the video stream.

Face Detection: The system begins with the face detection process using Histogram of Oriented Gradients (HOG) which is a feature descriptor used for object detection. This technique relies on distribution of intensity gradients or the edge directions for detection features. A detection window of specified pixels is passed over the image such that gradients are computed using Equation 1 for every pixel within the cell. Gradients include pixel orientation and magnitude.

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

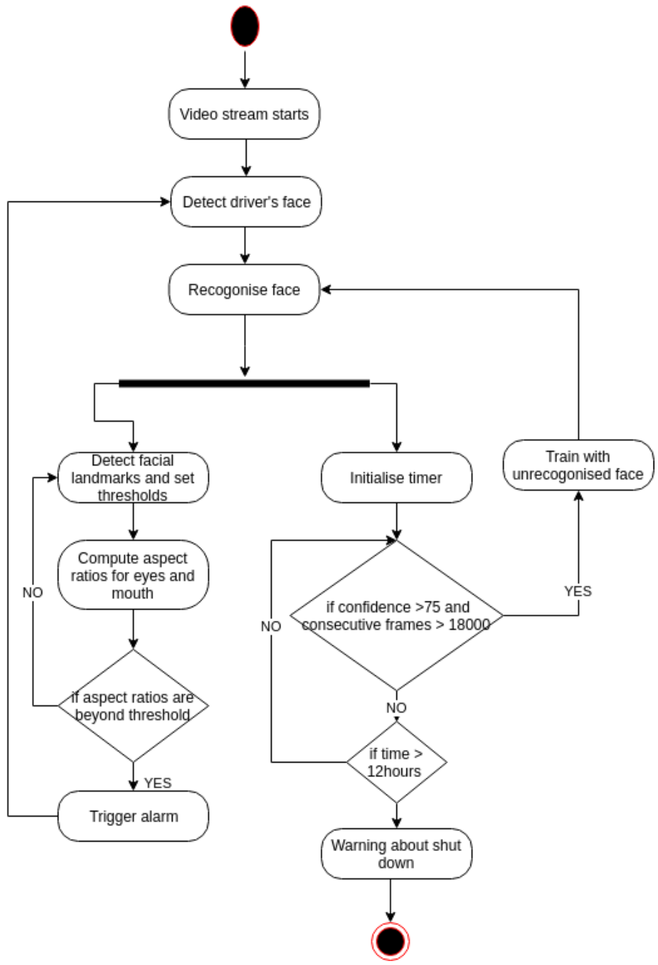


Fig. 1: An overview of our proposed work. Face recognition and sleepiness and yawning detection.

Collection of HOG is done over detection window by computing overlapping of blocks (combined cells) and finally stored in a feature vector. HOG is an in-built algorithm in dlib library that uses block size of particular dimension depending on image size with 50% overlap. Depending upon the gradient direction and gradient magnitude, histogram of gradient split over B bins.

We used Support Vector Machine (SVM) to recognize the face and non-face in each frame. SVM is a supervised learning model that analyses data for classification and regression analysis. In this application SVM is classifying facial features from non-facial features using linear classification. While we give this feature vector to train linear SVM and we have used the dlib librarys pre-trained HOG + Linear SVM detector.

Face Recognition: Local Binary Pattern (LBP) histogram is an efficient texture operator which is used for face recognition and works parallel with face detection. They are illumination invariant and works by dividing the image into cells of specified pixels as follows:

- LBP examines 9 pixels at a time. It is particularly interested at the center pixel and compare it to each of its 8 neighbours.
- If center pixel's value is greater than the neighbours value, then assign 0 else 1. This gives an 8-digit binary number (taken clockwise).
- Histograms are computed simultaneously for each cell and then concatenated to give feature vector of the entire window.

We have trained our proposed system on different people such that it computes the histogram individually and compares it with the histogram of input image by computing difference between histograms called confidence. Least confidence value is selected amongst the different histogram which implies the input image is most likely to be similar to that particular person under following condition:

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

Dlib facial landmarks: The next step is to acquire the facial landmarks. The basic idea of this technique is to locate 68 specific points on face such as corners of the mouth, along the eyebrows, on the eyes, and so forth. It is a pre-trained detector in the dlib [1] library that is able to find these 68 co-ordinates on any face. This predictor was trained on iBUG 300-W [22] dataset. Sample facial landmark are shown in Figure 2 and experiments on each frame are shown in experimental section.

EAR and MAR calculation: Eye aspect ratio can be calculated using Equation 3.

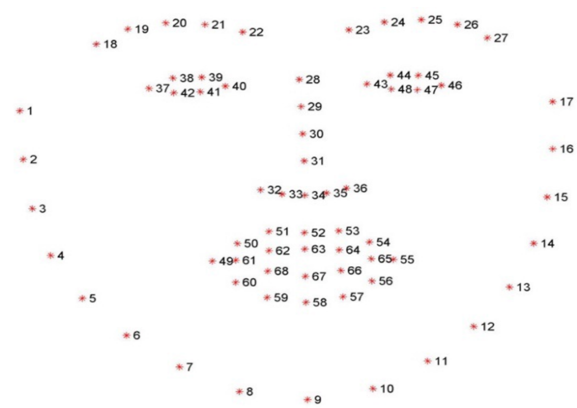
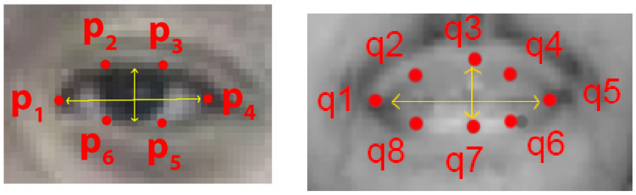


Fig. 2: shows the pre-defined 68 co-ordinates of face defined in dlib library

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

where, $p_1, p_2, ..., p_6$ are 6 eye landmark shown in Figure 3a. Similarly mouth aspect ratio (MAR) can be calculate using

[1] https:/www.pyimagesearch.com/2017/04/03/facial-landmarks-dlib-opencv-python/



(a) Each eye is represented by $6(x,y)$-coordinates facial landmark of eye region starting from left corner in clock wise direction.

(b) Mouth is represented by $8(x,y)$-coordinates facial landmark of mouth region starting from inner lip left corner.in clock wise direction

Fig. 3: Representation of landmark points for MAR and EAR calculation.

Equation 4

$$MAR = \frac{\parallel q_2 - q_8 \parallel + \parallel q_4 - q_6 \parallel}{2\times \parallel q_1 - q_5 \parallel} \tag{4}$$

where, $q_1, q_2, ..., q_8$ are 8 mouth landmark shown in Figure 3b.

Driver's Drowsiness Detection: Drowsiness is then detected by computing the aspect ratios of eye frames and mouth based on there facial landmarks. The threshold (θ) for eye is 0.15 and threshold (θ_1) for mouth is 0.1 such that if eye aspect ratio (EAR) is less than 0.15 or if Mouth aspect ratio (MAR) is greater than 0.1 over a specified period of frames then drowsiness alert must be triggered.

$$\text{Eyeclosed} = \begin{cases} True & \text{if } EAR \leq \theta \\ False, & \text{otherwise.} \end{cases} \tag{5}$$

$$\text{Yawn} = \begin{cases} True & \text{if } MAR \geq \theta_1 \\ False, & \text{otherwise.} \end{cases} \tag{6}$$

Drowsiness alert using dynamic timer: Initially the threshold values for EAR and MAR are assigned to 0.15 and 0.1 respectively and the count of timer is initially set to 0. Continuous frame threshold for eyes closed is consecutive eye (CE) and yawning is consecutive mouth (CM) are 50 and 90 respectively. Thresholds initialization depend upon the distance of the camera from the driver used to take the feed. These thresholds are adjusted for a particular distance and if distance is changed, thresholds will also need to be altered. Consecutive eye values and consecutive mouth values can be calculated using using Equation 7

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

where, 2.72 and 1.81 is a slope value of linear equation. TIME = $9 \times 60 \times 60 = 32400$, since decrement of threshold start after 3 hours, thus we take 9 hours for time and converted 9 hours in seconds.

As the driving time of a driver increases thresholds for continuous frames of eyes and mouth are start decreasing using Equation 7. So the system with time increases becomes more sensitive to detect drowsiness and triggered alarm. An average yawning time for a healthy person is studied to be 4 to 6 seconds. This system starts with CM threshold (continuous frames of yawning monitored) for 90 frames (6 seconds approx) and with the increases in time, it linearly decreases to about 70 frames (4.5 seconds approx). Similarly as per the study an average eye blink takes 400 milliseconds, so any duration more than that for closed eyes is treated as non-natural closing of eye. Therefore, CE (continuous framed monitored for closed eyes) threshold start with 50 frames (approx 3.5 seconds) and gets linearly reduced to 30 frames (approx 2 seconds) with time increases. This reduction take place after 3 hours of continuous drive, as the driver is usually active up to that much time.

Our proposed system waited for 6 seconds for yawning and about 4 seconds for closed eyes to trigger the alarm. After 3 hours of driving by same driver as time increases waiting time reduces about 4.5 seconds for yawning and 2 seconds for closed eyes to trigger the alarm.

This way the continuous frames threshold decrease linearly as time passes, hence the sensitivity of the program increases. Coming closer to 12 hours of continuous driving the system is highly sensitive and would alert over a very small interval of blink or yawn because at that stage driver reaches the state of complete tiredness and further driving could lead to a fatal accident. Finally as the timer hits 12 hours the system gives a continuous alert to the driver to stop the car and not drive anymore.

IV. Experimental Analysis

We perform our experiments on Intel Core i5-6200U CPU @ 2.3GHz with 4 GB RAM. We proposed a framework for driver drowsiness detection and alerting the driver's to be in attentive state. We have used HOG to detect face and used SVM to check detected portion is face or non-face. This detector returns the detected driver's face. A bounding box is drawn on detected face as shown in Figure 4.

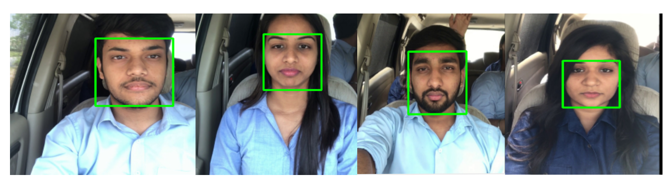


Fig. 4: shows face detection in bounding box region.

Further to detect the facial landmarks as shown in Figure 2, a pre-trained facial landmark detector which is present inside the dlib library is used which reads and detects the 68 facial points including the real time coordinates of eyes, mouth, nose, eyebrows and jawline. Results are shown in Figure 5.

As the driver may change after a particular period of driving, a separate timer has to be started for monitoring each new driver. This further requires the inclusion of face recognition algorithm which is achieved by the LBPH method. Based on the confidence value, this method first checks the detected face with the pre-trained dataset of different drivers. A confidence

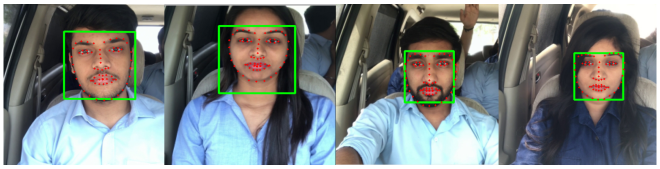


Fig. 5: shows 68 landmark co-ordinates of facial region

value is calculated using the histogram difference between database face and input face. If the confidence value > 75 then the person is unrecognized. As shown in Figure 6 as confidence value > 75 for continuous frames of 18000 i.e.20min approximately the driver is unrecognized.

After that it takes the samples of the driver for training and

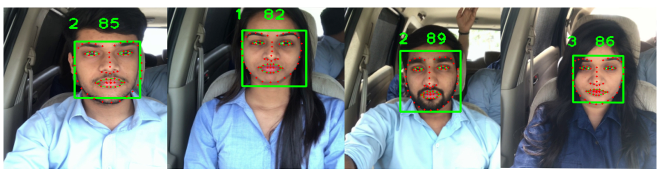


Fig. 6: shows the confidence values of the drivers as 85, 82, 89 and 86 respectively that means the face is unrecognized for the recognizer and needs to be trained for timer initialization.

then if matched i.e. confidence value < 75 assigns a new label to the driver as shown in Figure 7. It extracts the already assigned label of that matched dataset and displays it for the current driver.

Drowsiness is detected using the concept of Eye Aspect Ratio

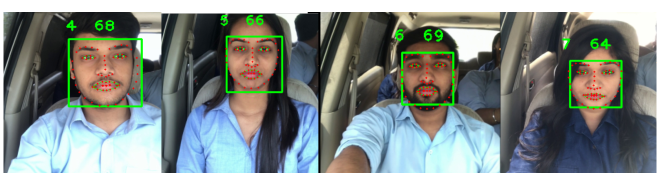


Fig. 7: shows new labels assigned to the drivers as 4,5,6,7 after dynamic training and thus confidence value gets reduced to 68, 66, 69, 64 respectively.

(EAR) Equation 3 and Mouth Aspect Ratio(MAR) Equation 4 respectively. EAR and MAR of the detected and recognized face are calculated using the extracted facial points for drowsiness alert. Two phases are then taken into consideration for the threshold values.

- Phase1(Timer up to 3 hours of driving) - Initially, the threshold values for eyes and mouth are assigned to be 0.15 and 0.1 respectively and continuous frame threshold for eyes and mouth as 50 and 90 respectively. This phase as shown in Figure 8 has static threshold so no change in threshold values with time. As CM reaches to continuous frames threshold for mouth, or CE reaches to continuous frames threshold for eyes, drowsiness alert is triggered.

Fig. 8: shows drowsiness alert at Phase1. CM: continuous frames for yawning, CE: continuous frames for eyes closed, CF: continuous frames for unrecognized person.

- Phase 2 (Between 3 to 12 hours of driving) - Both the threshold values of continuous frames for eyes and mouth are dynamically reduced with the help of the linear Equation 7 and then compared with the calculated EAR and MAR for drowsiness alert as shown in Figure 9. This makes the system alert the driver much prior as compared to that in phase 1.

Fig. 9: shows the CM reduced to 71 approximately from 90 with time and CE reduced to 39 from 50.

As per the study an average eye blink takes 400 milliseconds, any duration more than this for closed eyes is treated as non-natural closing of eye. So continuous frames threshold for eyes closed is reduced from 50 frames (approx. 3.5 seconds) to 30 frames (approx. 2seconds) linearly with the equation provided. This reduction takes place after 3 hours of continuous drive, as the driver is usually active up to that much time. As the timer reaches 11 hours system is highly sensitive to detect a yawn and closing of eyes, as it waits for a much less time to alert the driver, because at that stage driver also reaches the state of complete tiredness and further driving could lead to a fatal accident. Also when timer reaches 12 hours of continuous drive it alerts the driver to stop the car and not drive further.

A. *Accuracy and time analysis*

The real time accuracy of our proposed system is 90%. Most of the time it correctly detect drowsiness and triggered the alarm. Failure cases are when driver face is not towards the camera, our proposed framework not able to detect the drowsiness. This is quite obvious, camera is mounted at front and when driver is looking towards left, right or may be bend, proposed system detect it as non-face so further processing stopped. We calculated the accuracy using sensitivity formula given in Equation 8. Sensitivity formula measures the drowsiness when it is actually present. Thus our proposed system accuracy for 100 samples is 90%.

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

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

Fig. 10: Precision recall table of proposed approach. We took 100 samples and 83 time it correctly classifies and 10 times it misclassified.

Our proposed system works 15 frames per seconds.

V. Conclusion and Future work

The algorithms used in our proposed for face detection and recognition are efficient and of high accuracy, giving low false positive rates. We have introduced a concept where system is keeping track of driving schedule so as to make threshold dynamic after 3 hours of driving as driver becomes more prone to sleep at later stage of time. We have successfully implemented this concept by adding face recognition so that system can be viable for multiple drivers. Our proposed system can be used to monitor the driver's state and alert the driver, thereby reducing the number of road accidents.

As future scope, our methodology can be extended to detect drowsiness in extreme cases where external interferences causes failures in detection processes.

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