Dr B. R. Ambedkar National Institute of Technology

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Major Project Report

Semester - 8

Topic: Accident avoidance system that detects drowsiness of a driver based on facial cues and behavioral patterns.

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CERTIFICATE

We hereby certify that the work which is being presented in this report entitled, **"Accident avoidance system that detects drowsiness of a driver based on facial cues and behavioral patterns"** in partial fulfillment of the requirement for the award of Degree of Bachelor of Technology (Electronics and Communication Engineering) submitted in the Department of Electronics and Communication Engineering of Dr. B R Ambedkar National Institute of Technology, Jalandhar is a record of our work carried out during 2019-20 under the supervision of **Dr. R.K. Sunkaria .**

The matter presented in this report has not been submitted in part or full to any other University or Institute for the award of any Degree.

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This is to certify that the above statement made by candidates is correct to the best of my/our knowledge.

Signature of Supervisor(s):

Name of Supervisors: Dr. R.K. Sunkaria

Designation: Professor, Head of Department

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I take this opportunity to express gratitude to all of the Department faculty members for their help and support. I also thank my parents for the unceasing encouragement, support and attention.

I also place on record, my sense of gratitude to one and all, who directly or indirectly, have lent their hands in this venture.

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1. INTRODUCTION

According to a WHO report on Road Traffic Injuries [1], approximately 1.35 million people die as a result of road traffic crashes. Road traffic injuries are not only results in fatal injuries but also causes economic losses to the individual, their families and a nation as a whole. These accidents cost most countries 3 % of their GDP.

A study done by [2] assess the conditions of the incidents where the most likely cause of the accident was the driver falling asleep at the wheel. Sleep related vehicle accidents were identified based on the following criteria:

1. Blood alcohol levels
2. Vehicle ran off the road or ran into the back of another vehicle
3. No signs of break applied before the impact
4. Clear visibility and good weather conditions
5. Suspected sleepiness of the victim

The study concluded that sleep related accidents are largely dependent on the time of day and account for a considerable proportion of vehicle accidents across the globe.

It has been found that facial expression has the highest correlation with the brain waves as a general index of drowsiness during monotonous driving [3]. Thus, facial expressions can be considered a reliable measure of drowsiness.

Thus, an algorithm that analyses facial expressions and predicts the level of drowsiness can act as the basis for an accident avoidance system. Building upon the part work in the domain of computer vision and machine learning we intend to propose a computer vision based accident avoidance system.

Drowsiness: A detailed Study

The word drowsiness means to feel sleepy.

After the study and analysis by the researchers, the following traits have been found related to car accidents [33]:

- Driver doesn't have a company
- Occur mostly on highways
- Most common time is afternoon(2-4 Pm) and night (After 12 Am) when the driver is prone to feel drowsy
- A single vehicle is involved which runs off the street
- Any sign of breaks is not observed

It cannot be fully ascertained that these mishaps were caused by a single factor. It has many complex parameters. However, driver drowsiness can be one of the factors causing road crashes and it is important to alert the driver when he/she feels drowsy.

Drowsiness can be divided into three stages. Mostly stage 1 of NREM has been analyzed by the researchers when studying drowsiness detection system.

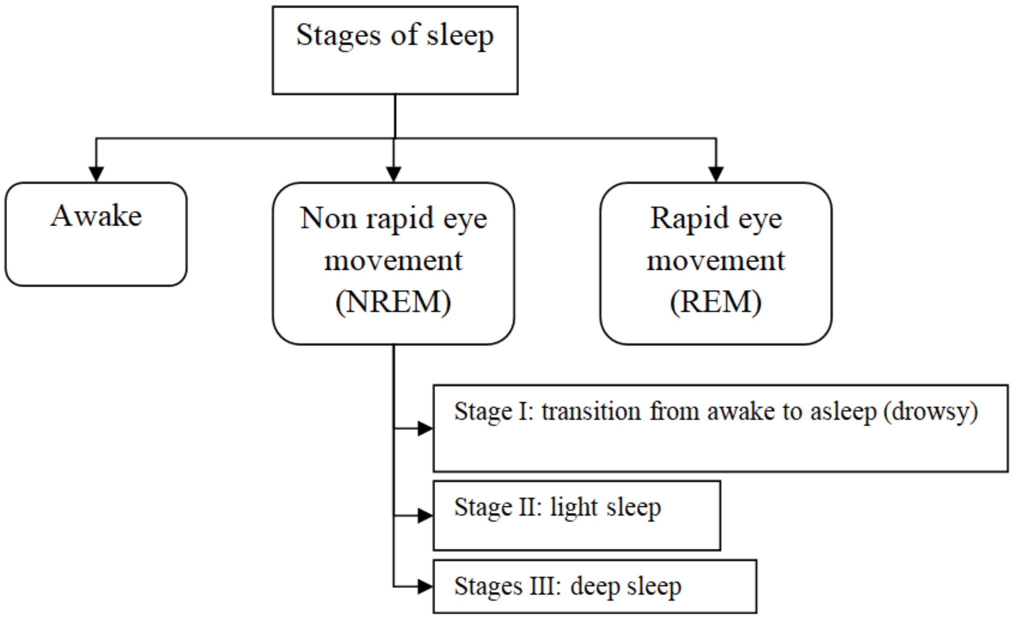


Fig 1. Stages of drowsiness

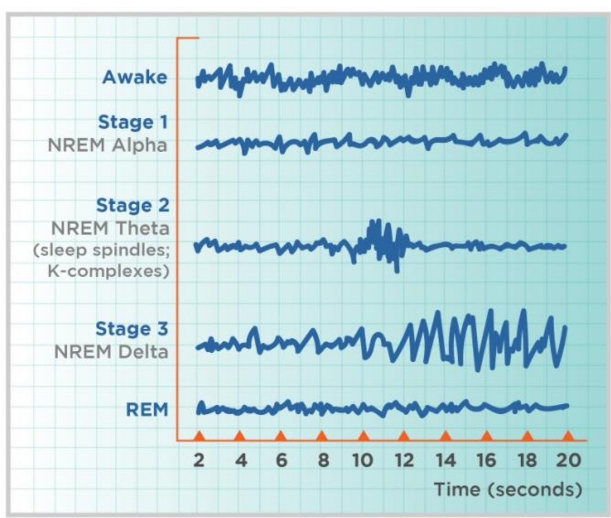


Fig 2. EEG recorded during different phases of sleep

2. PROBLEM DESCRIPTION

The contemporary image is processing and machine learning techniques have been able to solve of the biggest problems of our century. Our proposed solution, i.e. “A computer vision based system that detects the drowsiness of a driver based on facial cues and behavioral patters”, includes considerable amount of image processing and feature extraction.

Unlike conventional drowsiness detection methods, which are based on the eye states alone, we will use other facial expressions too to detect drowsiness/fatigue level. There are many challenges faced in making drowsiness detection systems. Among them, the important ones are: change of intensity due to lighting conditions, the presence of glasses and beard on the face of the person.

The design flow of the solution is as follows:

1. Face detection using pre-trained Machine Learning Model.
2. Landmark detection, identifying eyes, nose, mouth and jaw line.
3. Calculation of aspect ratios. Once the features of a face are extracted we need to calculate the aspect ratios of eyes (sleepy) and mouth (yawn).
4. Comparison of live aspect ratios with the threshold for the detection of drowsiness.
5. Alarming the driver. Once the drowsiness is detected we need to alert the driver using a sound/ alarm.

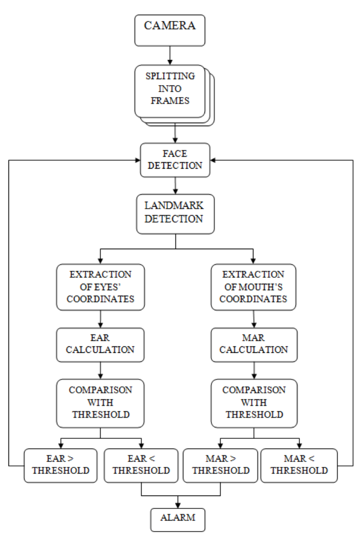


Fig 3. Architecture of proposed method

3. LITERATURE SURVEY

Fatigue and drowsiness are one of the leading contributors of road accidents. They can cause fatalities, injuries and economic losses. A study of statistics reveals that a reliable driver drowsiness detection system is needed so that the driver is alerted before a mishap happens.
The following techniques have been studied by researchers to determine driver drowsiness:
(1) Vehicle-based measures
(2) Behavioral measures and
(3) Physiological measures

3.1 VEHICLE-BASED MEASURES

One of the methods to detect driver drowsiness involves vehicle-based measurements. In this method, sensors are placed on various components of the vehicle such as steering wheel and acceleration pedal. After collecting the signals sent by the sensors, they are analyzed and the level of drowsiness is determined. Liu et al.[4] published a review on current vehicle-based measures. Some researchers found that sleep deprivation can result in a larger variability in the driving speed [5]. Steering wheel movement and the standard deviation of lane position are amongst the most widely used ones.

Steering Wheel Movement (SWM) is a widely used vehicle-based measure for detecting the level of driver drowsiness [6,7,5]. It is measured using steering angle sensor. The driver's steering behavior is measured by using the steering column mounted with an angle sensor. The number of micro-corrections on the steering wheel reduces when a person is drowsy when compared to normal driving [8]. Fairclough and Graham found that sleep deprived drivers made fewer steering wheel reversals than normal drivers [5]. The researchers considered only small steering wheel movements (between 0.5° and 5°) which are needed to adjust the lateral position within the lane [6]. This was done to eliminate the effect of lane changes. Hence, it becomes possible to determine the drowsiness level of the driver. Thus provide an alert if needed. In a simulated environment, light side winds pushing the car to the proper side of the road were added along a curved road. This was done to make variations in the lateral position and force the drivers to make corrective SWMs [7]. Car companies, such as Nissan and Renault, have adopted SWMs but it works in very limited situations [9]. This is because they will function reliably only at particular environments and are too hooked in to the geometric characteristics of the road and to a lesser extent on the kinetic characteristics of the vehicle [9].This is because they can function reliably only at particular environments and are too dependent on the geometric characteristics of the road and to a lesser extent on the kinetic characteristics of the vehicle [9].

Standard Deviation of Lane Position (SDLP) is another measure through which the level of driver drowsiness can be evaluated [10]. The software itself gives the SDLP in a simulated environment. In case of field experiments, however, the position of lane is tracked by using an external camera. Ingre *et al.* conducted an experiment in order to derive numerical statistics based on SDLP. It was found that, as the KSS ratings increased, SDLP (meters) also increased [10]. For example, KSS ratings of 1, 5, 8, and 9 corresponded to SDLP measurements of 0.19, 0.26, 0.36 and 0.47, respectively. The SDLP calculated supported the typical of 20 participants; however, with some drivers, the SDLP didn't exceeded 0.25 m even for a KSS rating of 9.In the above experiment, correlation analysis is performed on a subject to subject basis and significant difference is noted. SDLP is wholly dependent upon external factors such as road markings, climatic conditions and lighting conditions. It serves a big drawback for SDLP.

To summarize, many studies have concluded that vehicle-based measures are a poor indicator of performance error risk that happens due to drowsiness and fatigue. Also, SDLP is not specific to drowsiness. It can also be caused by impaired and inefficient driving, for example driving under the influence of alcohol and drugs [11, 12, 13].

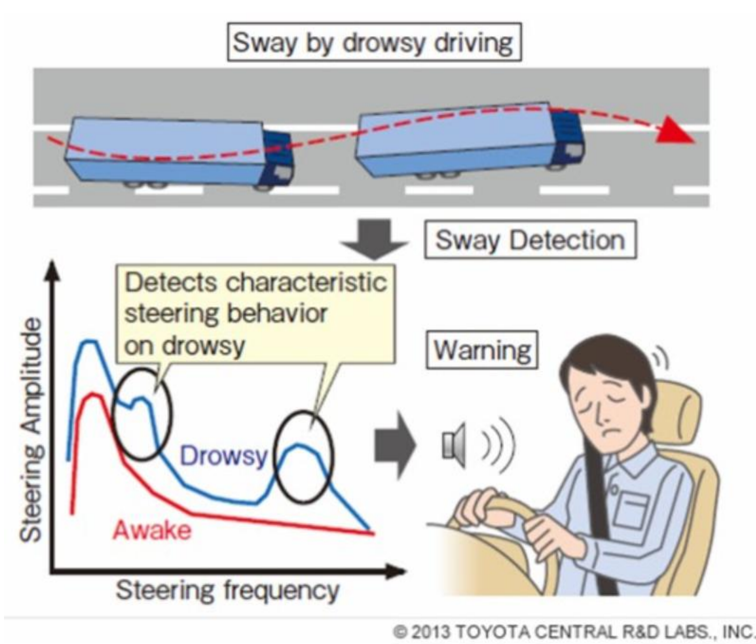


Fig 4. Drowsiness detection using vehicle based measures

3.2 BEHAVIORAL MEASURES

A drowsy person displays a variety of characteristic facial movements, like rapid and constant blinking, nodding or swinging their head, and frequent yawning [14]. For determining the drowsiness level of drivers, computerized, non-intrusive, behavioral approaches are widely used, which work by measuring their abnormal behaviors [15]. Most of the published studies on using behavioral approaches to determine drowsiness , focus on blinking [16, 17, 18]. PERCLOS (that is the percentage of eyelid closure over the pupil over time, reflecting slow eyelid closures, or "droops", instead of blinks) has been analyzed in many studies [19, 20–22]. This has been found to be a reliable measure in order to predict driver drowsiness [20] .It has also been used in commercial products such as Seeing Machines [23] and Lexus [24]. Multiple facial actions, including inner brow rise, outer brow rise, lip stretch, jaw drop and eye blink, have also been used by many researchers to detect drowsiness. The behavior of the driver, such as yawning, eye closure, eye blinking, head pose, etc., is monitored through a camera. The driver is alerted if any of these symptoms of drowsiness and fatigue are detected.

Sensor used	Drowsiness Measure	Detection techniques	Feature Extraction	Classification	Positive Detection rate
CCD micro camera with Infra-Red Illuminator	Pupil	Ada-boost	Red eye effect, Texture detection method	Ratio of eye-height and eye-width	92%
Camera and Infra-Red Illuminator	PERCLOS, eye closure duration, blink frequency, and 3 other	Two Kalman filters for pupil detection	Modification of the algebraic distance algorithm for conics Approximation & Finite State Machine	Fuzzy Classifier	Close to 100%
CCD camera	Yawning	Gravity-center template and grey projection	Gabor wavelets	LDA	91.97%
Digital Video camera	Facial action	Gabor filter	Wavelet Decomposition	SVM	96%
Fire wire camera and webcam	Eye Closure Duration & Freq of eye closure	Hough Transform	Discrete Wavelet Transform	Neural Classifier	95%
Camera	Multi Scale dynamic features	Gabor filter	Local Binary Pattern	Ada boost	98.33%
IR Camera	Eye State	Gabor filter	Condensation algorithm	SVM	93%
Simple Camera	Eye blink	Cascaded Classifiers Algorithm detects face and Diamond searching lgorithm to trace the face	Duration of eyelid closure, No. of continuous blinks, Frequency of eye blink	Region Mark Algorithm	98%
Camera with IR Illuminator	PERCLOS	Haar Algorithm to detect face	Unscented Kalman filter algorithm	SVM	99%

Fig 5. Previous work using behavioral measures

3.3 PHYSIOLOGICAL MEASURES

The correlation between physiological signals like electrocardiogram (ECG), electrooculogram (EoG), electromyogram (EMG), and electroencephalogram (EEG) and driver drowsiness has been studied by many researchers [25-29]. The study done by [30] investigated the use of features extracted from ECG and EEG signals for the detection of driver drowsiness. This experiment was performed with a simulator-based driving environment, having a sample of 22 subjects. Despite EEG being a reliable indicator of driver drowsiness, existing EEG systems are impractical in real driving conditions, because of their limited wearability.

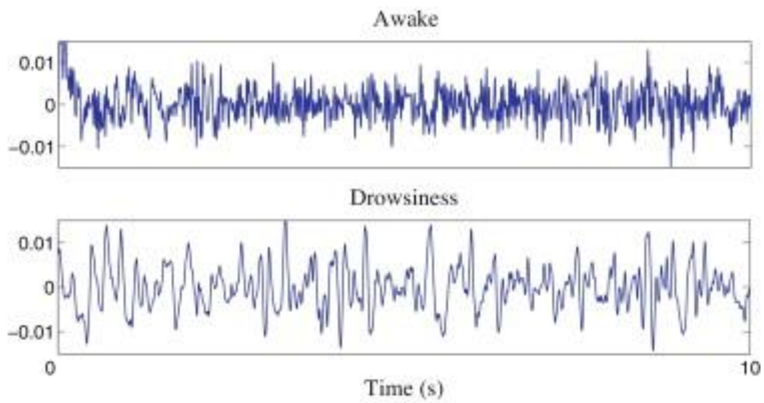


Fig 6. EEG signals for drowsiness detection

The driver drowsiness detection by using physiological signals is very highly precise, accurate and reliable when compared to other methods. However, a major drawback is the intrusive nature of measuring physiological signals. These intrusions make driver uncomfortable and thus is less preferred. To counter this drawback, researchers have used wireless devices to measure physiological signals in a less intrusive manner. This is done by placing the electrodes on the body and the obtaining signals using wireless technologies like Zigbee, Bluetooth. Some researchers have suggested measuring physiological signals in a non intrusive manner by placing electrodes on the steering wheel or on the driver's seat. The signals obtained were then processed in android based smart phone devices and the driver was alerted on time. Movement artifacts and errors that occur due to improper electrode contact make this technique less reliable and accurate and prone to errors. However, it is considered by the researchers due its user friendliness. Experiments are being conducted by the researchers to the validate non-intrusive systems.

Some researchers have proposed hybrid systems- including both intrusive and non intrusive measures for more accurate reading. If insights are taken for example from both ECG and SDLP, more robust system would be formed.

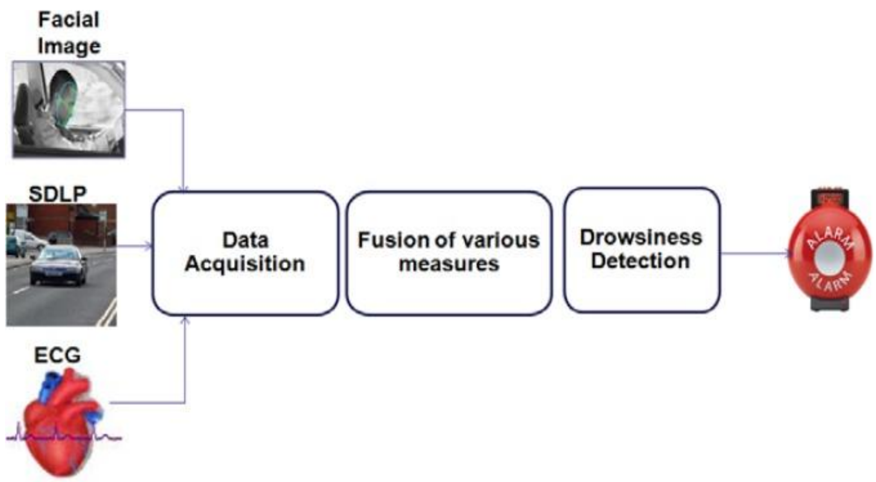


Fig 7. Hybrid drowsiness detection system

4. METHODOLOGY

The entire development of the accident avoidance system can be implemented in many interrelated steps as follows.

4.1 FACE DETECTION

Initially the most important task is to identify the subject, i.e. the driver in the image. Face detection is one of the most widely used applications of machine learning. It can be achieved using a no. of algorithms, to state a few methods

I. **Using OpenCV built-in Haar Cascades:**
It is an object detection algorithm using a machine learning approach. It is also called Viola-Jones detector. The classifier is trained on a lot of positive (the images in which there is object to be detected) and negative images(the images in which there isn't the object that we want to detect). This classifier is in-built in OpenCV(Open Source Computer Vision) which is a library used to do image processing and solve computer vision problems. However the Haar cascade detectors are old (proposed in 2001) and technology has quite advanced since then.

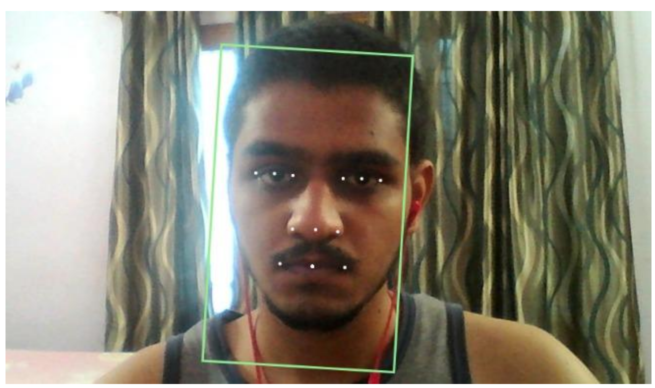


Fig 8. Face Detection using OpenCV

II. **Pre-trained HOG + Linear Support Vector Machine (SVM)** object detector specifically for the task of face detection:
The HOG (Histogram of Oriented Gradients) used in conjunction with a LSVM(Linear Support Vector Machine) gives more accurate results and is widely used. It makes a robust classifier.

HOG uses the property of different intensity distributions of different objects in the image. The image is divided into different blocks and gradients of intensity are calculated for each block. Each pixel has two vectors for intensity gradient in two directions (horizontal and vertical).
The SVM is then fed with a number of faces and gradient vectors and hence trained using them. SVM is a supervised machine learning model. It is used to divide and hence classify data. SVM returns a matching score for the input vector from HOG.

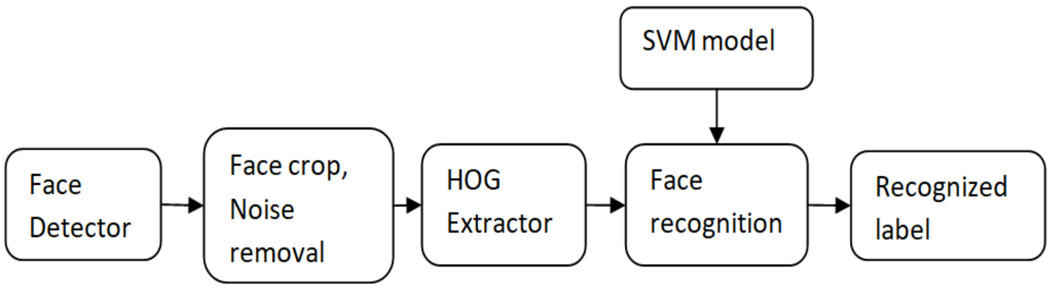


Fig 9. Block diagram showing face detection using HOG and Linear SVM

III. Deep learning based algorithms for face localization:
Multi-Task Cascaded Convolutional Neural Network is a widely used approach incorporating deep learning. This approach is used in the paper "Joint Face Detection and Alignment Using Multitask Cascaded Convolutional Networks" [31].

For the purpose of simplicity and getting more accurate results we can use pre-trained models for face detection.

The algorithm used won't matter much as long as you have obtained the X,Y coordinates of the face (the bounding box).

4.2 Landmark Detection

Once the face is detected we get a layout and a base for the implementation of our algorithm. The detected face is then used to find the landmarks. These landmarks define the boundary of the eyes, nose, mouth and jaw line. These detected contours can then be used to study the facial expression of an individual.

Detection of landmarks comprises of the following steps:

- **Localization of face in image:** This can be achieved by many ways. Open CV has built in HAAR cascade classifier for the same. A pre-trained Histogram of Object Gradients (HOG) and Linear Support Vector Machine object detector could also be used. Deep learning algorithms can also be applied for this purpose.

- **Localization of key facial regions:** There are the following methods for achieving it:
  - CNN(Convolutional Neural Network) based
  - RNN(Recurrnt Neural Network) based
  - Constructing 3D image from 2D
  - Dlib implementation

The Dlib implementation is based on “Ensemble of Regression trees” [32]. It uses pixel intensity gradients to identify various landmarks. The ensemble of regression trees iteratively updates the estimations to reduce the mean square error. It is a very fast algorithm.
To estimate the location of 68 (x, y)-coordinates that map to facial structures on the face, the pre-trained facial landmark detector inside the dlib library can be used. The indexes of these 68 coordinates can be visualized as on the following image:

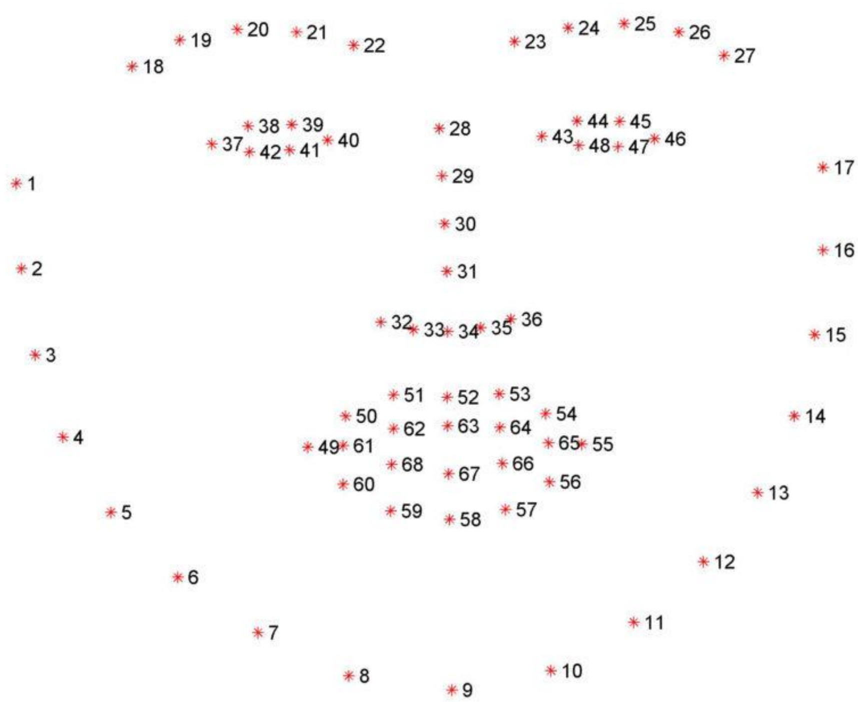


Fig 10. Visualizing the 68 facial landmark coordinates

These annotations are a part of the 68 point iBUG 300-W dataset (which the dlib facial landmark predictor was trained on).

Using the dictionary FACIAL_LANDMARKS_IDXS, we can extract various facial features and save into an array by using a string key.

The mappings for the various parts are as follows:

- Right Eye: [36, 42]
- Left Eye: [42, 48]
- Mouth: [48, 68]
- Right Eyebrow: [17, 22]
- Left Eyebrow: [22, 27]
- Nose: [27, 35]

4.3 Calculation of Eye Aspect Ratio

Now that we have obtained the eye regions, we can compute the eye aspect ratio in order to determine if the eyes are closed. An alarm will start to alert the driver if it is indicated by the eye aspect ratio that the eyes have been closed for a sufficiently long amount of time. Based on the work by Soukupová and Čech in their 2016 paper, *Real-Time Eye Blink Detection using Facial Landmarks*, an equation can be derived which reflects the relation between width and height of the eye coordinates. This factor is called the *eye aspect ratio* (EAR):

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

Fig 11. The eye aspect ratio equation.

Where *p1, …, p6* are the 2D facial landmark locations.

The eye aspect ratio is approximately constant while the eye is open, but will rapidly fall to zero when a blink is taking place as shown in the figure3.

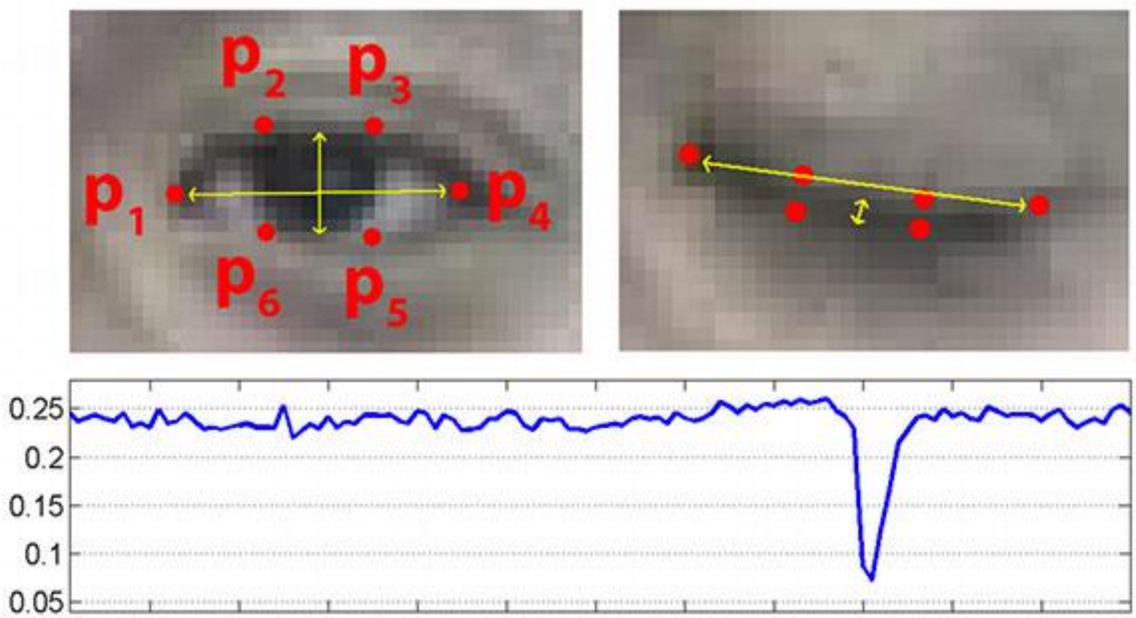


Fig 12. *Top-left:* A visualization of the eye landmarks when then the eye is open. *Top-right:* Eye landmarks when the eye is closed. *Bottom:* Plotting the eye aspect ratio over time. A dip in the eye aspect ratio indicates a blink

When determining if a blink is taking place in a video stream, the eye aspect ratio will have to be calculated. We will register a "blink" if the eye aspect ratio falls below a certain threshold and then rises above the threshold. This threshold is called EYE_AR_THRESH.

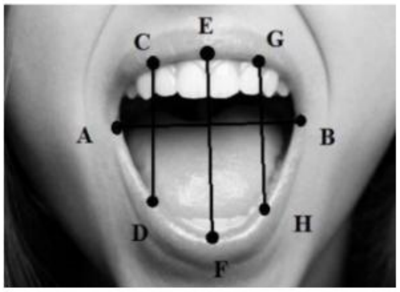
The same process can be implemented for the calculation the aspect ratio of mouth which indicates yawning.

4.4 Calculation of Mouth Aspect Ratio

Computationally similar to the EAR, the MAR, measures the ratio of the length of the mouth to the width of the mouth. Our hypothesis is that as an individual becomes drowsy, they are likely to yawn and lose control over their mouth, making their MAR to be higher than usual in this state.

The same principle as we applied in EAR can be implemented to calculate MAR.

Mathematically, MAR equals:



$$\text{MAR} = \frac{|EF|}{|AB|}$$

Fig 13. Mouth Aspect Ratio

Fig 14. Variation of MAR with mouth opening and closing

EAR and MAR are expected to maneuver in opposite directions if the state of the individual changes. This is the benefit of using this feature.

4.5 Thresholding

Intuitively we can understand that this aspect ratio differs from one individual to other, thus we need to fine tune our threshold based on the driver's features. Threshold act as a limit upto which an eye can be considered open or a person not yawning, any aspect ratio below a threshold EAR and above threshold MAR consider person to be drowsy or sleepy. This is the most important design step where the decision making takes place in our model.

4.6 Integration of the process and incorporating an alarm mechanism

Once the individual steps of face detection, landmark detection and calculation of aspect ratio takes place we need to integrate the whole process in a single infinite loop such that it continuously monitors the face and calculates aspect ratio, perform comparison on regular basis. Once the aspect ratios fall below the threshold we can raise an alarm to alert the driver.

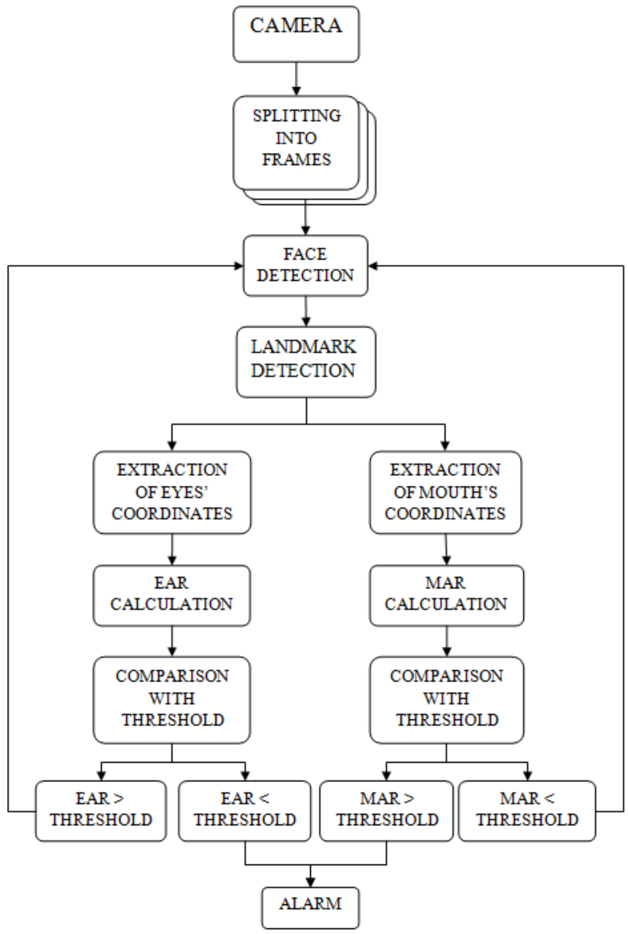


Fig 15. Architecture of proposed method

5. WORK DONE AND RESULTS

5.1 FACIAL LANDMARK DETECTION

Detection of facial landmarks is a subset of the shape prediction problem. In the context of our problem, we intend to detect the facial structures on the face using shape prediction methods.

Therefore detecting facial landmarks include:
1. Localization of face in an image
2. Detection of key facial structures

5.1.1 Localization of face in an image

Face detection has been one of the most researched problem in the domain of image processing and machine learning. It can be achieved using a no. of algorithms, to state a few methods:

I. Using OpenCV built-in Haar Cascades
II. Pre-trained HOG + Linear Support Vector Machine (SVM) object detector specifically for the task of face detection.
III. Deep learning based algorithms for face localization.

In our solution we use dlib's pre-trained face detector based on a modification to the standard Histogram of Oriented Gradients + Linear SVM method for object detection.

Fig 16. Bounding box around the detected face

Fig 17. The classifier is also able to detect multiple faces in a single frame

5.1.2 Detection of key facial structures

In our solution we have used the dlib library which is an implementation of **One Millisecond Face Alignment with an Ensemble of Regression Trees paper by Kazemi and Sullivan (2014).** In the following work a manually labeled dataset, specifying x-y coordinates surrounding facial structure was prepared. Now, given this data an ensemble of regression trees are trained for the estimation of landmark detection based on pixel intensity. It is noteworthy that this model doesn't perform feature extraction which considerably reduces the computation time.

Thus, it gives us a facial landmark detector that can be used to detect facial landmarks in real-time.

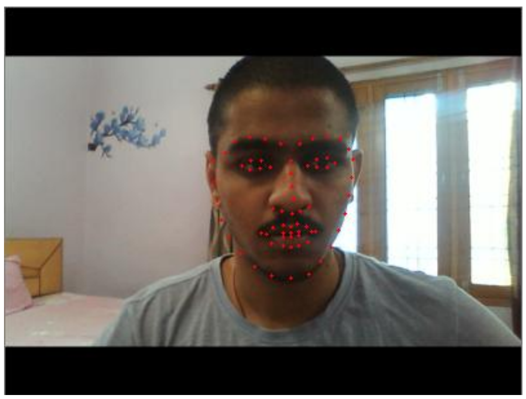


Fig 18. Landmark detection

5.2 CALCULATION OF EYE ASPECT RATIO

The eye aspect ratio is calculated using the following function:

```python
#function for calculation of aspect ratio

def eye_aspect_ratio(eye):
    # compute the euclidean distances between the two sets of
    # vertical eye landmarks (x, y)-coordinates
    A = dist.euclidean(eye[1], eye[5])  #P2-P6
    B = dist.euclidean(eye[2], eye[4])  #P3-P5

    # compute the euclidean distance between the horizontal
    # eye landmark (x, y)-coordinates
    C = dist.euclidean(eye[0], eye[3])   #P1-P4

    # compute the eye aspect ratio
    ear = (A + B) / (2.0 * C)
    # return the eye aspect ratio
    return ear
```

5.3 Calculation of mouth aspect ratio

The mouth aspect ratio is calculated using the following function:

```python
def get_mouth_aspect_ratio(mouth):
    horizontal=distance.euclidean(mouth[0],mouth[4])
    vertical=0
    for coord in range(1,4):
        vertical+=distance.euclidean(mouth[coord],mouth[8-coord])
    return vertical/(horizontal*3) #mouth aspect ratio
```

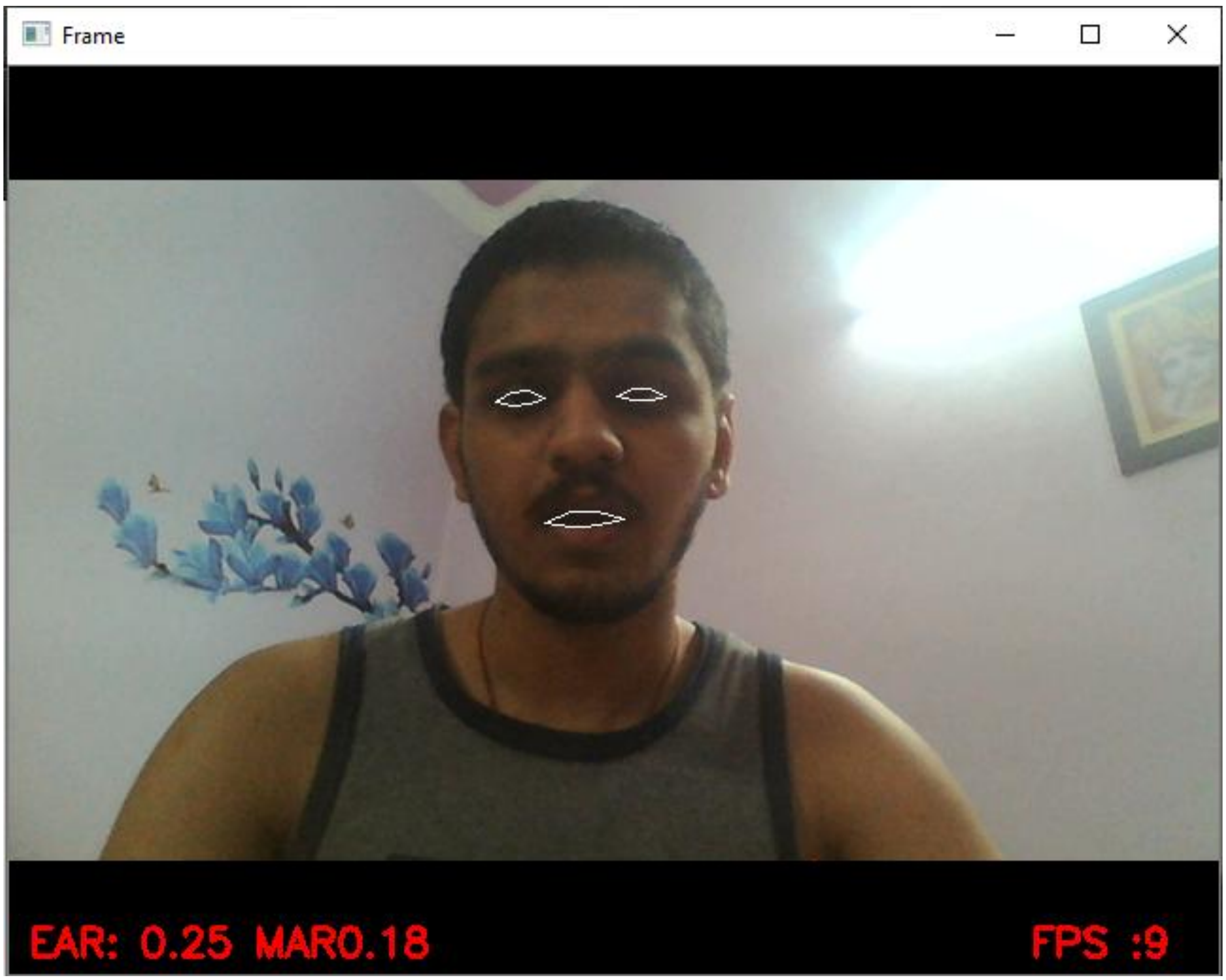


Fig 19. Calculation of EAR and MAR

5.4 THRESHOLDING

Now, as discussed above we need to set threshold values for each of our features. These threshold values are hardcoded and depend on individual's facial features. Experimentally we found the following threshold value suitable for our subject:

EYE_DROWSINESS_THRESHOLD = 0.25
MOUTH_DROWSINESS_THRESHOLD = 0.37

A fundamental issue with hard-coding and repeatedly checking threshold values is that EAR would reach below threshold even for a blink and this may misguide the system into believing that a person is asleep.

Therefore to counter this problem we set intervals which indicate the duration for which the system monitors the subject and it EAR remains below threshold for that interval, he will be considered drowsy. Similarly we can set threshold intervals for MAR and distraction as well. Experimentally these values were found to be the best based on web camera frame rate and system configuration:

MOUTH_DROWSINESS_INTERVAL = 1.0
DISTRACTION_INTERVAL = 3.0
EYE_DROWSINESS_INTERVAL = 2.0

Now, this can be very well understood that EAR Threshold and MAR Threshold depends on facial orientation and varies from person to person. Also, the respective intervals are a function of system and camera configuration. Thus, these values are defined keeping in concern the experimental setup.

5.5 INTEGRATION OF THE PROCESS AND INCORPORATING AN ALARM MECHANISM

Finally we stick together the pieces of our code into a single .py script. We define three variables and set them as false initially:
distracton_initlized = False
eye_initialized = False
mouth_initialized = False
These variables are Booleans used for initializing the condition of drowsiness and trigger alarm mechanism.
As shown in the flow diagram above if EAR<Threshold or MAR>Threshold; these expressions are reinitialized as ***True*** and monitors for a set time interval (depending on frames). If the condition of drowsiness is satisfied the alarm is triggered and driver alerted otherwise it iterated through the whole process again.

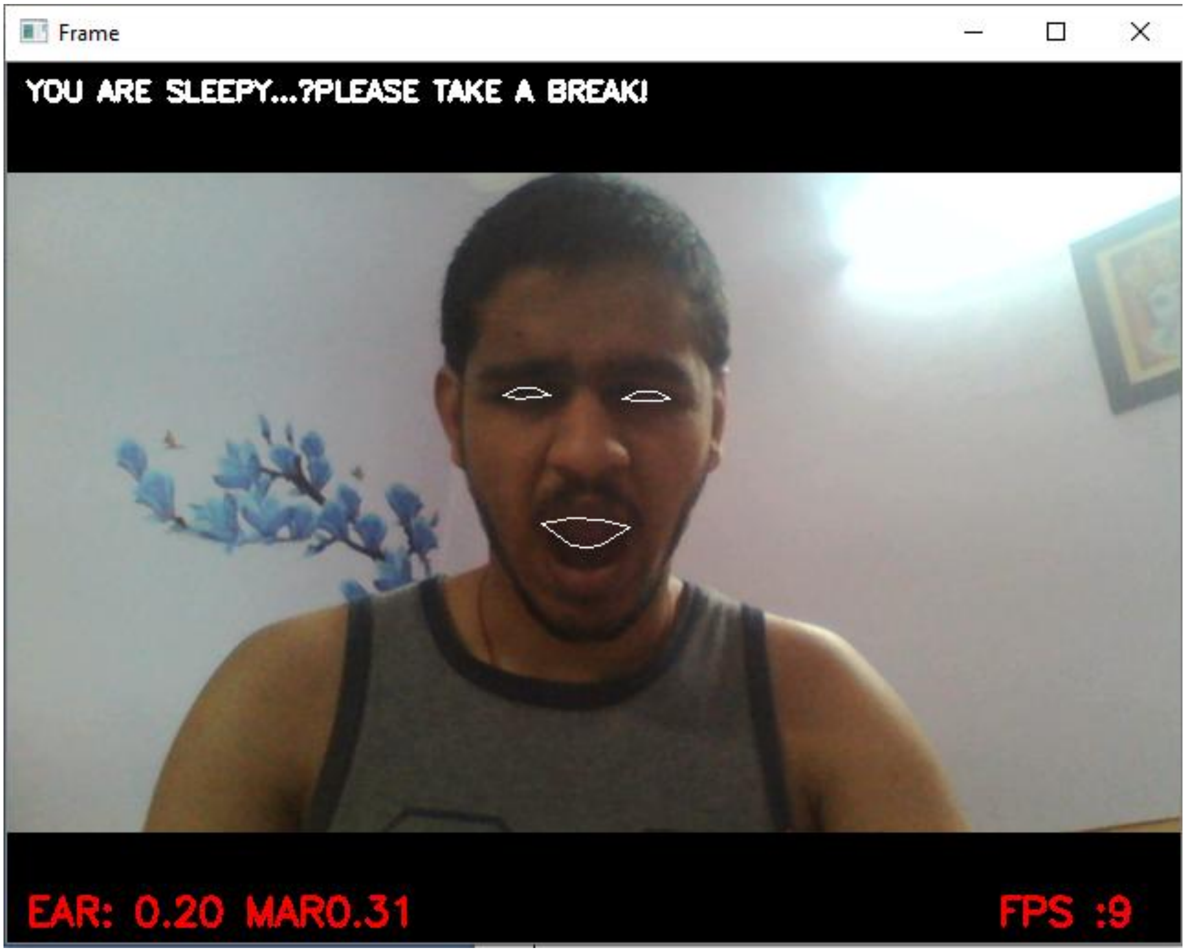


Fig 20. Alarm in case of distracted driving

6. CONCLUSION

The implemented algorithm is state of the art non contact solution for the detection of drowsiness. We are able to extract frames from a live feed real time video and apply our algorithm to extract important features of the face. This system is able to determine the face, eyes, mouth and other features of the driver which will be further used to analyze the state of driver. Face and eye detection is done using Haar Cascade classifier of OpenCV because it is the fastest amongst the other algorithms and also gives high accuracy results.

Visual behavior features like eye aspect ratio, mouth opening ratio are few of the most important cues of drowsiness detection; however a more robust model with high computational abilities can deploy other features such as nose length ratio and Pupil Circularity (PUC). Moreover, a more advanced and user friendly and reconfigurable system can be deployed which allows the user to set threshold values without explicitly coding them. This system can also be deployed in fleet management system to monitor driver behaviors and moderate their safety.

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