

DRIVER DROWSINESS DETECTION USING SVM ALGORITHM

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and
Engineering

By

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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
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BONAFIDE CERTIFICATE

This is to certify that this project report is the bonafide work of **YALLA RAHULSAI (37110864)** and **VENKATA SURENDRA KUMAR TANIKONDA (37110832)** who carried out the project entitled "**DRIVER DROWSINESS DETECTION USING SVM ALGORITHM**" under my supervision from **August 2020** to **March 2021**.

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ABSTRACT

Detection of objects is the primary step for numerous applications involving in object analysis such as Facial Recognition, Image Search and Object Recognition, Autonomous Vehicles and Robotics etc. In our project we are proposing an simple technique that uses the image of eyes of a driver in order to measure the drowsiness of the driver. The algorithm uses Haar Cascade (Viola Jones face Detection Algorithm) which extracts and selects the features and the SVM (Support Vector Machine) uses these features to detect the drowsiness. Using these Haar Cascade and SVM techniques achieves an accuracy of 80%. This algorithm gives the accurate and efficient results.

According to studies conducted by various educational institutions, most of the road accidents (nearly 40% of the highway accidents) are caused due to the in activeness of the driver for the short period of time .The drowsiness may be caused due to many reasons but the effect is very severe and dangerous . Keeping in mind the severe effects an effective measure is taken to minimize the errors caused by drowsiness.

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CHAPTER 1

INTRODUCTION

According to recent studies most of the car accidents are happening due to drowsiness or fatigue feeling that causes distraction in drivers, This results the increase in the probability of happening a major or minor car accidents. Fatigue or Drowsiness can be probably detected if the below listed actions of driver are observed or examined while driving.

Feeling difficult to keep eyes open, Yawning, Nodding (Head or Body), Feeling low (sad or depressed), Difficulty of focusing (keeping our concentration strong) , Very slow instincts and responses to surroundings. Every driver, faces numerous above listed actions while driving and with various degrees of affect can be detected if we closely examine the driver.

So in order to rectify these symptoms, We tried to implement a super simple system which can tell whether a driver is attentive or feeling drowsy. If we are able to record the actions of driver and segment or divide the captured video into frames of images and examine vital parts of a preliminary processed images, it would be very helpful and simpler to develop a completely automatic system which helps in giving an alarm or alert to the driver if he feels drowsy. This system can definitely used to support our decisions on understanding the driver fatigue and giving alert very early.

Given the impact of driver drowsiness on driving safety, there has been keen interest in developing a system that can monitor and quantify driver drowsiness and provide a real-time warning to the driver and/or a control output to the vehicle or other systems as warranted. Numerous drowsy driver monitoring systems are available on the market; however, nearly all of these technologies rely on a single predictor of driver drowsiness (e.g., eye closures, lane position, or steering). A negative aspect to using only one predictor of drowsiness is that such monitoring systems are susceptible to periodic intervals in which data are unavailable due to failures of the single sensor or operation outside of the sensor's capabilities.

The objective of this research project was to develop a robust prototype system that combines drowsiness metrics to alleviate some of the issues associated with a single measure device. Based on an information gathering task, it was determined that a machine vision-based (MV) eye monitoring technology, combined with analysis of operator/vehicle performance parameters, would provide a strong metric to reliably assess driver drowsiness. The hypothesis of this research was that a multimeasure approach to

detecting driver drowsiness would be superior to a single-measure approach.

CHAPTER 2

OBJECTIVE

- Detecting driver drowsiness is the safety technology that helps preventing the major or minor car accidents and save the life of the driver if he feels fatigue (drowsy).
- The objective of the proposed system is to primarily build a system that detect driver's drowsiness by monitoring driver using any camera and focusing on his eyes to judge whether he's attentive or not.
- The system is designed such that it is able to detect the feeling of driver even if he is wearing glasses.
- Whenever the system detects the driver is feeling drowsy the system gives alert by ringing very high sounded alarm.
- Vehicle's speed can be reduced when the alarm is heard.

Thereby we can maintain Traffic by reducing the accidents caused due to this drowsiness or Fatigue of driver.

CHAPTER 3

LITERATURE OVERVIEW

This portion of the report is a high-level review of research conducted on driver fatigue— namely, its measurement and detection. It is organized in terms of driver-based and vehicle-based approaches used to detect and monitor driver fatigue. Moreover, it serves as a guide to the technical specifications and needs for developing a robust DDMS. This review will assist in the development of a system that will effectively quantify driver drowsiness and provide real-time warnings to drivers.

3.1 Defining the Problem: Fatigue and Drowsiness

It is important to note that the terms *fatigue* and *drowsiness* are often used interchangeably in the literature. This work will use the terms interchangeably in the manner in which they are presented in the original literature sources. This is to ensure that the operational definitions and intentions of the original authors remain unchanged. However, a distinction between the terms is made at times, and this distinction is evident by comparing the definitions below.

Fatigue is defined as “a state of reduced physical or mental alertness which impairs performance”. Another definition provided by Dinges is “a neurobiological process directly related to the circadian pacemaker in the brain and to the biological sleep need of the individual.” Dinges further states that fatigue is something all humans experience, noting that it cannot be prevented by any “known characteristics of personality, intelligence, education, training, skill, compensation, motivation, physical size, strength, attractiveness, or professionalism”.

Drowsiness is defined as the “inclination to sleep” and is also commonly referred to as “sleepiness.” As noted above, fatigue is a reduced state of mental or physical alertness that impairs performance. Fatigue can occur without the subject actually being drowsy; therefore, *fatigue* and *drowsiness* are not exactly synonymous. While fatigue is the result of physical or mental exertion, drowsiness may result from boredom, lack of sleep, hunger, or other factors.

Drowsiness is a natural occurrence in the human body that can affect individuals in

different ways. The human body usually functions on a 24-hour circadian rhythm that is driven by light levels in the environment, as well as by specific physical states, such

as body temperature, melatonin levels, etc. During a 24-hour period, the human body usually experiences two drowsiness-related lows: the first in the middle of the night between approximately 12 a.m. and 6

a.m. and the second in the afternoon between 2 p.m. and 4 p.m. An illustration of this phenomenon is shown in Figure 1.

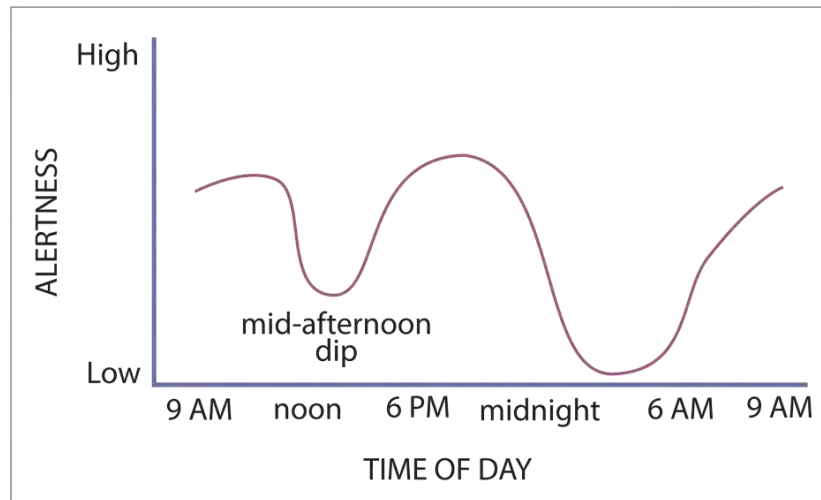


Fig 3.1 Human 24-Hour Circadian Rhythm

3.2 Attempts to Measure Drowsiness

According to Knippling and Wierwille, the full effects of drowsiness do not occur instantaneously. The period of onset of drowsiness can last for an hour or more and is often associated with a cumulative gradual decrease in performance coupled with measurable psycho- physiological signs. Over the past 2 decades, the trucking industry has seen a technological boom in on-board DDMS models designed to detect driver drowsiness and provide warnings when

triggered. This technology has shown promise, but no system is found to be infallible in detecting fatigued and drowsy driving.

One issue is that quantification of driver fatigue is not straightforward. Unlike other impaired driver states, such as alcohol or drug intoxication, fatigue cannot be quickly or objectively measured with a breath test or urine sample. The detection process is more inexact. Also, as stated above, the onset of fatigue and drowsiness is a cumulative process, which may not be detected until there is a noticeable difference in driving performance or the driver's physical characteristics or mannerisms.

However, progress is being made in the area of quantification. Recent advances in

fatigue monitoring technology have demonstrated the ability to detect potentially

dangerous levels of fatigue through a range of different approaches. These approaches include monitoring brain activity via electroencephalography (EEG), eye movements, head movements, and facial features, as well as driver performance measures such as lane deviations and steering.

Researchers are attempting to determine which of these salient indicators are most important so as to be able to measure drowsiness accurately and reliably through detection algorithms that can be implemented using technology.

3.3 Driver-based

Approaches EEG Measures:

It has been well documented that distinctive changes occur in EEG when an individual transitions from wake to sleep. While numerous physiological indicators measure level of alertness, the EEG signal may be the most reliable and predictive means to measuring alertness levels. Because of this, the EEG has been the standard for measuring alertness/drowsiness in the laboratory and, occasionally, in the field.

Simulator studies have shown a negative relationship between the EEG power of alpha and theta bands and alertness level of the driver. Increased alpha bands are generally regarded as the first sign of drowsiness, while an increase in theta bands is indicative of the early stages of sleep. In another driving simulator study, Lal and Craig found substantial increases in delta and theta activity, and smaller increases in alpha activity during transition to fatigue. A further finding by Petit, Chaput, Tarriere, LeCoz, and Planque demonstrated a strong correlation between steering wheel movement and the EEG power of alpha bands.

Although many studies have been conducted in this area, a reliable EEG-based fatigue detector has yet to be found. Lal, Craig, Boord, Kirkup, and Nguyen completed a simulation study in which they were able to detect fatigue and drowsiness using an EEG algorithm. However, this system needed further modifications to compensate for major artifacts in the EEG data, such as coughing, sneezing, vibration, and large body movements. The researchers therefore acknowledged that additional research is needed to produce a real-time, robust, and reliable fatigue detecting/alerting system.

Ocular Measures:

Building on EEG measures as a fatigue indicator, Akerstedt et al. make the assumption that the two most critical indicators of sleepiness are EEG and

oculomotor parameters. As noted, today's EEG technology does not afford an ideal opportunity to collect data in everyday driving situations. Fortunately, ocular movement/parameters research has demonstrated great promise in predicting a driver's state of drowsiness. Various technologies have been developed to measure oculomotor parameters, most

commonly in the form of eye closures, eye blinks, pupil responses, or other eye movements. Unfortunately, most of these devices have been tested in the laboratory and lack real-world driving exposure.

For example, technologies developed to monitor ocular movement often use infrared light, which is directed at the eye and then reflected back from the eye and recorded using a video camera.

This technique may work effectively in ideal low-light conditions, but may fail during daylight or well-lit road conditions.

Nonetheless, promising findings exist for using ocular measures as an indicator of fatigue. Specifically, two methods to measure ocular movement have provided the most consistent and promising results in gaining an understanding of eye behavior as it relates to fatigue; namely, slow eye closure and blinking behavior. Each of these is discussed below, based on seminal findings and recent research.

Percentage of Eye Closure: Percentage of eye closure is a mathematically defined proportion of a time interval in which the eyes are 80 percent to 100 percent closed. PERCLOS is based on a measure of slow eye closure, not including eye blinks. While an eye blink is typically a very quick closing and reopening of the eyes, "slow eye closures" are relatively gradual eye movements in which the eyelids droop and close slowly. Alert individuals generally do not exhibit drooping facial features and slow eye closures, while eye blinks are common no matter what one's state of alertness. Hence, PERCLOS makes a distinction between the two.

Eye Blinks:

The spontaneous eye blink is also considered a suitable ocular indicator of fatigue. This behavior can be measured in a noninvasive manner, recording blink rate via cameras and sensors. Sirevaag and Stern have found the analysis of spontaneous blinks to have the potential to provide information about the central nervous system activation process and fatigue. In a laboratory study simulating sudden inversion of the sleep-wake cycle to mimic the cycles of some shift workers, researchers measured smooth pursuit and saccadic eye movements of five participants as possible indicators of fatigue. The results suggested that saccadic performance, unlike smooth pursuit, seems to have increasing sensitivity to greater levels of sleepiness. Although this study was conducted with a small sample size, it encouraged further research on the topic of eye movements and, ultimately, blinking behavior.

Akerstedt, Peters, Anund, and Kecklund found that, with increased driving time and

after working a night shift, there were increased subjective sleepiness levels, longer blink durations, and increased instances of lane drift. Another study found a relationship between the Karolinska Sleepiness Scale, a subjective measure of sleepiness, and the

increased occurrence of slow eye movements. Additionally, Caffier, Erdmann and Ullsperger used a contact-free device to capture spontaneous eye movements and found blink duration and reopening time changed reliably with increased drowsiness. They concluded that measurements of eye blink behaviors have the potential to be used in a continuous fashion to monitor the onset of sleepiness.

A literature review on blink rate as a measure of fatigue by Stern et al. found strong support for the notion that blink rate increases as a function of time on task. However, this review found that variables other than time on task are sensitive to task demands such as fatigue effects as flurries of blinks, time with regard to information-processing demands, and blink closure duration. Galley, Reitter, and Andres measured saccades and blinks in 20 subjects during 40 6-hour trips on German highways. Fixation duration, saccadic velocity, blink rate, blink amplitude, eye closure velocity, and 19 additional parameters were measured and compared to subjective scores of fatigue and time on task. The research concluded that the subjective scores of fatigue could be better predicted by ocular motor and blink parameters than saccade parameters.

Individual Difference of Eye Blink Behaviors: Very little research has been conducted to understand distinct differences among individuals' eye blink behaviors as a result of fatigue. A study by Ingre, Akerstedt, Peters, Anund, and Kecklund sought to address these individual differences and to develop subject-specific relationships between subjective sleepiness measured with KSS scores, blink duration, and lane drift. The results of this study indicated that a relationship exists between KSS, lane drift, and blink duration. Specifically, the researchers found that the effect is curvilinear with a steeper rise at high subjective sleepiness levels, especially for the standard deviation of the lateral position. However, it is important to note that large differences were found between individuals in their overall driving performance and blink duration independent of sleepiness levels and that "serious behavioral and physiological changes do not occur until relatively high levels of sleepiness are reached" (p. 50). Ingre et al. further expressed an interest in the presence of individual differences and warned against making statistical errors associated with group average estimates. For example, statistical methods to identify individual differences are not always employed on individualistic data sets; if these methods are practiced, they are often not mentioned in the research methods or results.

3.4 Vehicle-based Approaches

For many years, researchers have studied the physical control of a vehicle that characterizes the driver's state of alertness. To date, two of the most promising approaches found are lane-related and steering measures. Using driving simulation, Skipper and Wierwille found that the standard deviation of lane position and the standard deviation of steering velocity (velocity as a measure of degrees of steering

angle per second) were significant fatigue indicators as measured by slow eye closures. A review of the most relevant research on vehicle-based approaches in identifying

salient fatigue indicators, specifically lane position/line-crossing and steering metrics, is presented in the following sections.

Lane Position/Line Crossing:

Measures of lane position have shown compelling evidence that they are valid indicators of fatigue. Early driving fatigue research established that unintentionally drifting out of the lane while driving is an indicator of fatigue. O'Hanlon and Kelly measured mean speed, standard deviation of speed, frequency of steering wheel movements, and lane drift frequency—determined by the number of times the left or right wheel crossed the lane line(s) per minute of driving—to determine whether any of these variables related to fatigue during a 4- to 5-hour drive. Of these metrics, lane drift frequency was determined to be the best indicator of fatigue.

Two early simulation studies investigating the effect of prolonged driving reported decrements in lane tracking and steering performance as driving time increased. Lane drift was also used as a measure of fatigue by Riemersma, Sanders, Wildervanck, and Gaillard, who defined lane drift as the standard deviation of lane position. Again, the major findings from this study indicate that lane drift appears to be sensitive to fatigue effects, and this was shown to vary during different phases of the driving trip. Specifically, lane drift gradually increased during the beginning of the trip, decreased after the driver stopped for fuel, and reached a maximum near the end of the 8-hour drive. More recent studies found that steering wheel variability and lane tracking variability were greater for drowsy events than for non-drowsy events.

Wierwille et al. studied simulator steering metrics and found that variations in lane-keeping, steering inputs, and speed maintenance were a function of fatigue. They also found that algorithms which include lane-related measures (mean square of lane position, variance of lateral position, standard deviation of lateral position relative to lane, proportion of time that any part of the vehicle crosses the lane boundary, mean square of the difference between the outside edge of the vehicle and the lane edge when the vehicle strays over the lane boundary, variance of the time derivative of lane position, and standard deviation of the time derivative of lane position) predict drowsiness better than algorithms that do not include lane-related measures. They concluded that constructing conditional criteria by using estimated PERCLOS outputs and the proportion of the time that any part of the vehicle strayed outside of the lane boundary was necessary to significantly improve the accuracy of detection of fatigue.

Steering:

Steering wheel inputs may indicate fatigue-induced impairment. During highway driving, a driver must continuously make small steering wheel movements to keep the vehicle in the center of the lane. Therefore, it is hypothesized that there is a

relationship between the driver's alertness state and steering wheel behavior. Specifically, alert drivers will respond to lane deviations early with many small-amplitude steering movements to correct the car's trajectory, whereas fatigued drivers will respond slowly

to lane deviations and make large steering wheel movements to correct for larger lane deviations. Most researchers agree that as fatigue-related impairment increases, a subsequent increase occurs in the variability of steering control. Beyond this general agreement, there is little consensus on what exact measure of steering is correlated with driver fatigue. Steering-related approaches are discussed below.

As mentioned above, some researchers believe studying micro-corrections of the steering wheel is a window into fatigue detection. For example, Petit et al. found that microcorrections lessen as driver impairment increases. Such research has led to the development of commercially available devices that claim to detect fatigue through steering movements. Examples include the steering attention monitor, which emits a warning sound when a predetermined "fatigue" threshold has been reached. The divided attention steering simulator is another example of a device that attempts to detect fatigue through the use of standard deviations of steering error. A study by Philip et al. used the DASS and found steering error on a simulator could be used to measure fatigue.

A study by Paul, Boyle, Tippin, and Rizzo evaluated microsleeps as an indicator of driver performance impairment in drowsy drivers with sleep disorders. Microsleeps involve a brief unintended loss of attention lasting 3–14 seconds. Twenty-four drivers with obstructive sleep apnea/hypopnea syndrome were tested to determine driving impairments when they were experiencing microsleeps, as compared to when they were not experiencing microsleeps.

Steering variability, lane position variability (standard deviation of lane position), time-to-lane crossing, and acceleration and velocity measures were measured in a driving simulator. The results indicated that driver performance measures, steering variability, lane position variability, and minimum time-to-lane crossing are sound indicators of poorer driving control for drivers with OSAHS during microsleep episodes. Greater steering variation was found in drivers with OSAHS during microsleeps.

Individual Differences of Vehicle-Based Behaviour:

O'Hanlon and Kelly investigated individual differences in lane drift and sleepiness and found a great deal of variance. Again, individual differences play a significant role in fatigue-related issues. Anecdotal and empirical evidence have shown that there are large individual differences in people's susceptibility to fatigue. Verwey and Zaidel attempted to predict driver behavior based upon a personality cluster classification. It was determined that those drivers who were classified as the "extraversion-boredom" personality type were more likely to go off the roadway because they had fallen asleep. Those classified as the "disinhibition-honesty" personality type did not fall asleep, but they were more likely to cross solid lane markings. Based on the driving performance variables collected, the researchers believe their results suggest that personality is a cluster of individual differences warranting further research for predicting fatigue-related driving behavior. This study

used a very small sample size; so this work is considered exploratory and should be treated as such.

Peters performed a driving simulator experiment on 10 shift workers in which the participants drove for 2 hours in the morning under two different conditions: sleep-deprived and non-sleep-deprived. The dependent variables included road departures, lateral lane position, derived measures of time-to-line-crossing and steering behavior, KSS scores, and eye blink behavior. The overall mean correlation between KSS scores and corresponding measures of interest includes the following: lateral position was 0.52, time-to-line-crossing was 0.49, and blink duration was 0.66. When analyzed on an individual level, the correlations were found to be higher. The researchers reported that their measures were moderately useful in detecting impaired driving behavior. Here again, the study bears witness to the effects of individual differences on fatigue and its effects. Again, caution must be exerted when interpreting results based on such a small sample size.

An important detail to consider with regard to steering is that it is considerably affected by such things as road type, road crown, curvature, environmental conditions, and vehicle steering system characteristics. These items must be taken into account as confounds of steering is used as a measure of fatigue.

3.5 Combination of Driver and Vehicle-based Approaches

As previously mentioned, several laboratory research studies have been conducted to evaluate a number of measures to assess driver alertness, including EEG, ocular measures, lane position, and steering. Heitmann et al. suggest no one measure can sufficiently and reliably indicate driver alertness; hence, the necessity for multiple measures. It is clear that further research is needed to understand more fully what metrics are necessary to capture drowsy driving in an effective, holistic fashion. Progress has been made toward obtaining a better understanding of driver-based and vehicle-based fatigue measurements independently, with each having their own unique strengths and limitations. However, relatively little research has been conducted in combining technology that uses both driver-based and vehicle-based fatigue metrics. It is believed that employing a systems approach, whereby several metrics are used to evaluate the situation, will be more effective in capturing drowsy driving as a complete phenomenon.

One example of a multimeasure approach is the European Union's AWAKE program. The aim of the study is to incorporate eyelid movement, changes in steering grip, lane tracking, and accelerator and brake pedal use as a means to monitor driver vigilance. This ongoing research effort demonstrates promise but remains exploratory. Another example of using more than one metric to identify fatigue via technology is research by Grace et al. They developed a prototype drowsy driver detection system for heavy vehicles and determined that the most viable approach would not only measure psycho-physiological changes, such as PERCLOS, but would also include measurements of driver performance changes. These researchers suggested driver performance measures to include the following: steering wheel

movements, lateral lane position information, longitudinal speed, lateral and/or longitudinal

acceleration, and vehicle braking. Although this study did not reach a conclusion regarding the most reliable driver performance fatigue indicator, it remains that a combination approach is the recommended avenue to fatigue detection.

To supplement the need for a multimetric approach, some researchers have discussed the fundamental problem of using only ocular movement in the assessment of fatigue. The problem with using only eye behavior is that changes to a driver's state are likely to happen late in the process of fatigue. It is believed that the driver will have driven through a period of increased risk (because of his/her fatigued state) before significant eye closure effects will be realized.

Further exacerbating the problem, Williamson and Chamberlain believe that in a situation in which late stages of fatigue are reached and signaled, the driver will have no other recovery option than to stop and sleep. An earlier warning may be more convenient for the driver and allow him or her to plan accordingly (e.g., having a caffeinated beverage with enough time for the caffeine to have an effect before drowsiness increases). Early detection may also be beneficial because the greater the driver's fatigue, the more difficult it is to overcome, leading to the need for a more substantial period of sleep. Under these circumstances, drivers may, in the long term, accept an early-detection feature more readily than a late-detection feature. On the other hand, drivers could consider an early warning to be a nuisance, which may lead to distrust and, ultimately, rejection of the system.

Further research supporting the need for a multivariable approach was implemented by Oron-Gilad and Hancock. These researchers attempted to distinguish between fatigue caused by the demands of the driving task and fatigue caused by driving while already sleep deprived. Their research determined that drivers can adopt coping strategies to deal with various road types and perceived level of fatigue. The researchers found that drivers were able to increase focus when critical elements of the roadway required attention. Because of these coping strategies, these authors caution against using a single or a limited number of performance measures to detect fatigue. Additionally, many individual differences were found among the participants, which included 10 professional military truck drivers and 17 university students. From the beginning of the drive, the student drivers tended to drive more poorly than the professional military truck drivers.

3.6 Literature Review Summary

This literature review began with a brief summary of literature pertaining to the identification of salient fatigue indicators. The ongoing debate of reliable and valid fatigue measurement continues, although progress toward consensus is being made. Based on the information presented above, it seems two of the most promising measures of fatigue are the PERCLOS and lane position/line crossing variables. It is

unclear which metric of lane measurement is the most appropriate. Nonetheless,

evidence suggests lane-related behaviors are salient fatigue indicators. It seems clear the research community agrees that steering wheel movements provide some insight into a driver's impaired state. However, as with lane-keeping measures, there is little consensus regarding what exact metric of steering correlates with fatigue.

Clearly, no single variable reliably predicts fatigue 100 percent of the time. Therefore, a multivariable approach will most likely provide a more reliable detection of fatigue. A particular metric may be more effective for a given driver while the other(s) may serve as a backup if the first fails to properly indicate fatigue in that individual. For example, if PERCLOS is determined to be the primary indicator of fatigue, then lane position could serve as an auxiliary to the eye closure warning algorithm if or when the latter fails to perform.

As discussed, most of the past research is based on group average estimates. It is well known that there are no "average" humans; therefore, care must be taken in basing conclusions on the "average," which may lead to forming inaccurate conclusions. Human factors researchers understand that individual differences exist, but accounting for the differences when developing a robust fatigue monitoring system affords unique challenges. The magnitude of these differences with reference to the effects of fatigue on the driving population remains in an exploratory stage at best. More research is needed to understand more fully the differences among individuals. Again, not enough information is available to be able to rely solely on one performance metric for the whole driving population. Therefore, at this time, it appears that it would be most useful to have multiple performance metrics to determine a driver's state.

One of the primary design principles of this project is to develop a prototype system that effectively detects drowsiness across the widest possible user population. While individual differences will be considered in the design of the system, the system's performance will be optimized for the majority of users.

CHAPTER 4

FEATURE EXTRACTION

The proposed process has two phases namely, Feature extraction using Haar cascades and providing real time results using SVM classifier using the Facial landmarks offered by dlib library in open-cv python.

1. Feature selection, Extraction is the process in which useful information is estimated and analyzed in a comparative form and size from images of captured video, then it is represented in a convenient domain using Haar cascades.
2. Importing useful libraries like Open CV, DLIB, face_recognition etc., and making use of inbuilt functions to compare the extracted facial features with idle facial landmarks.
3. Classification, here many models are created and used to extract features from every available domain using SVM classifier.
4. Decision Making, reliable decision is made accordingly when a real time frames are given to system.
5. The alert is given to driver based on the results of system.

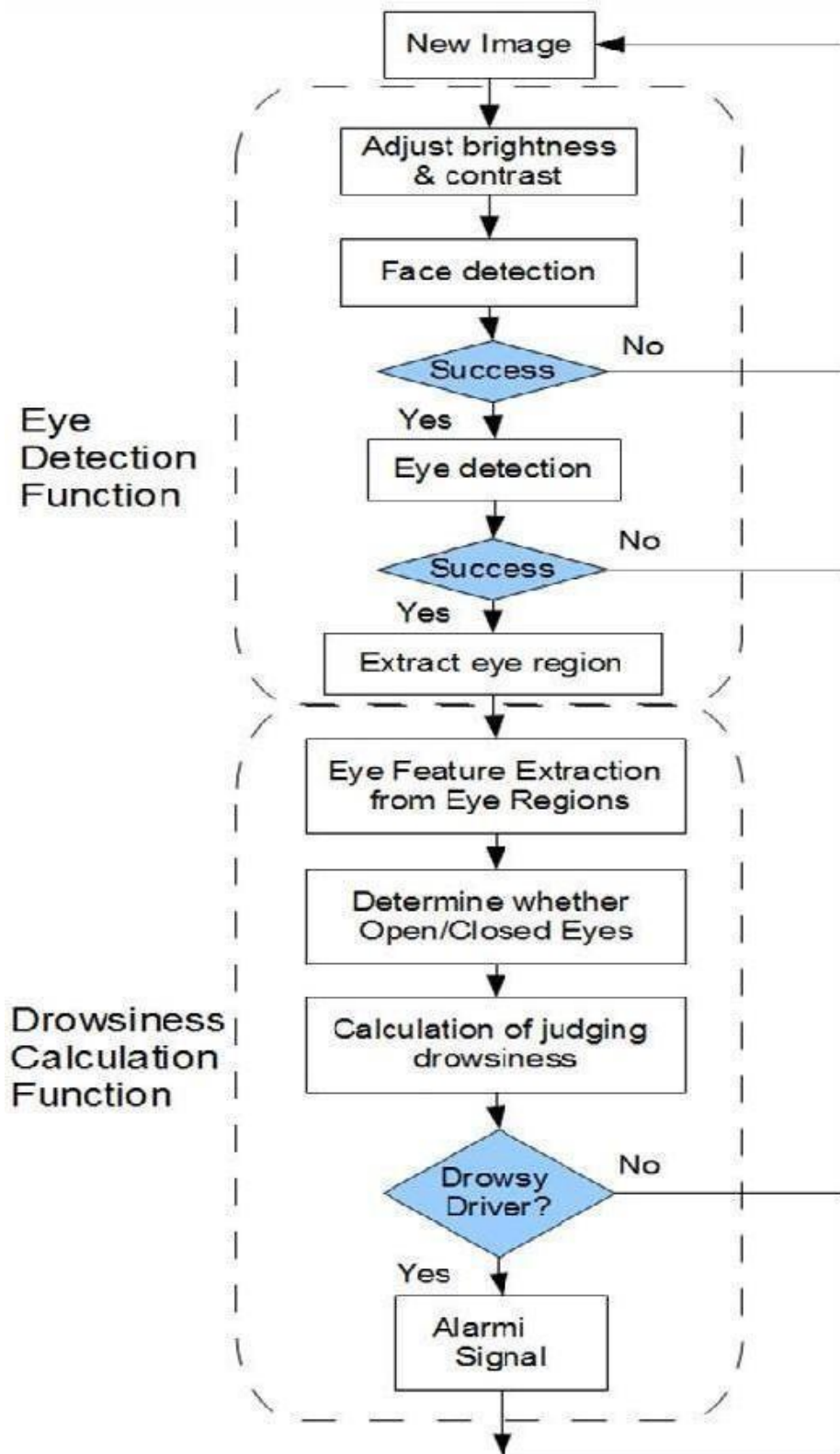


Fig 4.1 Drowsiness Detection Flow Chart

HAAR CASCADES:

The Haar Cascades are pretty much helpful in detecting faces in an image, it is dependent on the famous face detection algorithm called Viola Jones detection algorithm. Since it is a cascade classifier, it contains:

Haar features

Integral Image

Adaboost

Cascading

4.1 Haar Features:

Human activity recognition features are proposed by Alfred Haar. Back in 1909 these features are proposed. These are sequence of squared function which are re-scaled. These Human action recognition features matches with the convolution kernels learn in the Convolution Neural Networks theory. The application of these Haar features to all desired or specific parts of face in order to detect human face and perform the required action.

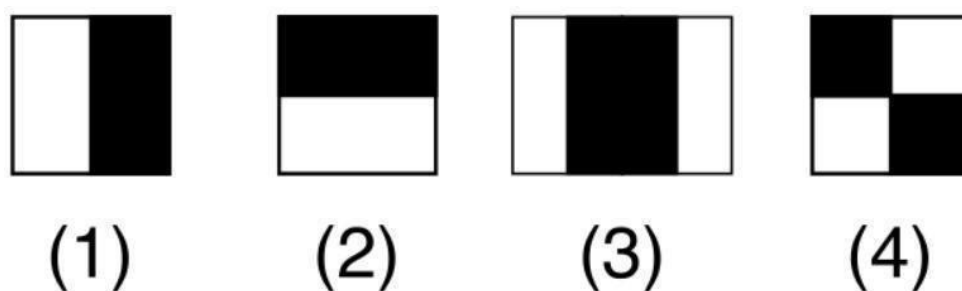


Fig 4.2 Haar Convolutional Kernals

In the above figure 4.2, the features (1) and (2) are edge features, and (3) is a line feature. They are black and white pixel intensities of value 0 or 1. But normally we have preliminary processed greyscale/colour images whose pixel intensities vary from 0 to

255. If we assume an ideal situation that we have greyscale images or black and

white images.

To detect different parts of the face we use different images shown above, if we are intended to detect eyebrow, we have to make use of edge features in fig 4.2 image(1), because the pixel intensities of forehead are and eyebrow are darker. Similarly, if we are intended to detect lips we must make use of line feature in fig 4.2 image(3) with white-black-white pixels. To detect nose, we can use white-dark edge like feature analogous to image(1).

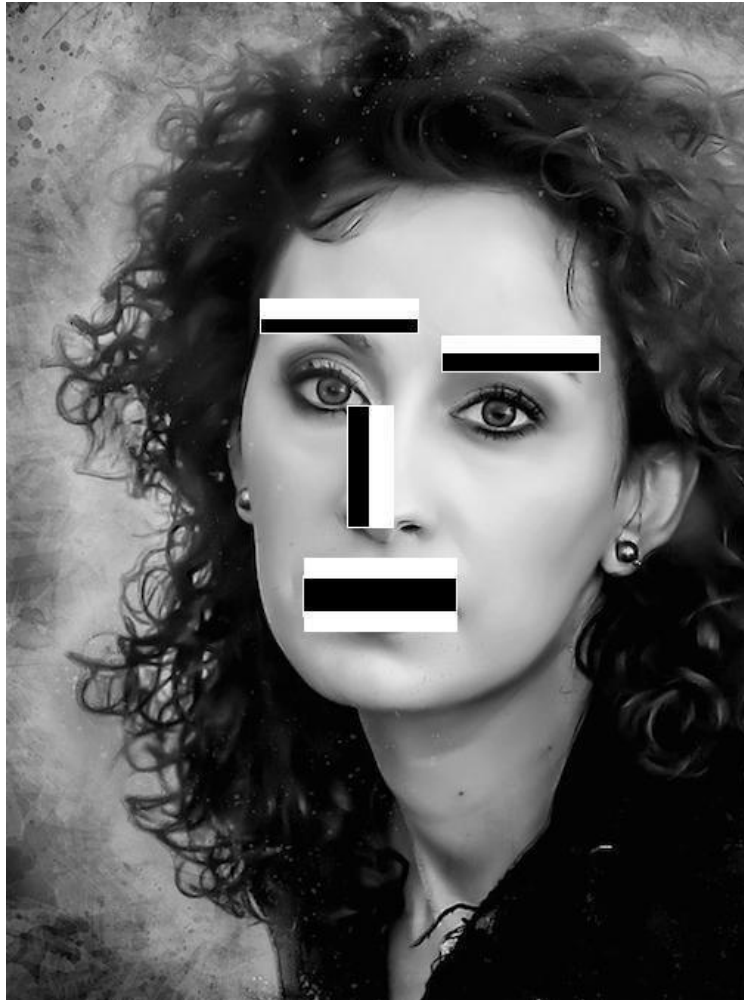


Fig 4.3 Relevant Features to detect face

To compute and tabulate human action recognition features, for a greyscale image black as depicted in the below image, pixel values are either low '0' or high '1', but in practical real time situations cases we have greyscale i.e., black and white image which are normalized as shown in below fig 4.4 containing floating picture element notations.

0	0	1	1
0	0	1	1
0	0	1	1
0	0	1	1

0.1	0.2	0.6	0.8
0.3	0.2	0.6	0.8
0.2	0.1	0.8	0.6
0.2	0.1	0.8	0.9

Fig 4.4 Pixel Intensities

According to the famous face detection Viola-Jonas algorithm, to detect and extract Human activity recognition features to detect a face in an image, the formula for delta should be used to get unitary(1) result. More the value closer to unity(1), greater is the chance of detecting Haar feature in image.

$$\Delta = \text{dark} - \text{white} = \frac{1}{n} \sum_{\text{dark}}^n I(x) - \frac{1}{n} \sum_{\text{white}}^n I(x)$$

Fig 4.5 Delta Formula

Ideal situation : $\Delta = (1/8)*(8) - (1/8)*0 = 1$

Real time situation : $\Delta = (1/8)*(5.9) - (1/8)*(1.3) = 0.57499$

another threshold parameter can be defined to detect edge features or human action recognition features. It is named as Delta. Assuming threshold to be half. If value of delta is greater than half we can surely say Haar feature is detected. This the process to be applied, in order to detect most redundant features on a desired image like ear, eyebrows, lips, nose, mouth, jawline etc...,

4.2 INTEGRAL IMAGE:

The Integral Image is used to accelerate features computation in many object detection applications. It plays a key role in object detection and extraction in real quick way. The integral image of a area at the position (x,y) in the summation area table is the aggregate of all picture elements upper and to the left to the position (x,y) also it must contain $i(x,y)$, from equation (1), where $i(x,y)$ is the computed result of the picture element at the position (x,y) .

1	2	3	4
5	6	7	8
1	2	3	4
5	6	7	8

Fig 4.6 Integral Image

To calculate the integral image at the point $(2,1)$, using equation (2), we have $II(2,1) = i(2,1) + II(1,1) + II(2,0) - II(1,1) = 7 + 14 + 6 - 3 = 24$, as can be seen in Figure (2).

1	3	6	10
6	14	7	8
1	2	3	4
5	6	7	8

1	3	6	10
6	14	24	8
1	2	3	4
5	6	7	8

$$II(2,1) = i(2,1) + II(1,1) + II(2,0) - II(1,1) = 7 + 14 + 6 - 3 = 24$$

Fig 4.7 Computation

The main advantage of this computed summation area table is that in the Integral domain the computation effort to calculate the area of a rectangle. To illustrate the computation of the area of the rectangle defined in the region $2 \leq x \leq 4$, $1 \leq y \leq 3$, let be S the sum of the rectangle. In the original image, $S = 2+3+4+6+7+8+2+3+4=39$. However, once the integral image is done, to calculate the same area in the Integral domain the formula $S=D+A-B-C = 46+0-0-7=39$ can be used as can be seen in Figure (3). This reduces the computational complexity from $O(m \times n)$ to $O(1)$.

1	2	3	4
5	6	7	8
1	2	3	4
5	6	7	8

0	0 _A	0	0	0 _B
0	1	3	6	10
0	6	14	24	36
0	7 _C	17	30	46 _D
0	12	28	48	72

Fig 4.8 Simplification Computation

4.3 ADABOOST:

According to previous statements we can get almost 160,000 plus feature values using a detector of base resolution 24×24 . which needs to be computed and integrated. Among these 160,000+ features in order to detect a face in an image there can be only few useful features and essential facial landmarks. To overcome this situation Adaboost is used. To remove unwanted features and choose only useful features those can detect faces Adaboost is quite helpful to fulfill this job.



Fig 4.9 Adaboost

Adaboost linear classifier that makes use of weak classifiers in order to build a strong classifier.

$$F(x) = \sum (\alpha_i * f_i(x))$$

here α_i are corresponding weights to each weak classifier $f_i(x)$.

4.4 CASCADING:

Considering each 24x24 window, we must compute nearly 2,500 useful features. That are solely chosen by AdaBoost from 160,000+ different features. Provided an input image we have to move the 24x24 window throughout each pixel in the image and calculate nearly 2,500 useful features, if we consider each distinct window and take a combination that is linear of each single output and check if it is exceeding the marginal threshold value or not.

For every image instead of calculating 2500+ features, the idea of cascades can be utilized. We must get x different useful cascades from 2500+ features using sampling method. After this each image is passed into the linear cascades built. If the image passed if satisfying the conditions of a face we can pass it to the next cascade if it passes the condition again it is passed to the next one and so on, if it fails any the cases we can simply discard the image straight away. If no face is found in a cascade we can discard the window move on to next one. This reduces the redundancy and at the same time reduces time complexity of the algorithm.

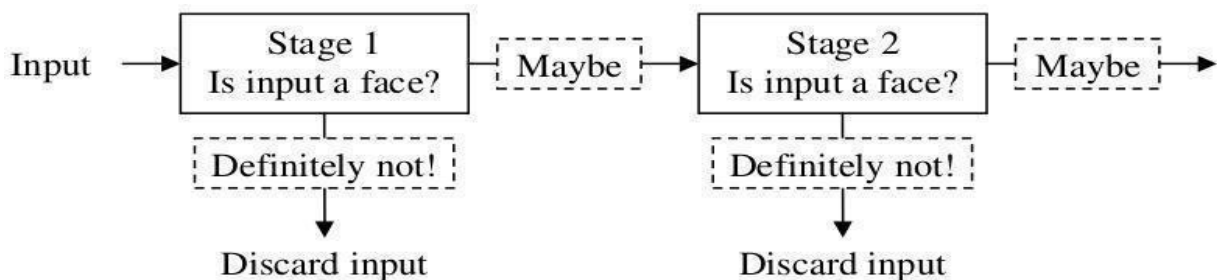


Fig 4.10 Cascading

CHAPTER 5

SVM CLASSIFIER

Support-vector machines is based on machine learning algorithm and it belongs to supervised learning models which related to simple training algorithms that examines data used for both classification and regression problem sets. For a given group of training instances, each instance marked belongs to any of the mentioned labels or sets, This SVM Classifier algorithm constructs a model or system that set new examples to either of the labels, this makes it a non-probabilistic binary linear classifier. A SVM model represents the label marked points in 3d space, thus the instances of the different labels mentioned are separated by a certain distance that is as dividable as possible to make them discrete. If any new set of instances are mapped into that same space of the previous mappings then they are predicted to belong to a label using this we can say which side of the space they can be placed.

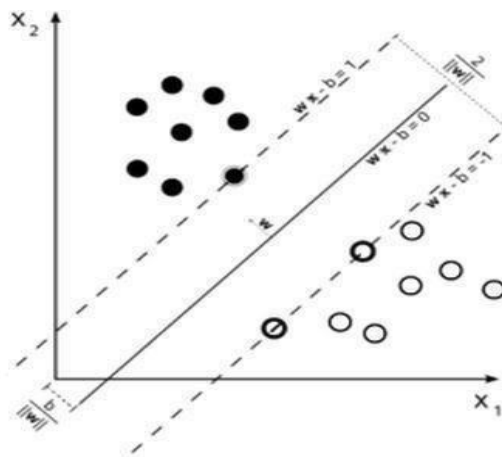


Fig 5.1 SVM Classifier

The SVM makes use of facial landmarks of python DLIB in order to get the euclidean distance between eyelids. The DLIB library contains a trained model that is trained with a 68 dots idle facial land marker.

So that we can easily predict the outline of eyes and represent each eye as a 6 dot ellipse and calculate the euclidean distances between width, length of eyes so that the ratio of these euclidean distances gives us EAR, using EAR we can simply predict whether the driver feeling fatigue or not.

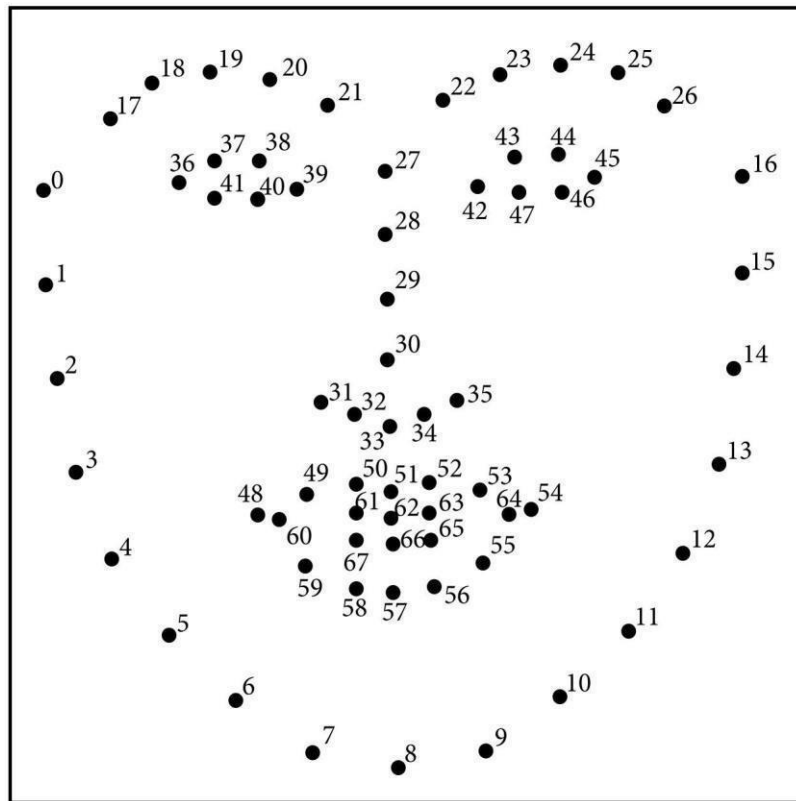


Fig 5.2 Facial Landmarks

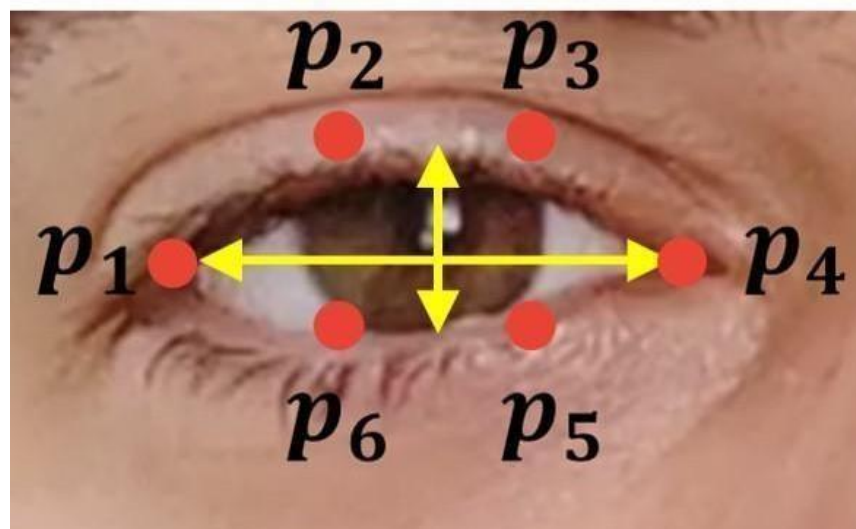


Fig 5.3 EAR(Ear Aspect Ratio)

The EAR (eye aspect ratio) is given by sum of euclidean distance between p_2 , p_6 and p_3 , p_5 divided by distance between p_1 and p_4

Decision making:

1. If EAR is greater than or equal to 0.25 then we can certainly say the driver is attentive.
2. If the EAR is in between 0.25 to 0.1 we can say the person who is driving is not so attentive but not drowsy.
3. If the EAR is less than 0.08 the driver is drowsy and we can give a big alert to the driver.

CHAPTER 6

RESULT

The following images provides the results we obtained through our real time drowsy detector alarm

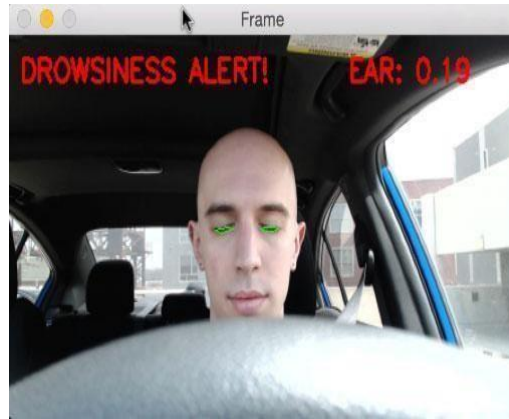


Fig 6.1 Result

The above result image depicts that the EAR is below 0.2 that means the driver is feeling drowsy and an immediate alert alarm must be given to him to make him attentive again before any worse accidents happened.

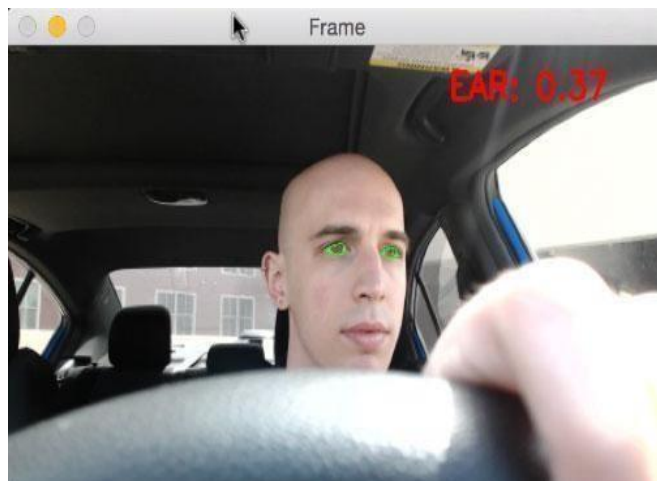


Fig 6.2 Result

The above result images depicts that the driver is fully attentive as the EAR is greater than 0.3 so we must keep monitoring him to give an immediate alert alarm whenever he feels drowsy i.e., when the EAR falls under 0.2.

CHAPTER 7

CODE

```
import numpy

from pygame import

mixer import time

import cv2

from tkinter import *

import

tkinter.messagebox


root=Tk()

root.geometry('500x570')

frame = Frame(root, relief=RIDGE, borderwidth=2)

frame.pack(fill=BOTH,expand=1)

root.title('Driver Cam')

frame.config(background='light

blue')

label = Label(frame, text="Driver Cam",bg='light blue',font=('Times 35

bold')) label.pack(side=TOP)

filename = PhotoImage(file="demo.png")

background_label = Label(frame)

background_label.pack(side=TOP)
```

```
def hel():  
    help(cv2)
```

```
def Contri():
```

```
    tkinter.messagebox.showinfo("Contributor","Stuti\n")
```

```
def anotherWin():
```

```
    tkinter.messagebox.showinfo("About",'Driver Cam version v1.0\n Made  
Using\n-OpenCV\n- Numpy\n-Tkinter\n In Python 3')
```

```
menu = Menu(root)
```

```
root.config(menu=menu)
```

```
subm1 = Menu(menu)
```

```
menu.add_cascade(label="Tools",menu=subm1)
```

```
subm1.add_command(label="Open CV  
Docs",command=hel)
```

```
subm2 = Menu(menu)
```

```
menu.add_cascade(label="About",menu=subm2)
```

```
subm2.add_command(label="Driver Cam",command=anotherWin)
```

```
subm2.add_command(label="Contributor",command=Contri)
```

```
def exitt():
```

```
    exit()
```

```
def web():
```

```
    capture =cv2.VideoCapture(0)
```

```
while True:

    ret,frame=capture.read()

    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

    cv2.imshow('frame',frame)

    if cv2.waitKey(1) & 0xFF ==ord('q'):

        break

capture.release()

cv2.destroyAllWindows()
```

```
def webrec():

    capture =cv2.VideoCapture(0)

    fourcc=cv2.VideoWriter_fourcc(*'XVID')

    op=cv2.VideoWriter('Sample1.avi',fourcc,11.0,(640,480))

    while True:

        ret,frame=capture.read()

        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

        cv2.imshow('frame',frame)

        op.write(frame)

        if cv2.waitKey(1) & 0xFF ==ord('q'):

            break

    op.release()

    capture.release()

    cv2.destroyAllWindows()
```

```
def webdet():

    capture =cv2.VideoCapture(0)

    face_cascade = cv2.CascadeClassifier('lbpcascade_frontalface.xml')

    eye_glass = cv2.CascadeClassifier('haarcascade_eye_tree_eyeglasses.xml')
```

```
while True:
```

```
    ret, frame = capture.read()
```

```
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
```

```
    faces = face_cascade.detectMultiScale(gray)
```

```
    for (x,y,w,h) in faces:
```

```
        font = cv2.FONT_HERSHEY_COMPLEX
```

```
        cv2.putText(frame,'Face',(x+w,y+h),font,1,(255,255,255),2,cv2.LINE_AA)
```

```
        cv2.rectangle(frame,(x,y),(x+w,y+h),(255,0,0),2)
```

```
        roi_gray = gray[y:y+h, x:x+w]
```

```
        roi_color = frame[y:y+h,
```

```
        x:x+w]
```

```
        eye_g = eye_glass.detectMultiScale(roi_gray)
```

```
        for (ex,ey,ew,eh) in eye_g:
```

```
            cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),2)
```

```
    cv2.imshow('frame',frame)
```

```
    if cv2.waitKey(1) & 0xff == ord('q'):
```

```
        break
```

```
capture.release()
```

```
cv2.destroyAllWindows()
```

```
def webdetRec():
```

```
    capture =cv2.VideoCapture(0)
```

```
face_cascade = cv2.CascadeClassifier('lbpcascade_frontalface.xml')  
eye_glass = cv2.CascadeClassifier('haarcascade_eye_tree_eyeglasses.xml')  
fourcc=cv2.VideoWriter_fourcc(*'XVID')
```

```
op=cv2.VideoWriter('Sample2.avi',fourcc,9.0,(640,480))
```

```
while True:
```

```
    ret, frame = capture.read()
```

```
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
```

```
    faces = face_cascade.detectMultiScale(gray)
```

```
    for (x,y,w,h) in faces:
```

```
        font = cv2.FONT_HERSHEY_COMPLEX
```

```
        cv2.putText(frame,'Face',(x+w,y+h),font,1,(255,255,255),2,cv2.LINE_AA)
```

```
        cv2.rectangle(frame,(x,y),(x+w,y+h),(255,0,0),2)
```

```
        roi_gray = gray[y:y+h, x:x+w]
```

```
        roi_color = frame[y:y+h,
```

```
        x:x+w]
```

```
        eye_g = eye_glass.detectMultiScale(roi_gray)
```

```
        for (ex,ey,ew,eh) in eye_g:
```

```
            cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),2)
```

```
    op.write(frame)
```

```
    cv2.imshow('frame',frame)
```

```
    if cv2.waitKey(1) & 0xff ==
```

```
        ord('q'): break
```

```
op.release()
```

```
capture.release()
```

```
cv2.destroyAllWindows()
```

```
def alert():  
    mixer.init()
```

```
alert=mixer.Sound('beep-07.wav')
```

```
alert.play()
```

```
time.sleep(0.1)
```

```
alert.play()
```

```
def blink():
```

```
    capture =cv2.VideoCapture(0)
```

```
    face_cascade =
```

```
    cv2.CascadeClassifier('lbpcascade_frontalface.xml') eye_cascade =
```

```
    cv2.CascadeClassifier('haarcascade_eye.xml') blink_cascade =
```

```
    cv2.CascadeClassifier('CustomBlinkCascade.xml')
```

```
while True:
```

```
    ret, frame = capture.read()
```

```
    gray = cv2.cvtColor(frame,cv2.COLOR_BGR2GRAY)
```

```
    faces = face_cascade.detectMultiScale(gray)
```

```
    for (x,y,w,h) in faces:
```

```
        font = cv2.FONT_HERSHEY_COMPLEX
```

```
        cv2.putText(frame,'Face',(x+w,y+h),font,1,(250,250,250),2,cv2.LINE_AA)
```

```
        cv2.rectangle(frame,(x,y),(x+w,y+h),(255,0,0),2)
```

```
        roi_gray = gray[y:y+h, x:x+w]
```

```
        roi_color = frame[y:y+h,
```

```
        x:x+w]
```

```
        eyes = eye_cascade.detectMultiScale(roi_gray)
```

```
        for(ex,ey,ew,eh) in eyes:
```

```
            cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),2)
```

```
blink = blink_cascade.detectMultiScale(roi_gray)
```

```
for(eyx,eyy,eyw,eyh) in blink:
```

```
    cv2.rectangle(roi_color,(eyx,eyy),(eyx+eyw,eyy+eyh),(255,255,0),2)
```

```

        alert()

cv2.imshow('frame',frame)

if cv2.waitKey(1) & 0xFF ==ord('q'):

    break


capture.release()

cv2.destroyAllWindows()


but1=Button(frame,padx=5,pady=5,width=39,bg='white',fg='black',relief=GROOVE,command
=web,text='Open Cam',font=('helvetica 15
bold')) but1.place(x=5,y=104)


but2=Button(frame,padx=5,pady=5,width=39,bg='white',fg='black',relief=GROOVE,command
=webrec,text='Open Cam & Record',font=('helvetica 15
bold')) but2.place(x=5,y=176)


but3=Button(frame,padx=5,pady=5,width=39,bg='white',fg='black',relief=GROOVE,command
=webdet,text='Open Cam & Detect',font=('helvetica 15
bold')) but3.place(x=5,y=250)


but4=Button(frame,padx=5,pady=5,width=39,bg='white',fg='black',relief=GROOVE,command
=webdetRec,text='Detect & Record',font=('helvetica 15
bold')) but4.place(x=5,y=322)


but5=Button(frame,padx=5,pady=5,width=39,bg='white',fg='black',relief=GROOVE,command
=blink,text='Detect Eye Blink & Record With Sound',font=('helvetica 15
bold')) but5.place(x=5,y=400)


but5=Button(frame,padx=5,pady=5,width=5,bg='white',fg='black',relief=GROOVE,text='EXI
T', command=exitt,font=('helvetica 15 bold'))

but5.place(x=210,y=478)

```

```
root.mainloop()
```

CHAPTER 8

CONCLUSION

Through this project we learned the technique of extracting the features (image of eyes) from Haarcascade and decision making using SVM (Support Vector Machine) technique. Though the Haarcascade technique is limited for only detecting the images of the eyes in this project, it can be developed to detect any objects. The main theme of this entire project is to detect the drowsiness of the drivers and alert them in order to avoid the accidents. However this project can further be developed for the performance improvement. Thus the proposed system is a successful prototype of drowsiness detection system using Open CV software DLIB library, Haar Classifiers, Facial Landmarks, SVM classifier. The system developed was successfully tested, its limitations identified and a future plan of action developed. In this project, we successfully built a drowsy driver alert system that gives alert to the person who is driving whenever he feels drowsy. We used Open CV to detect faces and eyes using a Haar cascade classifier and then we used Facial landmarks (DLIB), SVM to predict whether the driver is attentive or not.

- Alerts the driver and provides the drowsiness feedback.
- Discomfort and distraction caused to driver can be identified.

CHAPTER 9

REFERENCES

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- [3] **R. Nopsuwanchai, Y. Noguchi, M. Ohsuga, Y. Kamakura, and Y. Inoue,** "Driver- independent assessment of arousal states from video sequences based on the classification of eye blink patterns," in Intelligent Transportation.
- [4] **Rezaee, Khosro, et al.** "Real-time intelligent alarm system of driver fatigue based on video sequences." Robotics and Mechatronics (ICRoM), 2013 First RSI/ISM International Conference on. IEEE, 2013.
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CHAPTER 10

APPENDIX

DROWSY

ORIGINALITY REPORT

6%

SIMILARITY INDEX

6%

INTERNET SOURCES

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Monu U. Ragashe, M.M. Goswami, M. M. Raghuwanshi. "Approach towards real time face recognition in streaming video under partial occlusion", 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), 2015

Publication

<1%