

RTSC-DVM: A NOVEL METHODOLOGY
FOR REAL-TIME SIREN CALL TO HALT
DISTRACTED VEHICLE MISHAPS

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

By

ANUSHA S (38110041)
SUBIKSHA E(38110564)



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING

SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC
JEPPIAAR NAGAR, RAJIV GANDHI SALAI,
CHENNAI - 600 119

MAY - 2022



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with “A” grade by NAAC

Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600 119

www.sathyabama.ac.in



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Anusha S(38110041), Subiksha E(38110564)** who carried out the project entitled **“RTSC-DVM: A NOVEL METHODOLOGY FOR REAL-TIME SIREN CALL TO HALT DISTRACTED VEHICLE MISHAPS”** under my supervision from **Nov 2021 to May 2022**.

Internal Guide

Mr.VIGNESH. R, M.E., Ph.D.

Head of the Department

Dr. VIGNESHWARI S, M.E., Ph. D.

Dr. L. LAKSHMANAN, M.E., Ph.D.

Submitted for Viva voce Examination held on _____

Internal Examiner

External Examiner

DECLARATION

I, **Anusha S(38110041), Subiksha E(38110564)** hereby declare that the Project Report entitled “**RTSC-DVM: A NOVEL METHODOLOGY FOR REAL-TIME SIREN CALL TO HALT DISTRACTED VEHICLE MISHAPS**” done by us under the guidance of **Mr.Vignesh.R,M.E.,Ph.D** (Internal) is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE:

PLACE:

SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr.T.Sasikala M.E., Ph. D, Dean**, School of Computing, **Dr.S.Vigneshwari M.E., Ph.D.**, and **Dr.L.Lakshmanan M.E., Ph.D.**, Heads of the Department of Computer Science and Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Mr.Vignesh.R,M.E.,Ph.D**, for his valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

Distractions are unpredictable and may lead to careless mishaps which are difficult to prevent with population growth around the world. Researches have been conducted numerous times to find a solution to prevent loss of life. Passenger security is the main concern of the vehicle's designers and in order to provide better security for saving lives of passengers, airbags are designed but they do not prevent mishaps from happening. Distraction due to phone notifications and general tiredness are the main causes. A wide range of techniques based on behavioral measures using machine learning techniques have been examined to scope out driver distraction in the past. The recent growth of such technologies requires that these algorithms be improved to evaluate their accuracy in identifying distraction. There are numerous features of faces that are available to be extracted from any face to deduce the level of distraction. These include eyes closed for longer than 5 seconds, head movements and continuous yawning. However, the development of a shock system to push out the distraction and immediately give an alert is a challenging task as it requires accurate and robust algorithms. This study takes a novel approach by using convolutional neural networks to scope out the distraction and will immediately sound a loud siren to give a sensory shock which brings back alertness. When paired with proper guidance, the said hybrid approach would produce the best solution in real-time to such issues in the future.

TABLE OF CONTENTS

Chapter No.	TITLE	Page No.
	Abstract	v
	List of Figures	viii
1.	INTRODUCTION	1
2.	LITERATURE SURVEY	3
3.	AIM AND SCOPE OF THE PRESENT INVESTIGATION	6
	3.1. Aim of the investigation	6
	3.2. Scope of the present investigation	7
4.	EXPERIMENTAL OR MATERIALS AND METHODS; ALGORITHMS USED	9
	4.1. Existing System	9
	4.2. Proposed System	10
	4.3. System Design(Architecture)	12
	4.4. Procedure and Algorithms	14
	4.4.1. HOG (Histogram of Oriented Gradients)	14
	4.4.2. EAR (Eye Aspect Ratio)	14
	4.4.3. PERCLOS	18
	4.4.4. Head Position	19
	4.4.5. MAR (Mouth Aspect Ratio)	20
	4.4.6. Facial Landmark	22
	4.5. System Workflow	25
	4.5.1. Module Implementation	27
5.	RESULTS AND DISCUSSION & PERFORMANCE ANALYSIS	31

6.	SUMMARY AND CONCLUSIONS	32
	REFERENCES	33
	APPENDIX	34
	A. Source Code	34
	B. Screenshots	46
	C. Publication with Plagiarism Report	50

LIST OF FIGURES

Figure No.	Figure Name	Page No.
4.1.1	A representation of a driver drowsiness system using Raspberry Pi	10
4.3.1	System Architecture for Drowsiness Judgment	12
4.4.1	Eye Aspect Ratio Representation(open)	15
4.4.1	Eye Aspect Ratio Representation(close)	15
4.4.3	Eye Aspect Ratio Formula	15
4.4.4	Representation of eye-blinks	16
4.4.5	Representation of eye-lid blinks	17
4.4.6.	Representation of eye-lid distance	18
4.4.7	Representation of Head poses	19
4.4.8	Example of a slumped over driver	20
4.4.9	Mouth Aspect Ratio Representation	20
4.4.10	Mouth Aspect Ratio Formula	20
4.4.11	Representation of mouth height detection Using HOG algorithm	21
4.4.12	Representation of a mouth yawning	22
4.4.13	Facial Landmarks	23
4.4.14	Real-time representation of facial Landmarks(A)	23
4.4.15	Real-time representation of facial Landmarks(S)	24
4.4.16	Representation of Distraction Judgment	24
4.5.1	Workflow Diagram	25
4.5.2	Representation of Face Pattern generated using HOG	28
4.5.3	Representation of processing the facial features	28

CHAPTER 1

INTRODUCTION

In recent years, an increase in the demand for modern transportation simultaneously necessitates a faster car safety growth. At present, the automobile is the most essential mode of transportation for people. Although it has changed people's lifestyle and improved the convenience of conducting daily activities, it is also associated with numerous negative side-effects, such as road mishaps and traffic due to distraction, fatigue, and exhaustion. These are significant and latent dangers responsible for much loss of lives. In recent years, scientists have been trying to prevent any further loss by pre-emptively spotting such symptoms well in advance. These recognizing methods are categorized as subjective and objective detection. In the subjective detection method, a driver must participate in the evaluation, which is associated with the driver's subjective perceptions through steps such as self-questioning. Then, these data are used to estimate the danger of the vehicles being driven by exhausted drivers, assisting them to plan their schedules accordingly. However, their feedback is not required in the objective detection method as it monitors their physiological state and driving-behaviour characteristics in real time. The collected data are used to evaluate the driver's level of fatigue. Furthermore, objective detection is categorized into two: contact and non-contact. Compared with the contact method, noncontact is cheaper and more convenient because it only requires Computer Vision technology with sophisticated camera which allows the use of the device in large numbers. Owing to easy installation and low cost, the noncontact method has been widely used for our problem statement. For instance, Attention Technologies and SmartEye observe the movement of the driver's eyes and position of the driver's head to determine the level of their fatigue. In this study, we propose a non-contact method to detect the level of the driver's fatigue. Our method employs the use of only the vehicle-mounted camera, making it unnecessary for the driver to carry any on/in-body devices. Our design uses each frame image to analyze and detect the driver's concentration state.

Driver tiredness discovery may be a car security innovation which avoids mishaps

when the driver is getting lazy. Different considerations have been proposed that around 20% of all street mishaps are fatigue-related, up to 50% on certain streets. Driver weakness could be a critical reason in the large number of vehicle mishaps. Later measurements assess that yearly 1,200 passing's and 76,000 wounds can be credited to weariness related crashes. The improvement of technologies for recognizing or avoiding laziness at the wheel could be a major challenge within the field of accident evasion frameworks. Due to the risk that laziness or fatigue presents on the street, strategies have to be created for neutralizing its influences. Both driver tiredness and diversion, in any case, might have the same impacts, i.e., diminished driving execution, longer response time, and an expanded hazard of crash inclusion. Based on Procurement of video from the camera that's before driver, it performs real-time preparing of an approaching video stream in order together the driver's level of weariness on the off chance that the laziness is estimated at that point it'll deliver the caution by detecting the eyes, mouth and head posture.

CHAPTER 2

LITERATURE SURVEY

This problem statement has been extensively studied over the past 5 years by researchers and automotive companies in a bid to create a solution, and all their solutions vary from analyzing various patterns of distractive habits to analyzing health vitals of the driver.

The work of Dr. K.S. Tiwari et al introduced an eye-blink monitoring system and also provided a buzzer to alert the driver of his condition. Whereas the research paper of Ceerthi Bala et al proposed a system to alert the traffic department when distraction is perceived.

Some studies were conducted using neurocognitive information, especially, through EEG, and it has been used to show differences in brain dynamics when there occurs a change in alertness during driving. In Jap et al's research paper, we can understand their researches addressing drowsiness and fatigue detection using EEG, which showed that the ratio of slow to fast EEG waves were increased when the subject, in our case, the driver was distracted or influenced by fatigue.

Gharagozlou et al. suggested in his research paper that other different levels of fatigue and distraction can be estimated using band power features and EEG signal entropy features, showing a notable increase in alpha power corresponding to driver fatigue.

Rateb Jabbar et al suggested that accuracy of detecting sleepiness increased by using facial landmarks with a Convolutional Neural Network (CNN). In J Hu and J Min's paper, entropy features were used to combine with Gradient Boosting Decision Tree Model. Deep learning models for fatigue classification were proposed, as in H. Zeng et al's work, through a Residual Convolutional Neural Network (EEG-Conv-R), using data collected from 10 healthy subjects over 16 channels.

In P.P. San's research paper, a combination of a deep neural network with support vector machine (SVM) classifier at the last layer was also proposed. Other previous works are based on intra-subject approaches. Some cross-subject approaches have also been proposed by combining EEG samples from all subjects, followed by splitting them into training and testing randomly, like H. Zeng et al. This approach is naturally random and so it ends up mixing some training subjects' samples with the testing ones, which is not cross-subject.

In Y.Liu et al.'s research paper, the authors perform domain adaptation, a branch of transfer learning, to adapt the data distributions of source and target so that the classification could be more efficient in a cross-subject scenario.

Md. Yousuf Hossain et al. proposed a non-intrusive system using the eye closure ratio as the input parameter. In Y.Liu et al.'s paper, EEG features, statistics, higher order crossing, fractal dimension, signal energy, and spectral power were extracted and combined with several classifiers, such as logistic regression, linear discriminant analysis, 1-nearest neighbor, linear SVM, and naïve Bayes.

Mika Sunagawa et al. proposed a model that was accurately capable of sensing the entire range of stages of distraction, from weak to strong.

Monagi H. Alkinani et al. published an extensive analysis of comparisons between various deep learning based techniques for recognizing distraction, drowsiness, fatigue and aggressiveness of a driver. Whereas Joao Ruivo Paulo et al. explored the methodology for observing distraction using EEG signals in a sustained attention driving task, with results showing a better balanced accuracy of 75.87% and higher for leave-one-out cross-validation.

Wang et al., N. Hatami et al., and Z. Zhao et al.'s methodologies used (recurrence plots and gramian angular fields), they have been successfully applied in computer vision algorithms combined with deep learning, these have been used in recent works in the EEG research domain, but still are relatively unexplored.

Mkhuseli Ngxande et al. reviewed machine learning algorithms such as Support

Vector Machines (SVMs), Convolutional Neural Networks (CNNs) and Hidden Markov models in this context. The work of Naveen Senniappan Karuppusamy et al suggested an electroencephalography-based sleepiness detection system (ESDS) with accuracy of 93.91%.

Yaocong Hu et al proposed a new deep learning framework based on the hybrid of 3D conditional generative adversarial network and two-level attention bidirectional long short-term memory network. It was proposed for robust recognition aimed at extracting short-term spatial-temporal features designed as a 3D encoder-decoder generator with the condition of auxiliary information to generate high-quality fake image sequences and a 3D discriminator was devised to learn drowsiness-related representation from spatial-temporal domain. In addition, for long-term spatial-temporal fusion, they investigated the use of two-level attention mechanism to guide the bidirectional long short-term memory to learn the saliency of short-term memory information and long-term temporal information.

Mohamed Hedi Baccour et al's proposal consisted of an analysis of the potential eye-closure and head rotation signals of the driver to classify the driver's state using logistic regression models.

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

3.1 AIM OF THE INVESTIGATION:

Methodologies introduced previously mainly implemented this problem statement by using a pre-defined dataset of faces with closed eyes and opened eyes. The response time between detecting the distraction and alerting the driver is too long to prevent mishaps as well as the earlier techniques have less accuracy in identifying distraction, so it is not perfect. To combat the previously mentioned issues, a novel methodology is introduced which blares a loud siren call shocking the senses of the driver back to alertness. The main objective is to first design a system to perceive the distraction by continuously monitoring retina of the eye. There are many facial features that can be extracted from the face to infer the level of distractedness. These include eyes closed for >5 frames, head movements and continuous yawning. The system should work in spite of driver wearing spectacles and should work in various lighting conditions. This methodology helps in preventing unwanted loss of life, restricts rash driving, and helps in traffic monitoring.

There are various approaches to improve the street security for a vehicle driver. It ought to be noticed that one of the gigantic mainstream approaches introduced in past logical explores depends in the improvement of cutting-edge driver help frameworks.

These wellbeing frameworks permit to diminish street mishaps and furnish better collaboration and commitment with a driver. Some normal instances of driver security advancements for this sort of frameworks are vehicle impact shirking framework, path keep partner, driver laziness and interruption observing what's more, cautioning.

General utilization of such frameworks can be depicted as a certain arrangement of sequential orders along these lines: observing driver conduct, condition of the vehicle or street circumstance by utilizing distinctive inherent assistant gadgets,

including short and long range radars, lasers, video stream cameras to see the environmental factors; ceaseless investigation of readings from sensors and

deciding risky circumstances while driving; cautioning driver about perceived perilous in-lodge and street circumstances; and taking control of the vehicle if driver response isn't adequate or missing.

Right now, driver security frameworks vigorously depend on information gathered from various in-vehicle sensors.

3.2 SCOPE OF THE PRESENT INVESTIGATION:

Our methodology is a car safety technology to help save the life of the driver and the passengers by warning the occupants if we detect any symptoms of distraction while driving. The main objective is to first design a system to perceive the driver's mannerisms and concentration by continuously monitoring the retina of the eye, his face movements etc. This is a novel methodology is introduced which blares a loud siren call shocking the senses of the driver back to alertness. There are numerous features of faces that are available to be extracted from any face to deduce the level of distraction. This can also help in reducing over-speeding and rash driving. Traffic management can be maintained by using our software for greater benefit worldwide.

More and more professions nowadays require concentration over the long term. Drivers must keep a near eye on the street, so they can respond to sudden occasions quickly. Driver fatigue typically becomes an instantaneous reason behind several traffic accidents. In this manner, there ought to be creations of the frameworks that will distinguish and inform a driver of her/his terrible psychophysical condition, which may essentially diminish the number of fatigue-related car mishaps. Developing these devices, though, will be through experiencing several difficulties linked to swift and proper identification of the exhaustion signs of a driver. One of the specialized conceivable outcomes to execute driver tiredness discovery frameworks is to utilize the vision-based approach. Here we are identifying the driver drowsiness by evaluating vision framework, mouth yawning as well as head slump positions and angles. If the

driver is distracted or asleep, that means the automatic drive mode will be started along with a loud siren alarm will be played to shock the senses of the driver back to alertness.

The motive is to demonstrate the implementation of a driver's fatigue detection through image processing. Studies suggest that about one-fourth of all serious road accidents occur because of the vehicle drivers' drowsiness where they need to take, confirming that drowsiness gives rise to more road accidents than accidents occur through Drink and Drive.

This system is designed by employing vision-based concepts. The system's main component is a small camera pointing towards the driver's face scan and monitoring the driver's eyes, yawning mouth and head slumped position angle and posture to detect drowsiness and fatigue.

There are various methods like detecting objects which are near to vehicle and front and rear cameras for detecting vehicles approaching near to vehicle and airbag system which can save lives before an accident is accorded.

CHAPTER 4

EXPERIMENTAL OR MATERIALS AND METHODS;

ALGORITHMS USED

4.1. EXISTING SYSTEM:

Looking at the disadvantages of all the above methodologies used in previous systems, the most common point that pops up is most of these systems implemented this problem statement using only a pre-defined dataset of faces with closed eyes and opened eyes. Also they had only visual types of alerting system to inform the driver of his state, which is not an effective alarm because visual alarms require one to be alert to see the alarm, which defeats the whole purpose at hand. Also, some of these systems' response time between finding the state of the driver and alerting the driver of his state was found to be too long to prevent mishaps in time. Some systems were found to be too sensitive to the eye blinks and yawns and other systems gave alarms continuously for a long time resulting in spamming the system. Our system aims to overcome all these issues with the previously existing systems and address these issues while giving the best accuracy in the results. Our basic idea is to monitor the physical state of the driver while he's driving using a live camera. We are making use of facial parameters to track the retina in the eye of the beholder, in case of frequent eye blinks while the driver is tired and also keep track of their mouth movements in case of yawning. When our system detects either of these changes our model will immediately emit an alarm sound as loud as a siren alarm to immediately awaken the driver from his poor state back to alertness.

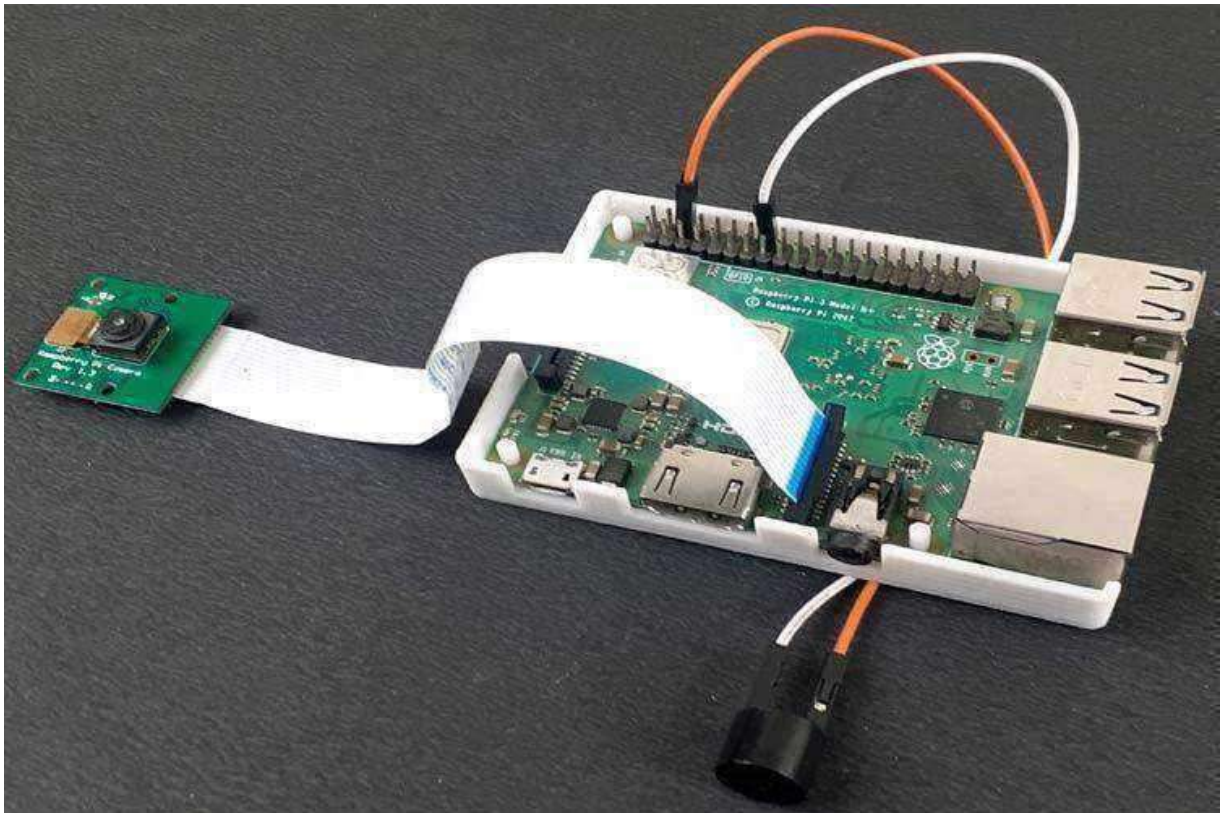


Fig 4.1.1: A representation of a driver drowsiness system using Raspberry Pi

4.2. PROPOSED SYSTEM:

Fatigue is a safety problem that has not yet been deeply tackled by any country in the world mainly because of its nature. Fatigue, in general, is very difficult to measure or observe unlike alcohol and drugs, which have clear key indicators and tests that are available easily. Probably, the best solutions to this problem are awareness about fatigue-related accidents and promoting drivers to admit fatigue when needed. The former is hard and much more expensive to achieve, and the latter is not possible without the former as driving for long hours is very lucrative. Our proposed system is an authoritative welfare technology to safeguard driver's life and passengers by preventing an accident when a driver is unfocused while traveling. The main purpose is to continuously monitor the retina of the eye, and continuously monitor the movement of the face to build a system that enforces the driver's safety by observing their manual movements and bearings. The system

works despite the different lighting conditions that are possible and successfully scan the driver. The main goal is to revive the driver from all kinds of disturbance using a siren alarm sound that is so shocking to the hearing sense that they'll immediately become alert. Traffic management can be maintained with our software to be used all over the world. The previously familiarized methodologies mainly executed this issue using predefined dataset records of various closed and opened eyes in different face structures. It is not perfect because the response time between the discovery of the distress and the detection of the driver's alarm is too long and the accuracy is too little when identifying the various physical gestures of the driver in the car. In order to fight the aforementioned issues, our novel prototype brings about a loud siren call to impact sensory shock and alert the driver. The main purpose is to build a system to perceive the different types of diversions and exhaustion by continuous monitoring of the ocular retina. There are facial landmark features that can be extracted from the face to infer the level of distraction. These include eyes closed for more than 5 seconds, head tilt movements, and continuous yawning.

The system should work even for people wearing glasses and under various lighting conditions. This methodology prevents unnecessary loss of life, curbs reckless driving, and assists in traffic monitoring. Most existing systems use external factors to notify the user about the problem and rescue the user only after an accident. However, research shows that most accidents are due to user errors such as drowsiness and sleep while driving. Since these methods cannot detect facial expressions, yawning head nods, and primarily blinking frequency thereby concluding their accuracy is not good, we introduce an easier and better model to combat all these errors and also do a good deed for the humanity by saving lives.

4.3. SYSTEM DESIGN (ARCHITECTURE):

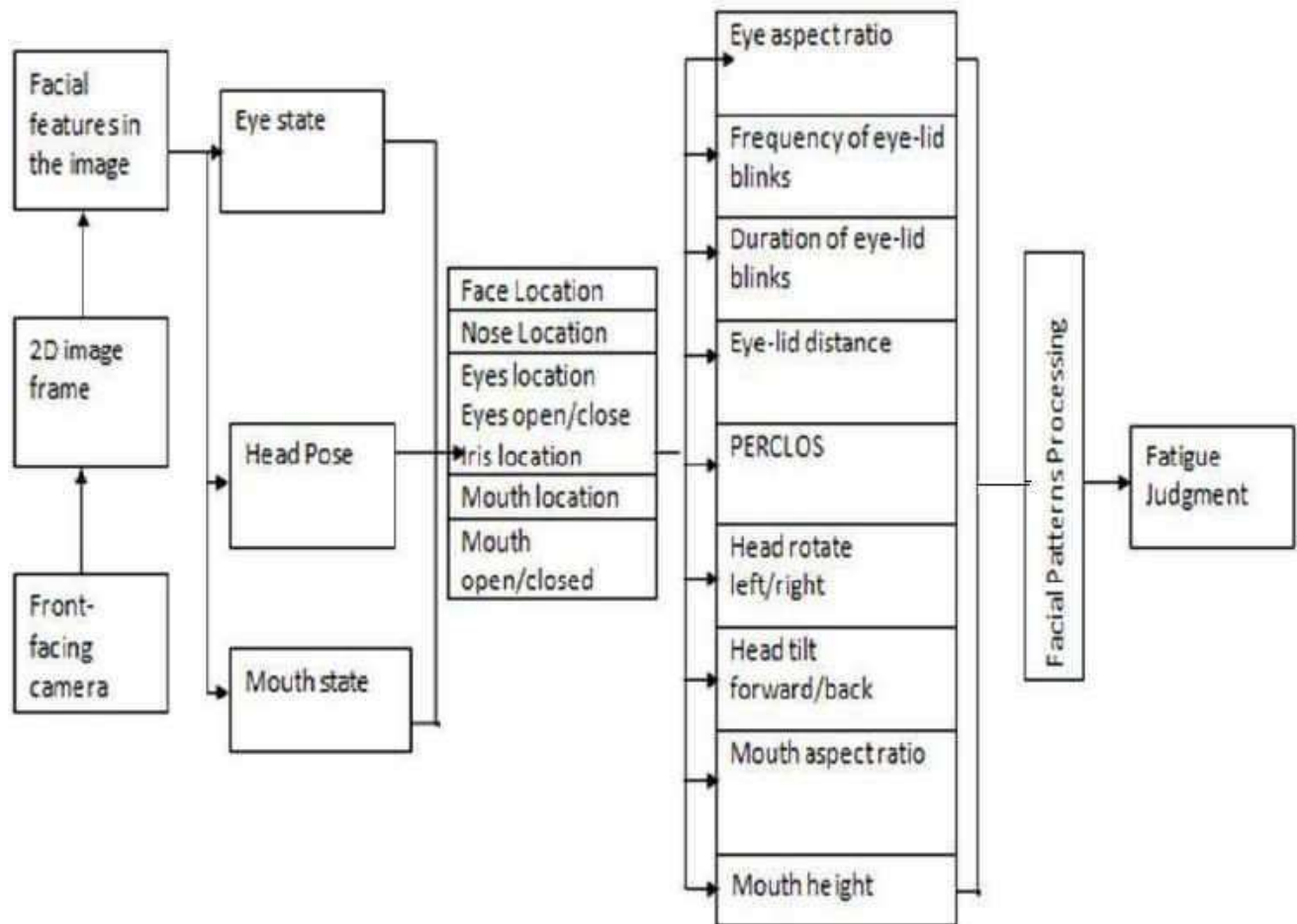


Fig 4.3.1: System Architecture for Drowsiness Judgment

The block diagram of the proposed system has been shown in the above figures. The camera captures the image of the person inside the car and sends that to the HOG model to train and it detects each feature from the face using facial landmark technique in the system. The next step in the process would be as it starts to find the position and condition of each feature to analyze, it should detect whether the person is sleeping or not. If any of the features especially the eye and the head pose/state of the person are detected to be abnormal then automatically the system starts to produce the siren sound. This is where we will get the final

judgment of the state of the driver, whether he is concentrated or distracted.

SOFTWARE REQUIREMENTS:

- Operating system: Windows 9, Coding Language: python
- Libraries Used: Numpy , Scipy , Playsound , Dlib, Imutils, opencv, argparse
- Processor: Pentium processor of 400 MHz or higher.
- RAM: minimum 64MB primary memory
- Hard disk: minimum 1 GB hard disk space.
- Monitor: preferable color monitor (16 bit color) and above.
- Web camera
- Compact disk drive
- A keyboard and mouse.
- PyCharm-Python IDE used.
- Using pip install few python packages(mainly opencv).

Python Packages:

Numpy: The NumPy array that contains the 68 facial landmark coordinates that map to various facial parts.

Scipy: SciPy provides algorithms for optimization, integration, interpolation, eigenvalue problems, algebraic equations, differential equations, statistics, signal and image processing.

Playsound: The *playsound* module contains only a single function named `playsound()`. It requires one argument: the path to the file with the sound we have to play. It can be a *local file*, or a *URL*.

Dlib: It's a landmark's facial detector with pre-trained models, the dlib is used to estimate the location of 68 coordinates (x, y) that map the facial points on a person's

Imutils: Imutils are a series of convenience functions to make basic image processing functions such as translation, rotation, resizing, skeletonization, and displaying Matplotlib images easier with OpenCV and both Python 2.7 and Python 3.

Opencv: OpenCV is a video and image processing library and it is used for image

and video analysis, like facial detection, license plate reading.

argparse: argparse is the “recommended command-line parsing module in the Python standard library.” It’s what you use to get command line arguments into your program

4.4. PROCEDURE & ALGORITHMS:

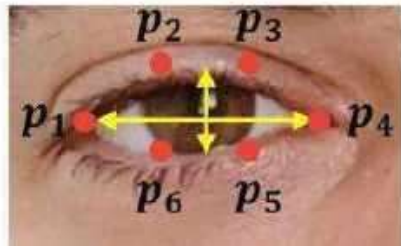
4.4.1 HOG(Histogram of Oriented Gradients):

The H.O.G(Histogram of Oriented Gradients) is a feature descriptor used in computer vision for image processing for the purpose of object detection. HOG is a descriptor of feature that is often used to extract features from image data. It is broadly used in computer vision tasks for object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This is done by extracting the gradient and orientation (or you can say magnitude and direction) of the edges. Basically, the faces are discovered using a Haar Cascade Classifier on an image in combination with the cropping of the cardinal section of face. The H.O.G(Histogram of Oriented Gradients) is a feature descriptor used in computer vision for image processing for the purpose of object detection. HOG, or Histogram of Oriented Gradients, is a descriptor of feature that is often used to extract features from image data. It is broadly used in computer vision tasks for object detection. This is done by extracting the gradient and orientation (or you can say magnitude and direction) of the edges. The Eye Aspect Ratio is an approximate measure of the eye opening state. A code can decide if a person's eyes are closed if the EAR falls under a unique threshold value. Clmtrackr is also a facial landmark plotter.

4.4.2 EAR(Eye Aspect Ratio):

The Eye Aspect Ratio is an estimate of the eye opening state. A code can determine if a person's eyes are closed if the Eye Aspect Ratio falls below a certain threshold value. If you notice, each eye is represented using 6 landmarks points.

Eye aspect ratio will be larger and relatively constant over time when eye is open



Eye aspect ratio will be almost equal to zero when a blink occurs

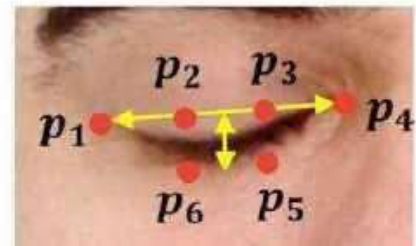


Fig 4.4.1 and 4.4.2: Eye Aspect Ratio Representation

The eye aspect ratio is a much better solution that involves a very basic calculation based on the ratio of distances between facial landmarks of the eyes. This method for eye blink detection is fast, efficient, and easy to implement. The EAR for a single eye is calculated using this formula:

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

Fig 4.4.3: Eye Aspect Ratio Formula

If the EAR value is more that means the eye is open more wider. The numerator of this equation computes the distance between the vertical eye landmarks while the denominator computes the distance between horizontal eye landmarks, weighting the denominator appropriately since there is only *one* set of horizontal points but *two* sets of vertical points. The eye aspect ratio is approximately constant while the eye is open, but will rapidly fall to zero when a blink is taking place. Using this simple equation, we can *avoid image processing techniques* and simply rely on the *ratio of eye landmark distances* to determine if a person is blinking. In this picture, we have an eye that is fully open — the eye aspect ratio here would be large(r) and relatively constant over time. However, once the person blinks (*top- right*) the

eye aspect ratio decreases dramatically, approaching zero. The *bottom* figure plots a graph of the eye aspect ratio over time for a video clip. As we can see, the eye aspect ratio is constant, then rapidly drops close to zero, then increases again, indicating a single blink has taken place.

Frequency of Eye-lid blinks:

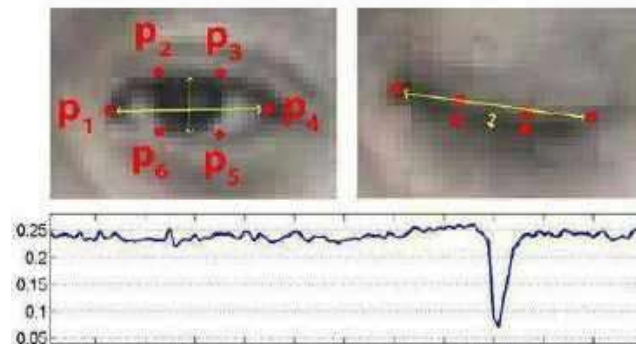


Fig 4.4.4: Representation of eye-blinks

Blinking is essential process in a human! On average, most people blink around 15 to 20 times each minute. Blink frequency and duration have been associated with the performance of other attention related tasks (e.g., driving, piloting aircraft) and correlate with subjective sleepiness scales and the EEG. Suppression or reduction of blinking occurs with tasks that have a high visual attention demand, such as reading. Blink duration correlates with increased sleepiness or fatigue and may provide a more significant index for alertness than blink frequency.

Duration of eye-lid blinks:

On average the human blink lasts only a tenth of a second which is 100 milliseconds. Sometimes, it can even last up to 400 milliseconds. It's safe to say that humans blink a lot. The average person blinks between 15 to 20 times per

minute. This means that our eyes are closed for roughly 10% of the time that we are awake. In our system, if the eye is closed for more than 5 seconds, or if the driver blinks continuously, the alarm will be sounded. The duration of eye blinks or eyes closed is essential for our methodology. In order to overcome the sensitivity disadvantage of previous methodologies, we could only sound the alarm after the person had been distracted for a certain length of frames in the video feed and not too immediately after finding the smallest fatigue symptoms. So our system will keep monitoring the eyes of the driver and if he has closed eyes for a continuous number of frames in the video, then the alarm will be sounded immediately.



Fig 4.4.5: Representation of eye-lid blinks

Eye lid distance:

Eyes express the most direct reaction when driver is drowsy or inattentive and eye blinking is always used as the basis for driver fatigue detection. The margin reflex distance is the distance between the upper eyelid margin and the corneal light reflex indicating the centre of the pupil. Firstly, the face is located using the characteristics of skin colours, then the eyes are detected by projections and finding connected components and is used as the dynamic templates for eye tracking. Finally, it will be used to finalise whether the driver is fatigued or not.

The training that we give to the facial landmark detector to detect the eye landmarks is done with careful precision because the detector should concentrate only on the cornea area and especially on the pupil. The detector should be able to differentiate between the eyelids and the cornea area. This is achieved using contouring. Based on the colours of the cornea and the eyelids, the system will be able to differentiate between them and will concentrate only on the eye. If it detects the eyelid for a continuous number of frames in the video feed, it will immediately sound the alarm. The facial landmarks have been trained to accurately identify the eye corners and the shape of the eye to perfectly track its movements.

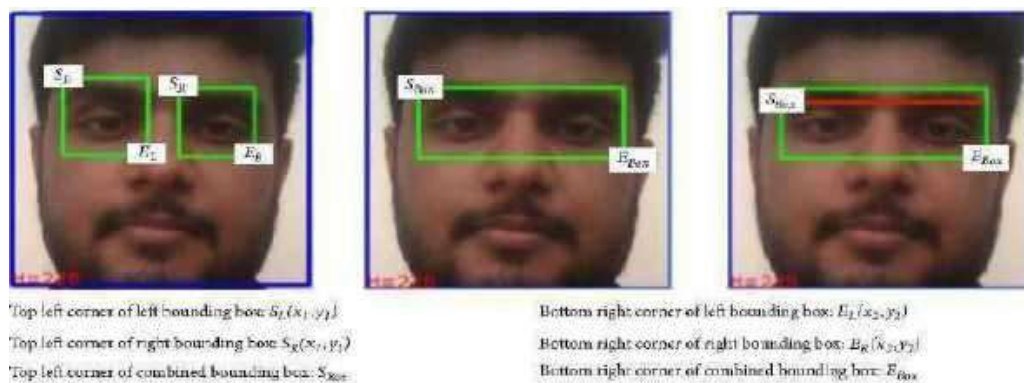


Fig 4.4.6: Representation of eye-lid distance

4.4.3. PERCLOS:

PERCLOS is the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures ("drows") rather than blinks. A PERCLOS drowsiness metric is the proportion of time in a minute that the eyes are at least 80% closed. PERCLOS assessment and propriety developed software is used to determine the onset of fatigue and improve the accuracy and ability to track eye movement, eyelid behavior, head and face poses under all possible circumstances. A camera module on a rotating base that is mounted on the dashboard inside the cab can be used. The device has a large field of view to accommodate operator head

movements. The equipment uses eye-tracking software with a structured illumination approach that depends on the high contrast between the pupils and the face to identify and track the operator's pupils. It provides head and face tracking which include eye, eyelid and gaze tracking. These systems now provide real time feedback without the use of wire, magnets or headgear.

4.4.4. HEAD POSITION:

Head rotation – left/right:

Head pose estimation is a key element of human behavior analysis. Many applications would benefit from automatic and robust head pose estimation systems such as driver drowsiness detection, it gives the vital information. The approach is to estimate the head pose from monocular images. We can determine the head pose in the three-dimensional space by three Euler angles of rotation around three axis orthogonal to each other.

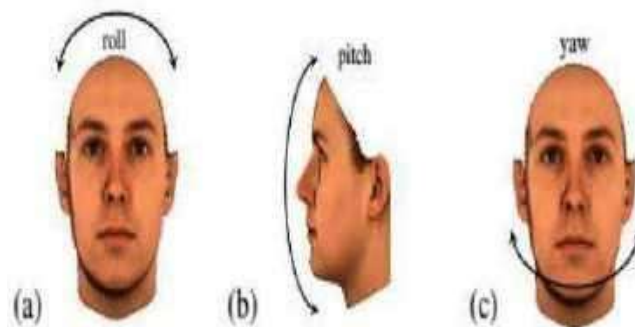


Fig 4.4.7: Representation of Head poses

Head tilt – forward/back:

While most of the existing approaches for head pose estimation deal only with poses that vary around the vertical axis. It is possible to estimate the 3D rotation and translation of a 3D object from a single 2D photo, if an approximate 3D model of the object is known and the corresponding points in the 2D image are known. If the driver is slumped over, i.e. if he or she is bent down and is not looking at the road in front, our system will generate the siren alarm and will initiate the “SELF-DRIVING MODE” which can be used to keep the speed steady until the driver concentrates again and regains his control over the car.



Fig 4.4.8: Example of a slumped over driver

4.4.5 MAR(Mouth Aspect Ratio):

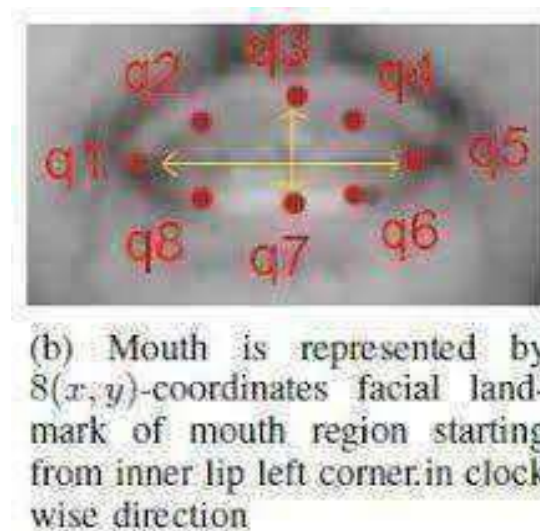


Fig 4.4.9: Mouth Aspect Ratio Representation

The Mouth Aspect ratio(MAR) involves the solution that requires a very simple calculation based on the ratio of distances between facial landmarks of the mouth. With the height of lip and mouth height functions we can check whether the mouth is open or not.

This MAR is adjustable and defines how much the mouth is open. We can simply put ratio = 1 which means the mouth is open more than lip height. Mouth Aspect ratio can be calculated using the following equation:

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

Fig 4.4.10: Mouth Aspect Ratio Formula

Mouth Height:

We understand that the mouth region is the lowest one-third of the detected face region. The lower one-third of the face image is extracted and recorded, and the middle half of the image is extracted and set as the mouth ROI, as shown in the green box in the figure. When the height of the facial region is expanded one-fifth downward, we obtain the complete mouth region, as shown. However, when the mouth opens narrowly, the region is too large, and it will affect the extraction of the mouth internal contour; thus, it is necessary to accurately locate the mouth. Based on the difference between the colors of the lips and the skin, the mouth region is precisely positioned according to lip segmentation, and we split the lips according to the value of chromatics of the RGB space. When the person yawns, the facial landmarks of the mouth region move along with the movement of the lips which will immediately alert the system that the person is yawning.

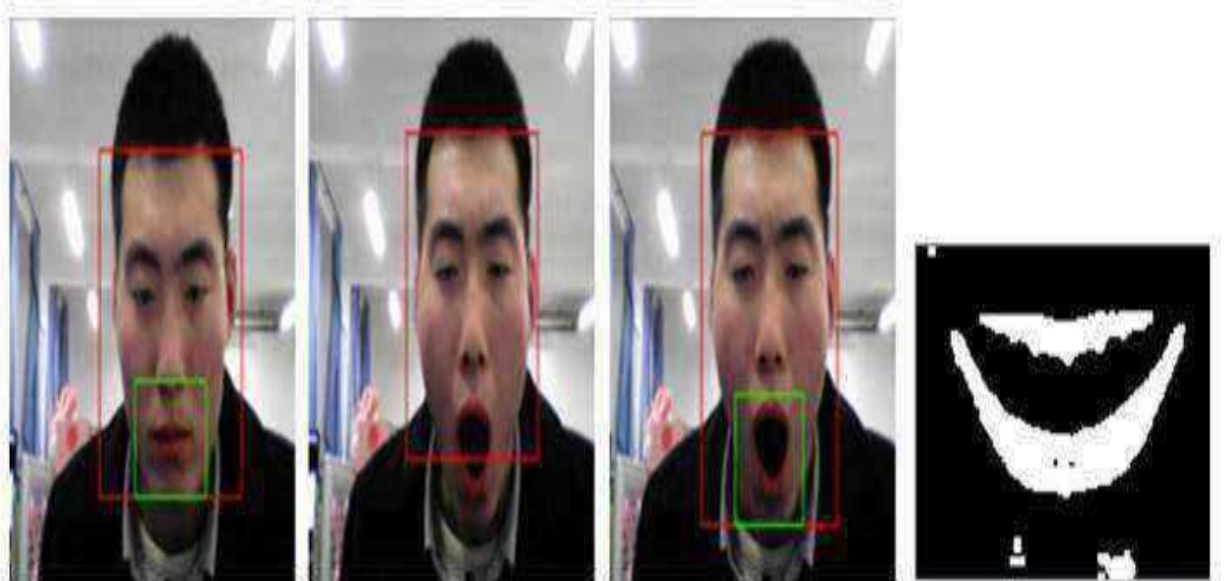


Fig 4.4.11: Representation of mouth height detection using HOG algorithm

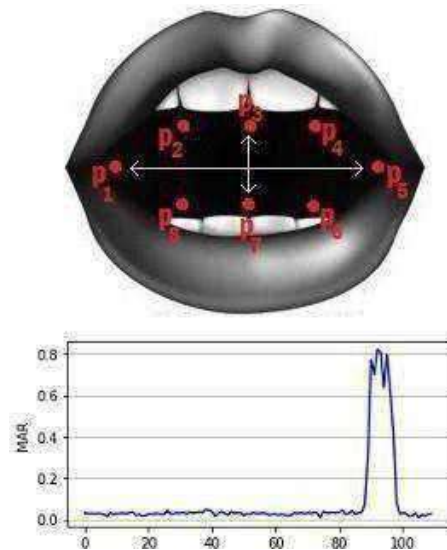


Fig 4.4.12: Representation of a mouth yawning

4.4.6 FACIAL LANDMARK:

The task is to detect key landmarks on the face and track them. Facial landmarks are used to incorporate and constitute vital areas of the face, inclusive of mouth, eyes, eyebrows, nose, jawline etc. In our project this facial landmark is used to represent the eyes and mouth especially, because these play a major role to detect the fatigue of the subject. It evaluates the time taken by each blink of the eye, the eye remaining closed or opened, interval of eye opened and closed, yawning etc.

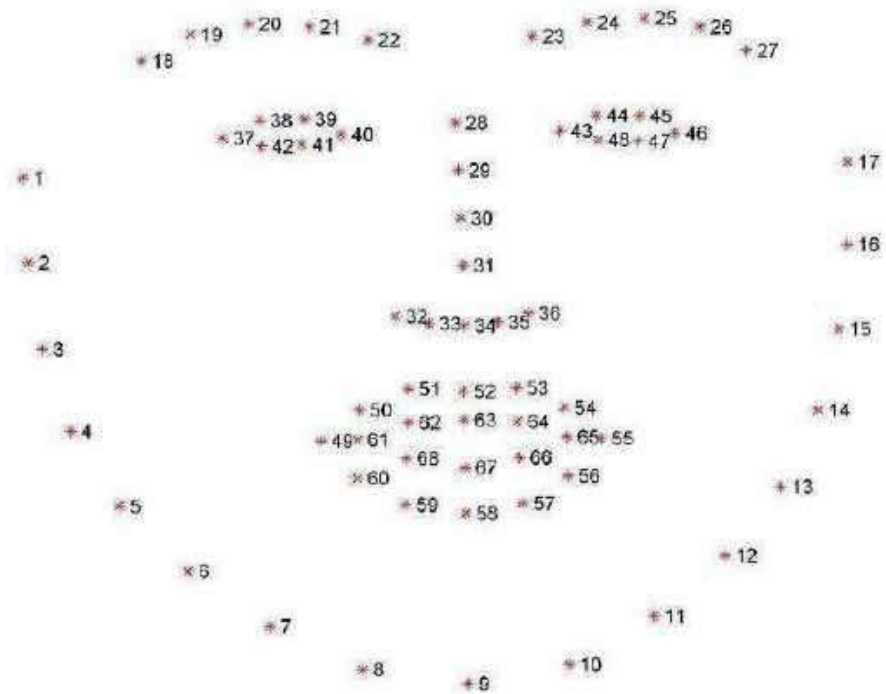


Fig 4.4.13: Facial Landmarks

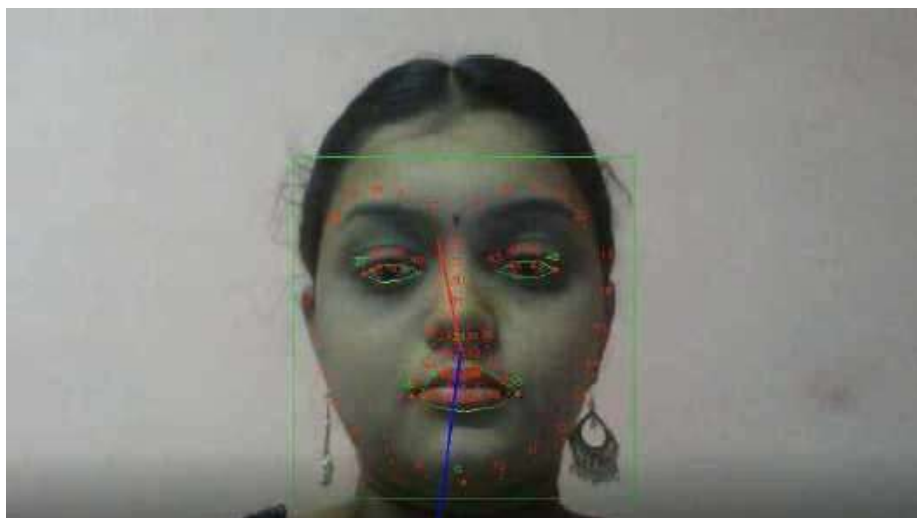


Fig 4.4.14: Real-time representation of Facial Landmarks (A)

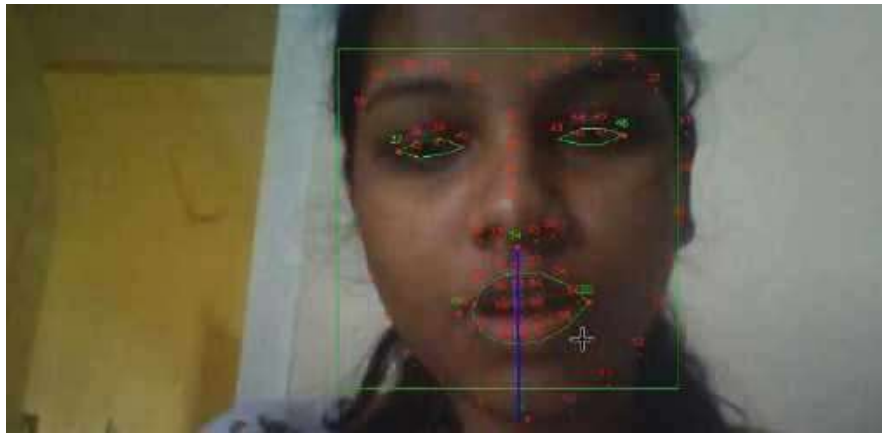


Fig 4.4.15: Real-time representation of Facial Landmarks (S)

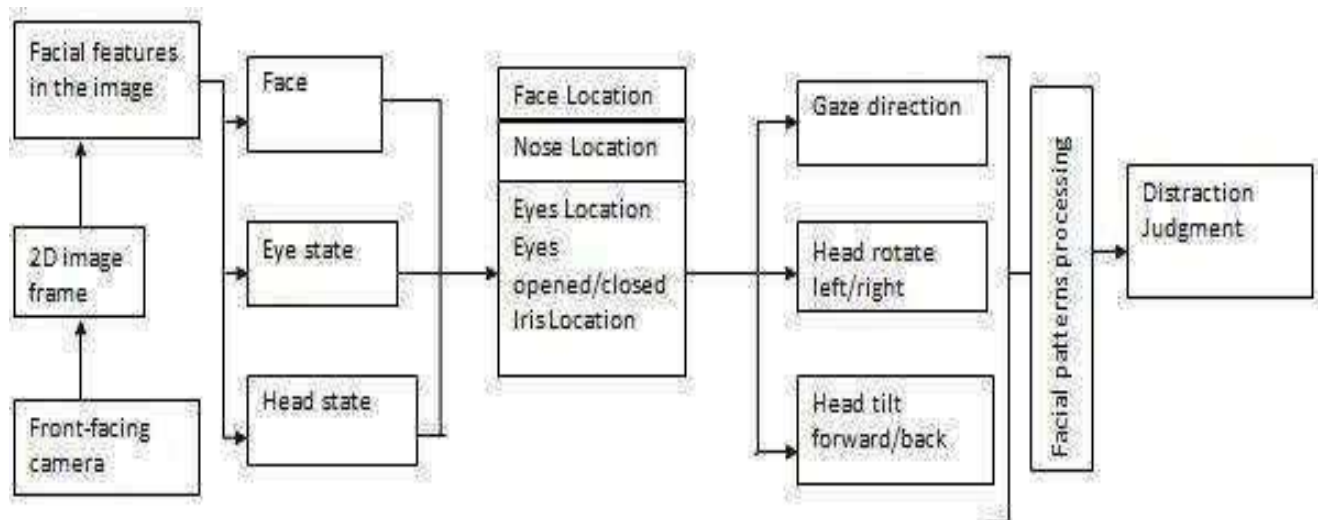


Fig 4.4.16: Representation of Distraction Judgment

Initially from the video input, from the web camera, the face would be detected in real time (live) and it extracts the features from the face such as the state of eye, mouth and head state. Then it evaluates the eye closure and blinking rate from the eye state, head position angle from head pose and mouth opening and closure from mouth state. All these things are classified together to determine whether the driver is concentrated or not .If the evaluated value lies in a particular range that is required by the model no warning and no siren would be produced else the siren alarm would be produced inside the car.

4.5 SYSTEM WORKFLOW:

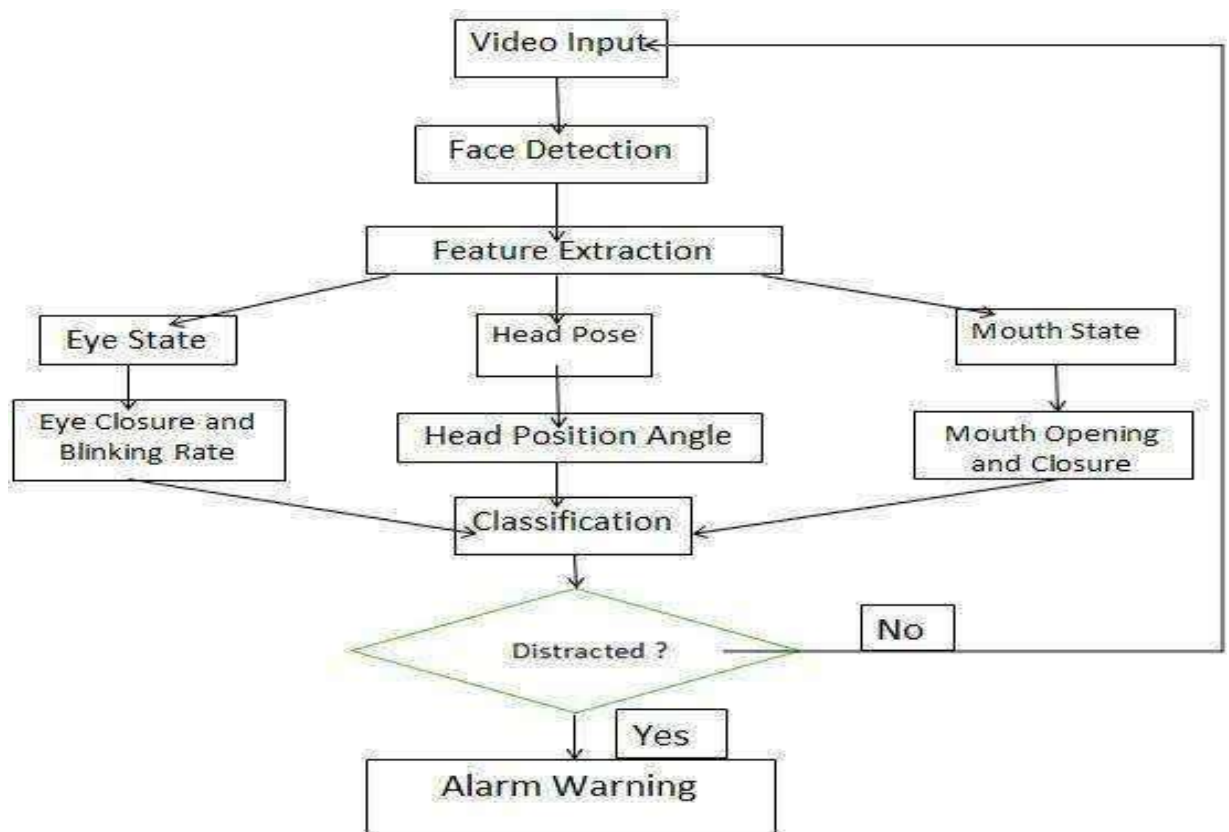


Fig 4.5.1: Workflow Diagram

Training data is the initial data used to train machine learning models. Training datasets are fed to machine learning algorithms to teach them how to make predictions or perform a desired task. For creating the dataset, a code should be written that captures eyes and facial landmarks from a camera and stores in our local disk. They are separated into labels 'Open' or 'Closed'. The data is manually live captured from the web cameras for building the model. Now, we can use this model to classify if a person's eye is open or closed. The training dataset used to train the Haar Cascade classifier. It consists of images that were taken anytime while driving. While experimenting with this model at night, it was observed that the Haar Cascade classifier was able to detect the facial landmarks from the video frames of the driver. The system would calculate the EAR value of the driver's eye and the MAR value as well. A demanding task in the past was detection of faces and their features like eyes, nose, mouth and even deriving emotions from their shapes. This task can be now solved by this model. Here the features were extracted using OpenCV. The eyelids were monitored to calculate the drowsiness based on the blinks per minute. The opening of mouth (yawning) and mainly the movements of the Eyelids were considered for drowsiness measurements in this model. The examination of the reaction time with unique ranges of sleep deprivation and environmental disturbances has been done with which the behavioural traits of the motive force can be determined. As observed the common pattern in the distracted state has been inferred because the sluggish drifting of the vehicle from the lane and the fast counter- guidance for correction. Many features were monitored to categorize and get the drowsy guidance sample. HOG is the main algorithm used. This gives the pattern classification of the driver's behavior, with one of the classification being the drowsy condition of the driver. A bell or buzzer is a sound flagging gadget, is used to produce the alarm. If the driver is slumped down in his seat or if his head posture is not erect, then the system will issue a "Self – Driving Mode" alarm, which will make the car to switch to Self Driving Mode rather than Manual Driving Mode. This model has designed to cover all drowsiness stages, drowsiness stages, from mild to severe, as well as all distraction and aggressive states of a human being. The posture data can be changed to be especially beneficial in conjunction with blink information due to the fact the posture index showed higher sensitivity to vulnerable drowsiness than

traditional information and changed to be capable of making amends for the shortcomings of the blink information. The driver wakes up when the siren is heard so automatically the buzzer sound gets halted, and the model again starts to proctor the driver for any further occurrences again.

4.5.1. MODULE IMPLEMENTATION:

a) Training the Model with the facial landmarks:-

Training data (or a training dataset) is the initial data used to train machine learning models. Training datasets are fed to machine learning algorithms to teach them how to make predictions or perform a desired task. In our case, our motto is to train the system to detect full faces of any one and identify the positions of their facial features using a 68-model facial landmarks. The data is manually live captured from the web camera for building the model. After training the model on our facial landmarks, any face shown by the camera will be plotted using our trained facial landmark shape predictor. Now, based on these landmarks, our system will determine if a person's eye is open or closed or if they're yawning and if they're in a slumped position.

b) Testing with the pre-trained Model:-

Our initiative was to train the model to recognize the facial landmarks on any faces appropriately for all sorts of environmental conditions. It consisted of images that were taken anytime during driving. While carrying out the experiment at night, it was observed that it was successfully able to detect the facial landmarks from the video frames of the driver. The system could calculate the EAR value of the driver's eye and the MAR value as well along with the head tilt degree.

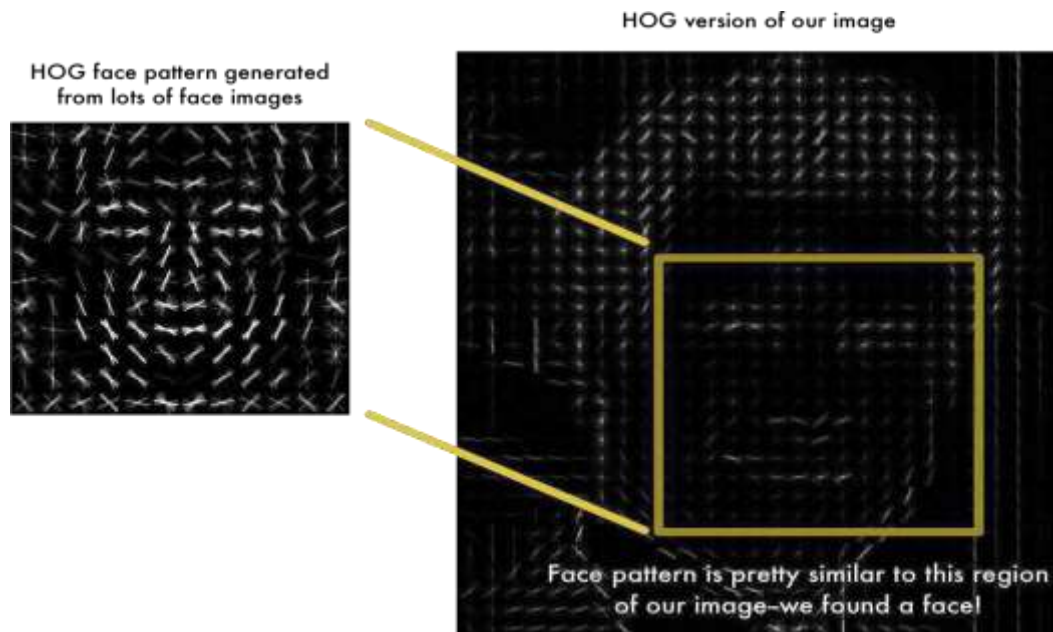


Fig 4.5.2: Representation of Face Pattern generated using HOG

c) Processing the facial features:-

A challenging task in the past was detection of faces and their features like eyes, nose, mouth while deriving emotions from their shapes. This task has now been solved. After the features have been extracted, we process them using OpenCV. The eyelids and the shape of the mouth will be monitored based on the number of blinks and yawns for a specified number of frames.

These features are essential for distraction measurement.

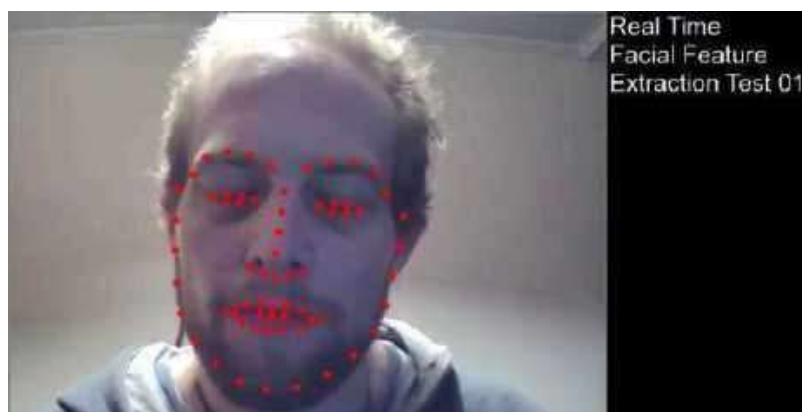


Fig 4.5.3: Representation of processing the facial features

d) Perceiving all physical symptoms of distraction/fatigue:-

The features of the face extracted can then be processed further, as is the case for PERCLOS (percentage of eyelid closure) or EAR (eye aspect ratio) for eye analysis or MAR (mouth aspect ratio) for yawning analysis. Our algorithms will transform the RGB images into grayscale for contouring and segmentation to concentrate only on eyes and mouth along with the head tilt. Physical symptoms include keeping eyes closed or yawning for a continuous number of frames. This algorithm is also very reliable to keep track of the head tilt degree and slumped position of the driver. The EAR algorithm involves a calculation based on the ratio of the distances between various facial landmarks of the eyes.

e) Sounding the siren alarm inside the car to alert the driver:-

As soon as the symptoms of distraction/fatigue are found, the system immediately blares the siren alarm inside the car, which will instantly rouse the driver from his distracted state. Our system is accurate and not too sensitive and therefore will not disturb the concentration of the driver unless he/she is distracted. If the driver is too deep asleep or is not immediately awake, the siren alarm will continue to ring. It will stop ringing only if the system detects alertness of the driver. The system will then continue to monitor for any such further signs of distraction and fatigue. This will be a continuous loop process.

f) Perceive any further distraction to repeat the alarm:-

This model is designed to cover all levels of distraction, from slight to severe. The posture information was particularly useful in conjunction with blink information because the posture index showed higher sensitivity to weak drowsiness than conventional information and was able to compensate for the shortcomings of the blink information. Since blink and posture information can be obtained even while not driving, this knowledge has the potential to contribute to drowsiness detection for occupants during automated driving in addition to manual driving.

g) Stop the alarm after recognizing alert state of the driver:-

Once driver wakes up the when the siren is heard ,automatically the alarm sound stops ringing ,the model again continues to perceive the driver closely for any more signs of further distraction or fatigue. The alarm will be buzzed again if there are some more physical symptoms of distraction found. The system will show a “Self- Driving Mode” if the driver is slumped on the seat and has closed eyes for too many continuous frames in the video feed. This is to indicate that the driving mode will now be automatic because the driver has been distracted for too long.

CHAPTER 5

RESULTS AND DISCUSSION, PERFORMANCE ANALYSIS

We have created a real-time methodology which alerts the driver if they are fatigued at the wheel while driving. Our implementation uses a triple approach to detect such symptoms by correctly identify signs of distraction such as closure of eyes or continuously blinking, yawning continuously and measuring the forward head tilt angle. This is possible in all lighting conditions and also with sunglasses.

Our methodology also includes the measurement of eye aspect ratio (to detect closure of eyes) and measurement of mouth aspect ratio (to detect yawning). After detecting these physical symptoms of distraction and fatigue, the system will emit a loud siren alarm which is used to bring the driver back to consciousness with the shock to the senses.

If the driver is recorded as distracted for a continuous number of frames in the live camera feed, the car will automatically shift to “Self-Driving Mode” which will keep the speed of the car at a constant measure and will help in regulating the movement of the car to prevent mishaps while also ringing the loud alarm to immediately alert the driver.

CHAPTER 6

SUMMARY AND CONCLUSIONS

SUMMARY & CONCLUSION:-

In this methodology, a smart real time alert system was developed successfully. The general drowsiness detection generally limits the only detection in general, where the sequel process was never invented. This system attempts to overcome this limitation. Our paper introduced an improved system based on HOG algorithm with Machine Learning. The foremost goal is to offer a methodology that is well organized and coherent to be carried out in all systems while sustaining and producing the highest and best performance. The system becomes capable of detecting facial landmarks (facial features) from the snapshots captured from the live camera and pass it to a trained Machine Learning model which is HOG-based, to discover and detect unusual or bizarre driving behavior. Thus the result here is the creation and presentation of a model that is simple and efficient and most importantly, relatively high in accuracy.

FUTURE WORK:-

In the future, researchers might focus on the use of other factors such as state of vehicle, sleeping hours, weather conditions, etc. for drowsiness measurement. This is a major problem statement in today's society for the drivers, passengers and the society in general. High annual mileage, exposure to the challenging environmental condition, and demanding work schedules all contribute to serious safety issues. Monitoring the drowsiness state of driver and providing feedback on their condition so that they can take necessary action is one vital step in a series of preventive measure to this problem. Currently there is no implementation in zoom or direction of the camera during the process. Future work may be automatically zoom in on eyes once they are monitored. This would avoid arbitration between having wide field of view in order to locate the eyes, and narrow view to detect drowsiness. Other systems can be developed to detect any issues in the car engine too to prevent mishaps.

REFERENCES:-

- [1] Dr. K.S. Tiwari, Supriya Bhagat, Nikita Patil, Priya Nagare, IOT Based Driver Drowsiness Detection&Health Monitoring System.
- [2] Rateb Jabbar, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al-Khalifa, Moez Krichen, Kamel Barkaoui, Driver Drowsiness Detection Model using CNN Techniques for Android App.
- [3] Md. Yousuf Hossain, Fabian Parsia George, IOT based Real-time Drowsy Driving Detection System for the Prevention of Road Accidents.
- [4] Mika Sunagawa, Shin-ichi-Shikii, Wataru Nakai, Makoto Mochizuki, Koichi Kusakame, and Hiroki Kitajima, Comprehensive Drowsiness Level Detection Model Combining Multimodal Information.
- [5] Monagi H. Alkinani, Wazir Zada Khan, and Quratulain Arshad, Detecting Human Driver Inattentive and Aggressive Driving Behaviour using Deep Learning: Recent Advances, Requirements, and Open Challenges.
- [6] Mkhuseli Ngxande, Jules-Raymond Tapamo and Michael Burke, Driver drowsiness detection using Behavioural measures and Machine Learning Techniques: A review of state-of-art techniques.
- [7] Joao Ruivo Paulo, Gabriel Pires, and Urbano J. Nunes, Cross-Subject Zero Calibration Driver's Drowsiness Detection: Exploring Spatiotemporal Image Encoding of EEG Signals for CNN Classification.
- [8] Naveen Senniappan Karuppusamy, Bo-Yeong Kang, Multimodal System to Detect Driver Fatigue using EEG, Gyroscope, and Image Processing.
- [9] Yaocong Hu, Mingqi Lu, Chao Xie, and Xiabo Lu, Driver Drowsiness Recognition via 3D Conditional GAN and Two-level Attention BiLSTM.
- [10] Ceerthi Bala U.K, Sarath TV, Internet of things based Intelligent Drowsiness Alert System, Fifth International Conference on Communication and Electronics Systems (ICCES 2020).

APPENDIX

A. SOURCE CODE

```
Detection.py
#!/usr/bin/env python
from scipy.spatial import distance as dist
from imutils.video import VideoStream
from imutils import face_utils
import argparse
import imutils
import time
import dlib
import math
from cv2 import cv2
import numpy as np
from EAR import eye_aspect_ratio
from MAR import mouth_aspect_ratio
from HeadPose import getHeadTiltAndCoords
import pygame
from tkinter import *
from tkinter import messagebox

# initialize dlib's face detector (HOG-based) and then create the
# facial landmark predictor
pygame.init()

pygame.mixer.music.load("alarm.wav")
print("[INFO] loading facial landmark predictor...")
detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor(
    'shape_predictor_68_face_landmarks.dat')

# initialize the video stream and sleep for a bit, allowing the
# camera sensor to warm up
print("[INFO] initializing camera...")
```

```

vs = VideoStream(src=0).start()
# vs = VideoStream(usePiCamera=True).start() # Raspberry Pi
time.sleep(2.0)

# 400x225 to 1024x576
frame_width = 1024
frame_height = 576

# loop over the frames from the video stream
# 2D image points. If you change the image, you need to change vector
image_points = np.array([
    (359, 391),    # Nose tip 34
    (399, 561),    # Chin 9
    (337, 297),    # Left eye left corner 37
    (513, 301),    # Right eye right corne 46
    (345, 465),    # Left Mouth corner 49
    (453, 469)     # Right mouth corner 55
], dtype="double")

(lStart, lEnd) = face_utils.FACIAL_LANDMARKS_IDXS["left_eye"]
(rStart, rEnd) = face_utils.FACIAL_LANDMARKS_IDXS["right_eye"]

EYE_AR_THRESH = 0.25
MOUTH_AR_THRESH = 0.79
EYE_AR_CONSEC_FRAMES = 3
COUNTER = 0

# grab the indexes of the facial landmarks for the mouth
(mStart, mEnd) = (49, 68)

while True:
    # grab the frame from the threaded video stream, resize it to

```

```

# have a maximum width of 400 pixels, and convert it to
# grayscale
frame = vs.read()
frame = imutils.resize(frame, width=1024, height=576)
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
size = gray.shape

# detect faces in the grayscale frame
rects = detector(gray, 0)

# check to see if a face was detected, and if so, draw the total
# number of faces on the frame
if len(rects) > 0:
    text = "{} face(s) found".format(len(rects))
    cv2.putText(frame, text, (10, 20),
                cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255), 2)

# loop over the face detections
for rect in rects:
    # compute the bounding box of the face and draw it on the
    # frame
    (bX, bY, bW, bH) = face_utils.rect_to_bb(rect)
    cv2.rectangle(frame, (bX, bY), (bX + bW, bY + bH), (0, 255, 0), 1)
    # determine the facial landmarks for the face region, then
    # convert the facial landmark (x, y)-coordinates to a NumPy
    # array
    shape = predictor(gray, rect)
    shape = face_utils.shape_to_np(shape)

    # extract the left and right eye coordinates, then use the
    # coordinates to compute the eye aspect ratio for both eyes
    leftEye = shape[lStart:lEnd]
    rightEye = shape[rStart:rEnd]

```

```

leftEAR = eye_aspect_ratio(leftEye)
rightEAR = eye_aspect_ratio(rightEye)
# average the eye aspect ratio together for both eyes
ear = (leftEAR + rightEAR) / 2.0

# compute the convex hull for the left and right eye, then
# visualize each of the eyes
leftEyeHull = cv2.convexHull(leftEye)
rightEyeHull = cv2.convexHull(rightEye)
cv2.drawContours(frame, [leftEyeHull], -1, (0, 255, 0), 1)
cv2.drawContours(frame, [rightEyeHull], -1, (0, 255, 0), 1)

# check to see if the eye aspect ratio is below the blink
# threshold, and if so, increment the blink frame counter
if ear < EYE_AR_THRESH:
    COUNTER += 1
    # if the eyes were closed for a sufficient number of times
    # then show the warning
    if COUNTER >= EYE_AR_CONSEC_FRAMES:
        cv2.putText(frame, "Eyes Closed!", (500, 20),
                     cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

if COUNTER >= 10:
    try:
        pygame.mixer.music.play()
    except:
        pass

if COUNTER >= 20:
    print("Self Driving Mode Start")
    cv2.putText(frame, "Self Driving Mode Start!", (500, 45),
                 cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

```

```

        # otherwise, the eye aspect ratio is not below the blink
        # threshold, so reset the counter and alarm
    else:
        COUNTER = 0

    mouth = shape[mStart:mEnd]

    mouthMAR = mouth_aspect_ratio(mouth)
    mar = mouthMAR
    # compute the convex hull for the mouth, then
    # visualize the mouth
    mouthHull = cv2.convexHull(mouth)

    cv2.drawContours(frame, [mouthHull], -1, (0, 255, 0), 1)
    cv2.putText(frame, "MAR: {:.2f}".format(mar), (650, 20),
                cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

    # Draw text if mouth is open
    if mar > MOUTH_AR_THRESH:
        cv2.putText(frame, "Yawning!", (800, 20),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

    # loop over the (x, y)-coordinates for the facial landmarks
    # and draw each of them
    for (i, (x, y)) in enumerate(shape):
        if i == 33:
            # something to our key landmarks
            # save to our new key point list
            # i.e. keypoints = [(i,(x,y))]
            image_points[0] = np.array([x, y], dtype='double')

```

```

# write on frame in Green
cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
cv2.putText(frame, str(i + 1), (x - 10, y - 10),
            cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
elif i == 8:
    # something to our key landmarks
    # save to our new key point list
    # i.e. keypoints = [(i,(x,y))]
    image_points[1] = np.array([x, y], dtype='double')
    # write on frame in Green
    cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
    cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
elif i == 36:
    # something to our key landmarks
    # save to our new key point list
    # i.e. keypoints = [(i,(x,y))]
    image_points[2] = np.array([x, y], dtype='double')
    # write on frame in Green
    cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
    cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
elif i == 45:
    # something to our key landmarks
    # save to our new key point list
    # i.e. keypoints = [(i,(x,y))]
    image_points[3] = np.array([x, y], dtype='double')
    # write on frame in Green
    cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
    cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
elif i == 48:
    # something to our key landmarks

```

```

        # save to our new key point list
        # i.e. keypoints = [(i,(x,y))]
        image_points[4] = np.array([x, y], dtype='double')
        # write on frame in Green
        cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
        cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
    elif i == 54:
        # something to our key landmarks
        # save to our new key point list
        # i.e. keypoints = [(i,(x,y))]
        image_points[5] = np.array([x, y], dtype='double')
        # write on frame in Green
        cv2.circle(frame, (x, y), 1, (0, 255, 0), -1)
        cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 255, 0), 1)
    else:
        # everything to all other landmarks
        # write on frame in Red
        cv2.circle(frame, (x, y), 1, (0, 0, 255), -1)
        cv2.putText(frame, str(i + 1), (x - 10, y - 10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.35, (0, 0, 255), 1)

#Draw the determinant image points onto the person's face
for p in image_points:
    cv2.circle(frame, (int(p[0]), int(p[1])), 3, (0, 0, 255), -1)

(head_tilt_degree, start_point, end_point,
 end_point_alt) = getHeadTiltAndCoords(size, image_points,
frame_height)

cv2.line(frame, start_point, end_point, (255, 0, 0), 2)
cv2.line(frame, start_point, end_point_alt, (0, 0, 255), 2)

```

```

    if head_tilt_degree:
        cv2.putText(frame, 'Head Tilt Degree: ' + str(head_tilt_degree[0]),
(170, 20),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255), 2)

```

```

    # extract the mouth coordinates, then use the
    # coordinates to compute the mouth aspect ratio
    # show the frameq
    cv2.imshow("Frame", frame)
    key = cv2.waitKey(1) & 0xFF

```

```

    # if the `q` key was pressed, break from the loop
    if key == ord("q"):
        break

```

```

# print(image_points)

```

```

# do a bit of cleanup
cv2.destroyAllWindows()
vs.stop()

```

EAR.py

```

from scipy.spatial import distance as dist

```

```

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])
    B = dist.euclidean(eye[2], eye[4])
    # compute the euclidean distance between the horizontal
    # eye landmark (x, y)-coordinates
    C = dist.euclidean(eye[0], eye[3])

```

```

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

```

HeadPose.py

```
import numpy as np
```

```
import math
```

```
from cv2 import cv2
```

```
# 3D model points.
```

```

model_points = np.array([
    (0.0, 0.0, 0.0),      # Nose tip 34
    (0.0, -330.0, -65.0), # Chin 9
    (-225.0, 170.0, -135.0), # Left eye left corner 37
    (225.0, 170.0, -135.0), # Right eye right corne 46
    (-150.0, -150.0, -125.0), # Left Mouth corner 49
    (150.0, -150.0, -125.0) # Right mouth corner 55
])

```

```
# Checks if a matrix is a valid rotation matrix.
```

```
def isRotationMatrix(R):
```

```
    Rt = np.transpose(R)
```

```
    shouldBeIdentity = np.dot(Rt, R)
```

```
    I = np.identity(3, dtype=R.dtype)
```

```
    n = np.linalg.norm(I - shouldBeIdentity)
```

```
    return n < 1e-6
```

```
# Calculates rotation matrix to euler angles
```

```
# The result is the same as MATLAB except the order
```

```
# of the euler angles ( x and z are swapped ).
```

```
def rotationMatrixToEulerAngles(R):
```

```

assert(isRotationMatrix(R))
sy = math.sqrt(R[0, 0] * R[0, 0] + R[1, 0] * R[1, 0])
singular = sy < 1e-6
if not singular:
    x = math.atan2(R[2, 1], R[2, 2])
    y = math.atan2(-R[2, 0], sy)
    z = math.atan2(R[1, 0], R[0, 0])
else:
    x = math.atan2(-R[1, 2], R[1, 1])
    y = math.atan2(-R[2, 0], sy)
    z = 0
return np.array([x, y, z])

```

```

def getHeadTiltAndCoords(size, image_points, frame_height):
    focal_length = size[1]
    center = (size[1]/2, size[0]/2)
    camera_matrix = np.array([[focal_length, 0, center[0]], [
        0, focal_length, center[1]], [0, 0, 1]], dtype="double")

    # print "Camera Matrix :\n {}".format(camera_matrix)

    dist_coeffs = np.zeros((4, 1)) # Assuming no lens distortion
    (_, rotation_vector, translation_vector) = cv2.solvePnP(model_points,
image_points,
                                                    camera_matrix, dist_coeffs,
                                                    flags =
cv2.SOLVEPNP_ITERATIVE) # flags=cv2.CV_ITERATIVE)

    # print "Rotation Vector:\n {}".format(rotation_vector)
    # print "Translation Vector:\n {}".format(translation_vector)
    # Project a 3D point (0, 0 , 1000.0) onto the image plane
    # We use this to draw a line sticking out of the nose_end_point2D

```

```

(nose_end_point2D, _) = cv2.projectPoints(np.array(
    [(0.0, 0.0, 1000.0)]), rotation_vector, translation_vector,
camera_matrix, dist_coeffs)

#get rotation matrix from the rotation vector
rotation_matrix, _ = cv2.Rodrigues(rotation_vector)

#calculate head tilt angle in degrees
head_tilt_degree = abs(
    [-180] - np.rad2deg([rotationMatrixToEulerAngles(rotation_matrix)[0]]))

#calculate starting and ending points for the two lines for illustration
starting_point = (int(image_points[0][0]), int(image_points[0][1]))
ending_point = (int(nose_end_point2D[0][0][0]),
int(nose_end_point2D[0][0][1]))

ending_point_alterate = (ending_point[0], frame_height // 2)

return head_tilt_degree, starting_point, ending_point,
ending_point_alterate

```

MAR.py

```

from scipy.spatial import distance as dist

```

```

def mouth_aspect_ratio(mouth):
    # compute the euclidean distances between the two sets of
    # vertical mouth landmarks (x, y)-coordinates
    A = dist.euclidean(mouth[2], mouth[10]) # 51, 59
    B = dist.euclidean(mouth[4], mouth[8]) # 53, 57

    # compute the euclidean distance between the horizontal
    # mouth landmark (x, y)-coordinates
    C = dist.euclidean(mouth[0], mouth[6]) # 49, 55

```

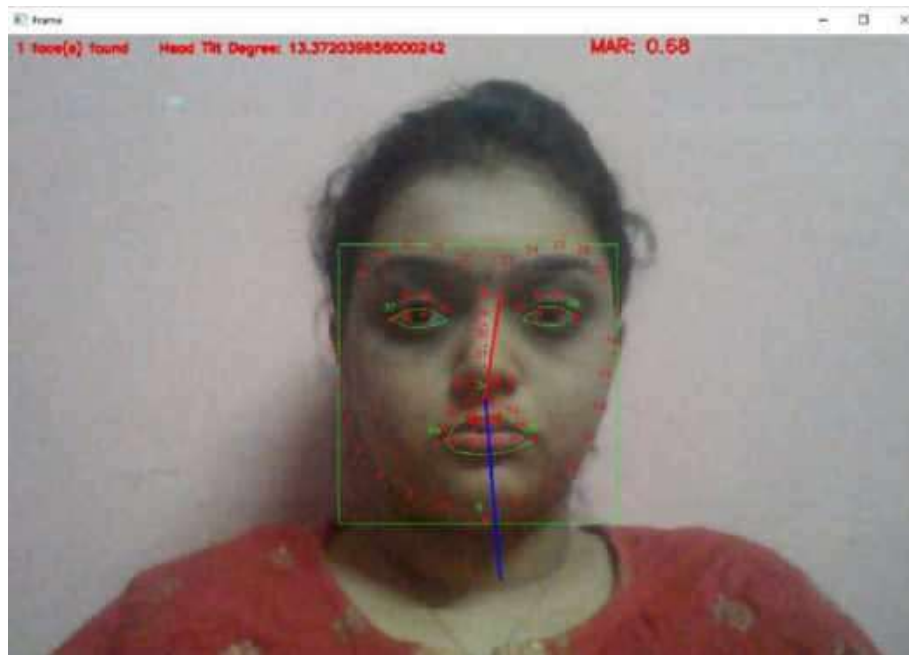
```
# compute the mouth aspect ratio
```

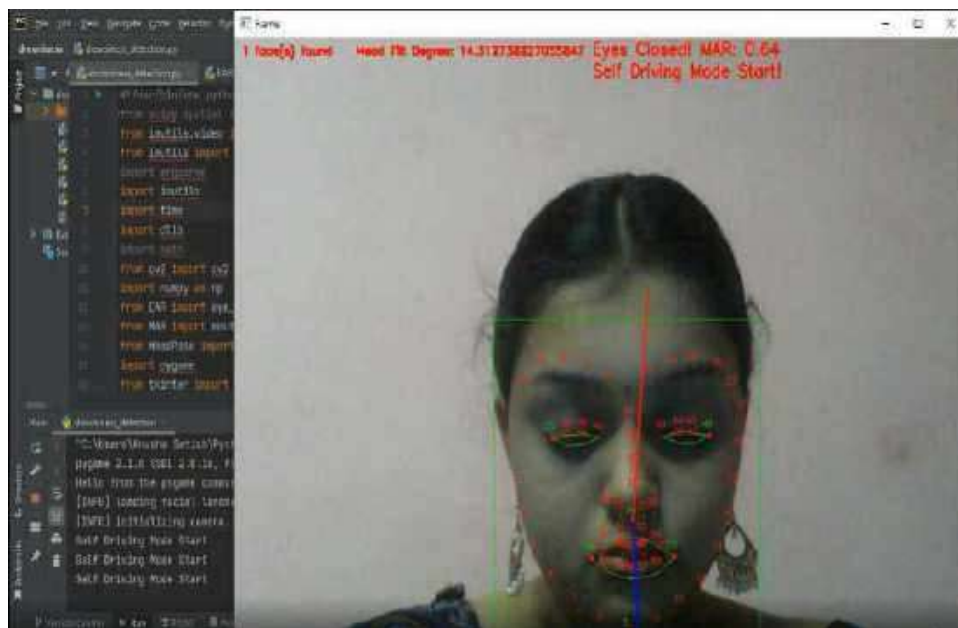
```
mar = (A + B) / (2.0 * C)
```

```
# return the mouth aspect ratio
```

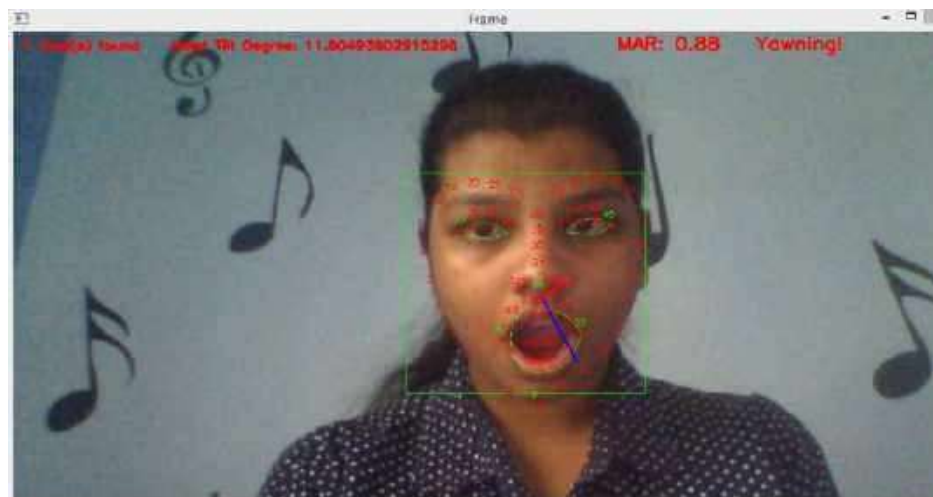
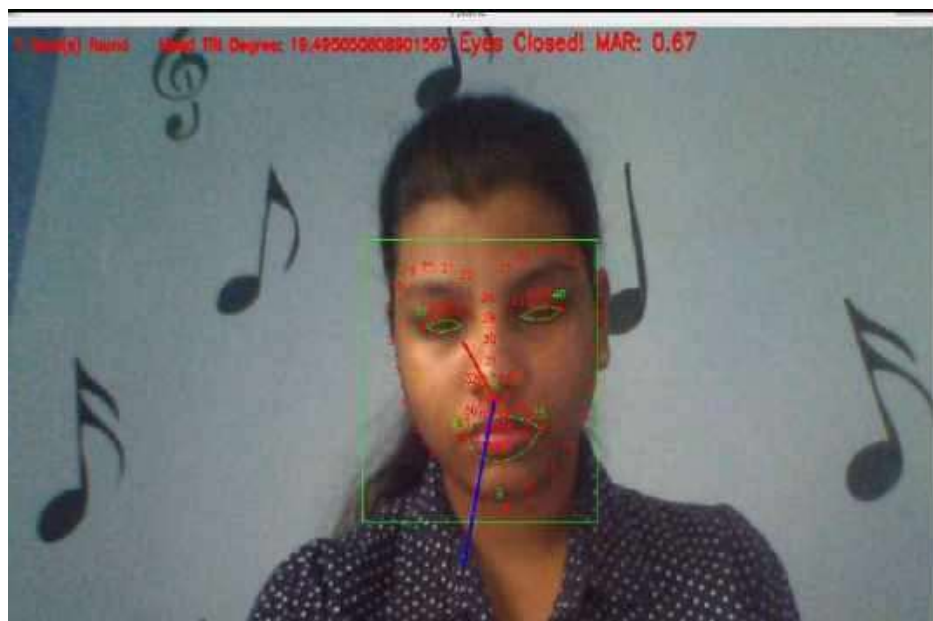
```
return mar
```

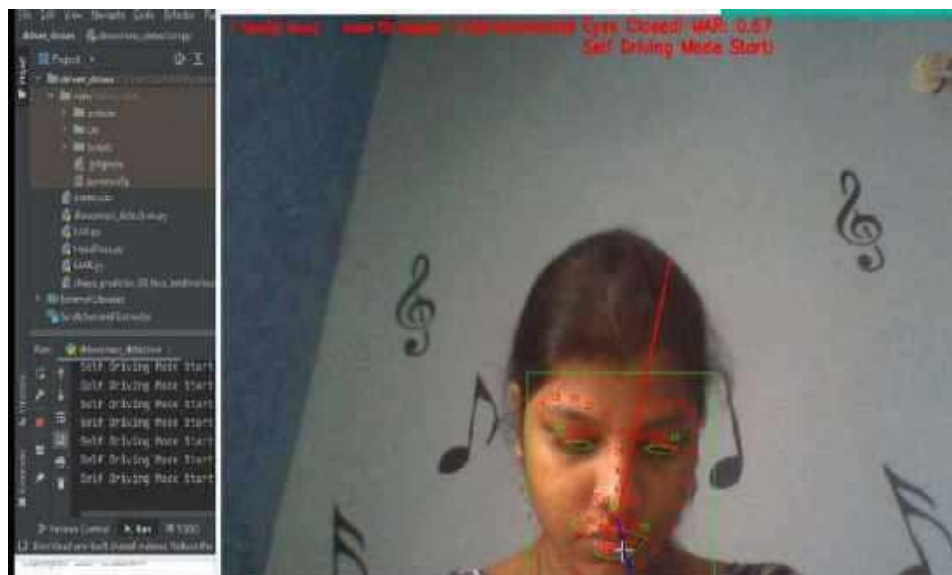
B. SCREENSHOTS OF OUTPUT OF ABOVE CODE :-
ANUSHA S (38110041) :-





SUBIKSHA E (38110564):-





Document Information

Analyzed document	Anusha Subiksha Paper New Version (1).pdf (D131141178)
Submitted	2022-03-22T09:58:00.0000000
Submitted by	R. Vignesh
Submitter email	vignesh.cse@sathyabama.ac.in
Similarity	9%
Analysis address	vignesh.cse.sathya@analysis.urkund.com

Sources included in the report

	URL: https://www.semanticscholar.org/paper/Driver-Drowsiness-Recognition-via-3D-Conditional-Hu-Lu/fed50b6e4411a15bdec1dc85680fc0ddb60e107b Fetched: 2022-03-22T09:58:27.9430000	 1
	URL: https://www.ijisrt.com/assets/upload/files/IJISRT21MAY360.pdf Fetched: 2021-09-30T15:19:11.0670000	 3
	URL: https://dl.ucsc.cmb.ac.lk/jspui/bitstream/123456789/4536/1/2017%20MCS%20060.pdf Fetched: 2021-10-11T08:26:37.6230000	 2
	URL: https://scholar.google.ru/citations?user=uAqYP1EAAAAJ&hl=th Fetched: 2022-03-22T09:59:26.9400000	 1
	URL: https://arxiv.org/abs/2002.03728 Fetched: 2020-04-22T15:56:55.2900000	 2
	URL: https://www.grafiati.com/en/literature-selections/attention-drowsiness/journal/ Fetched: 2022-03-22T09:58:27.4330000	 1
	URL: https://www.semanticscholar.org/paper/An-Analytical-Approach-for-Soil-and-Land-System-Deorankar-Rohankar/4a214d990cafb93fec2c283fe54c11107d6b Fetched: 2021-09-03T07:44:17.8500000	 1
	URL: https://link.springer.com/article/10.1007/s11571-018-9496-y Fetched: 2021-12-28T10:24:18.9130000	 1
	URL: https://www.semanticscholar.org/paper/Cross-Subject-Zero-Calibration-Driver%E2%80%99s-Drowsiness-Paulo-Pires/ba894aeadfdeb264b55a1ad306dcf2a95a1ee6ea Fetched: 2021-12-27T07:34:23.5800000	 2
	URL: https://www.hindawi.com/journals/cin/2019/3761203/ Fetched: 2021-06-13T12:20:45.1730000	 1
	URL: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0188756 Fetched: 2019-10-05T16:10:08.4630000	 1
	URL: http://www.ijitee.org/wp-content/uploads/papers/v9i6/E2779039520.pdf Fetched: 2021-02-05T16:56:38.3870000	 1

Entire Document

RTSC-DVM: A Novel Methodology for Real-Time Siren Call to Halt Distracted Vehicle Mishaps Anusha S [1] , Subiksha E [2] , Vignesh R [3] UG Student [1][2] , Department of Computer Science, Sathyabama Institute of Science and Technology, Chennai, 600119, India Assistant Professor [3] , Department of Computer Science, Sathyabama Institute of Science and Technology, Chennai, 600119, India getask7@gmail.com , subikshadarnel@gmail.com , vignesh.cse@sathyabama.ac.in

with the driver's subjective perceptions through steps such ABSTRACT:- Distractions are unpredictable and may lead to careless mishaps which are difficult to prevent with population growth around the world. Researches have been conducted numerous times to find a solution to prevent loss of life. Passenger security is the main concern of the vehicle's designers and in order to provide better security for saving lives of passengers, airbags are designed but they do not prevent mishaps from happening. Distraction due to phone notifications and general tiredness are the main causes. A wide range of techniques based on behavioral measures using machine learning techniques have been examined to scope out driver distraction in the past. The recent growth of such technologies requires that these algorithms be improved to evaluate their accuracy in identifying distraction. There are numerous features of faces that are available to be extracted from any face to deduce the level of distraction. These include eyes closed for longer than 5 seconds, head movements and continuous yawning. However, the development of a shock system to push out the distraction and immediately give an alert is a challenging task as it requires accurate and robust algorithms. This study takes a novel approach by using convolutional neural networks to scope out the distraction and will immediately sound a loud siren to give a sensory shock which brings back alertness. When paired with proper guidance, the said hybrid approach would produce the best solution in real-time to such issues in the future. Keywords: HOG, PERCLOS, EAR, MAR, DLIB, IMUTILS, OPENCV INTRODUCTION: - In recent years, an increase in the demand for modern transportation simultaneously necessitates a faster car safety growth. At present, the automobile is the most essential mode of transportation for people. Although it has changed people's lifestyle and improved the convenience of conducting daily activities, it is also associated with numerous negative side-effects, such as road mishaps and traffic due to distraction, fatigue, and exhaustion. These are significant and latent dangers responsible for much loss of lives. In recent years, scientists have been trying to prevent any further loss by pre- emptively spotting such symptoms well in advance. These recognizing methods are categorized as subjective and objective detection. In the subjective detection method, a driver must participate in the evaluation, which is associated as self- questioning. Then, these data are used to estimate the danger of the vehicles being driven by exhausted drivers, assisting them to plan their schedules accordingly. However, their feedback is not required in the objective detection method as it monitors their physiological state and driving-behavior characteristics in real time. The collected data are used to evaluate the driver's level of fatigue. Furthermore, objective detection is categorized into two: contact and non-contact. Compared with the contact method, noncontact is cheaper and more convenient because it only requires Computer Vision technology with sophisticated camera which allows the use of the device in large numbers. Owing to easy installation and low cost, the noncontact method has been widely used for our problem statement. For instance, Attention Technologies and SmartEye observe the movement of the driver's eyes and position of the driver's head to determine the level of their fatigue. In this study, we propose a non-contact method to detect the level of the driver's fatigue. Our method employs the use of only the vehicle- mounted camera, making it unnecessary for the driver to carry any on/in-body devices. Our design uses each frame image to analyze and detect the driver's concentration state. Our methodology is a car safety technology to help save the life of the driver and the passengers by warning the occupants if we detect any symptoms of distraction while driving. The main objective is to first design a system to perceive the driver's mannerisms and concentration by continuously monitoring the retina of the eye, his face movements etc. The system works in spite of the driver wearing spectacles and especially works well in various lighting conditions. The main objective is to bring the driver back from all kinds of distraction by using a buzzing siren alarm sound inside the car. This can also help in reducing over-speeding and rash driving. Traffic management can be maintained by using our software for greater benefit worldwide. Methodologies introduced previously mainly implemented this problem statement by using a pre-defined dataset of faces with closed eyes and opened eyes. The response time between detecting the distraction and alerting the driver was also too long to prevent mishaps plus the earlier techniques had less accuracy in identifying distraction. To combat the previously mentioned issues, a novel methodology is introduced which blares a loud siren

call shocking the senses of the driver back to alertness. There are numerous features of faces that are available to be extracted from any face to deduce the level of distraction. We infer based on EAR (Eye Aspect Ratio), MAR (Mouth Aspect Ratio) and Facial Landmarks. Symptoms include eyes closed for <5 seconds, head movements and continuous yawning. LITERATURE SURVEY:- This problem statement has been extensively studied over the past 5 years by researchers and

automotive companies in a bid to create a solution, and all their solutions vary from analyzing various patterns of distractive habits to analyzing health vitals of the driver. The work of Dr. K.S. Tiwari et al introduced an eye- blink monitoring system and also provided a buzzer to alert the driver of his condition. Whereas the research paper of Ceerthi Bala et al proposed a system to alert the traffic department when distraction is perceived. Some studies were conducted using neurocognitive information, especially, through EEG, and it has been used to show differences in brain dynamics when there occurs a change in alertness during driving. In Jap et al's research paper, we can understand their researches addressing drowsiness and fatigue detection using EEG, which showed that the ratio of slow to fast EEG waves were increased when the subject, in our case, the driver was distracted or influenced by fatigue. Gharagozlou et al. suggested in his research paper that other different levels of fatigue and distraction can be estimated using band power features and EEG signal entropy features, showing a notable increase in alpha power corresponding to driver fatigue. Rateb Jabbar et al suggested that accuracy of detecting sleepiness increased by using facial landmarks with a Convolutional Neural Network (CNN). In J Hu and J Min's paper, entropy features were used to combine with Gradient Boosting Decision Tree Model. Deep learning models for fatigue classification were proposed, as in H.Zeng et al's work, through a Residual Convolutional Neural Network (EEG- Conv-R), using data collected from 10 healthy subjects over 16 channels. In P.P. San's research paper, a combination of a deep neural network with support vector machine (SVM) classifier at the last layer was also proposed. Other previous works are based on intra-subject approaches. Some cross-subject approaches have also been proposed by combining EEG samples from all subjects, followed by splitting them into training and testing randomly, like H. Zeng et al. This approach is naturally random and so it ends up mixing some training subjects' samples with the testing ones, which is not cross-subject. In Y.Liu et al's research paper, the authors perform domain adaptation, a branch of transfer learning, to adapt the data distributions of source and target so that the classification could be more efficient in a cross- subject scenario. Md. Yousuf Hossain et al proposed a non-intrusive system using the eyeclosure ratio as the input parameter. In Y.Liu et al's paper, EEG features, statistics, higher order crossing, fractal dimension, signal energy, and spectral power were extracted and combined with several classifiers, such as logistic regression, linear discriminant analysis, 1-nearest neighbor, linear SVM, and naïve Bayes. Mika Sunagawa et al proposed a model that was accurately capable of sensing the entire range of stages of distraction, from weak to strong. Monagi H. Alkinani et al published an extensive analysis of comparisons between various deep learning based techniques for recognizing distraction, drowsiness, fatigue and aggressiveness of a driver. Whereas Joao Ruivo Paulo et al explored the methodology for observing distraction using EEG signals in a sustained attention driving task, with results showing a better balanced accuracy of 75.87% and higher for leave-one- out cross- validation. Wang et al., N. Hatami et al., and Z. Zhao et al.,'s methodologies used (recurrence plots and gramian angular fields), they have been successfully applied in computer vision algorithms combined with deep learning, these have been used in recent works in the EEG research domain, but still are relatively unexplored. Mkhuseli Ngxande et al reviewed machine learning algorithms such as Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs) and Hidden Markov models in this context. The work of Naveen Senniappan Karuppusamy et al suggested an electroencephalography-based sleepiness detection system (ESDS) with accuracy of 93.91%. Yaocong Hu et al proposed

92%

MATCHINGBLOCK 1/17



<https://www.semanticscholar.org/paper/Driver-D...>

a new deep learning framework based on the hybrid of 3D conditional generative adversarial network and two-level attention bidirectional long

short-term memory network. It was proposed for robust recognition aimed at extracting short-term spatial-temporal features designed as a 3D encoder-decoder generator with the condition of auxiliary information to generate high-quality fake image sequences and a 3D discriminator was devised to learn drowsiness-related representation from spatial-temporal domain. In addition, for long-term spatial-temporal fusion, they investigated the use of two-level attention mechanism to guide the bidirectional long short-term memory to learn the saliency of short-term memory information and long- term temporal information. Mohamed Hedi Baccour et al's proposal consisted of an analysis of the potential eye- closure and head rotation signals of the driver to classify the driver's state using logistic regression models. SYSTEM ANALYSIS:- Looking at the disadvantages of all the above methodologies, the most common point that pops up is most of these systems implemented this problem statement using only a pre- defined dataset of faces with closed eyes and opened eyes. Also they had only visual types of alerting system to inform the driver of his state, which is not an effective alarm because visual alarms require one to be alert to see the alarm, which defeats the whole purpose at hand. Also, some of these systems' response time between finding the state of the driver and alerting the driver of his state was found to be too long to prevent mishaps in time. Some systems were found to be too sensitive to the eye blinks and yawns and other systems gave alarms continuously for a long time resulting in spamming the system. Our system aims to overcome all

these issues with the previously existing systems and address these issues while giving the best accuracy in the results. Our basic idea is to monitor the physical state of the driver while he's driving using a live camera. We are making use of facial parameters to track the retina in the eye of the beholder, in case of frequent eye blinks while the driver is tired and also keep track of their mouth movements in case of yawning. When our system detects either of these changes our model will immediately emit an alarm sound as loud as a siren alarm to immediately awaken the driver from his poor state back to alertness.

SYSTEM METHODOLOGY:- HOG(Histogram of Oriented Gradients): Basically, the faces are discovered using a Haar Cascade Classifier on an image in combination with the cropping of the cardinal section of face. The H.O.G(Histogram of Oriented Gradients) is a feature descriptor used in computer vision for image processing for the purpose of object detection. HOG, or Histogram of Oriented Gradients, is a descriptor of feature that is often used to extract features from image data. It is broadly used in computer vision tasks for object detection. This is done by extracting the gradient and orientation (or you can say magnitude and direction) of the edges. The Eye Aspect Ratio is an approximate measure of the eye opening state. A code can decide if a person's eyes are closed if the EAR falls under a unique threshold value. Clmtrackr is another facial landmark plotter. Fig 1: Eye Aspect Ratio Representation EAR(

73%

MATCHING BLOCK 2/17



<https://www.ijisrt.com/assets/upload/files/IJI ...>

Eye Aspect Ratio): The eye aspect ratio is instead a much better solution that involves

a very basic calculation based on

100%

MATCHING BLOCK 4/17



<https://www.ijisrt.com/assets/upload/files/IJI ...>

the ratio of distances between facial landmarks of the eyes. This method for eye blink detection is

fast, efficient, and easy to implement. The EAR for a single eye is calculated using this formula: Fig 2: Eye Aspect Ratio Formula If the EAR value is more that means the eye is open more widely. MAR(Mouth Aspect Ratio): Fig 3:Mouth

35%

MATCHING BLOCK 3/17



<https://www.ijisrt.com/assets/upload/files/IJI ...>

Aspect Ratio Representation The Mouth Aspect ratio(MAR) involves the solution that requires a very simple calculation based on the ratio of distances between facial landmarks of the

mouth. With the height of lip and mouth height functions we can check whether the mouth is open or not. This MAR is adjustable and defines how much the mouth is open. We can simply put ratio = 1 which means the mouth is open more than lip height. Mouth Aspect ratio can be calculated using the following equation: Fig 4: Mouth Aspect Ratio Formula **FACIAL LANDMARK:** The task is to detect key landmarks on the face and track them. Facial landmarks are used to incorporate and constitute vital areas of the face, inclusive of mouth, eyes, eyebrows, nose, jawline etc. In our project this facial landmark is used to represent the eyes and mouth especially, because these play a major role to detect the fatigue of the subject. It evaluates the time taken by each blink of the eye, the eye remaining closed or opened, interval of eye opened and closed, yawning etc. **SYSTEM DESIGN:-** Fig 5: System Architecture for Drowsiness Judgment

Fig 6: System Architecture for Distraction Judgment The block diagram of the proposed system has been shown in the above figures. The camera captures the image of the person inside the car and sends that to the HOG model to train and it detects each feature from the face using facial landmark technique in the system. The next step in the process would be as it starts to find the position and condition of each feature to analyze, it should detect whether the person is sleeping or not. If any of the features especially the eye and the head pose/state of the person are detected to be abnormal then automatically the system starts to produce the siren sound. This is where we will get the final judgment of the state of the driver, whether he is concentrated or distracted. Fig 7: Workflow of our System Initially from the video input, from the web camera, the face would be detected in real time (live) and it extracts the features from the face such as the state of eye, mouth and head state. Then it evaluates the eye closure and blinking rate from the eye state, head position angle from head pose and mouth opening and closure from mouth state. All these things are classified together to determine whether the driver is concentrated or not .If the evaluated value lies in a particular range that is required by the model no warning and no siren would be produced else the siren alarm would be produced inside the car. **IMPLEMENTATION:-**

Training data is the initial data used to train machine learning models. Training datasets are fed to machine learning algorithms to teach them how to make predictions or perform a desired task. For creating the dataset, a code should be written that captures eyes and facial landmarks from a camera and stores in our local disk. They are separated into labels 'Open' or 'Closed'. The data is manually live captured from the web cameras for building the model. Now, we can use this model to classify if a person's eye is open or closed. The training dataset used to train the Haar Cascade classifier. It consists of images that were taken anytime while driving. While experimenting with this model at night, it was observed that the Haar Cascade classifier was able to detect the facial landmarks from the video frames of the driver. The system would calculate the EAR value of the driver's eye and the MAR value as well. A demanding task in the past was detection of faces and their features like eyes, nose, mouth and even deriving emotions from their shapes. This task can be now solved by this model. Here the features were extracted using OpenCV. The eyelids were monitored to calculate the drowsiness based on the blinks per minute. The opening of mouth (yawning) and mainly the movements of the Eyelids were considered for drowsiness measurements in this model. The examination of the reaction time with unique ranges of sleep deprivation and environmental disturbances has been done with which the behavioural traits of the motive force can be determined. As observed the common pattern in the distracted state has been inferred because the sluggish drifting of the vehicle from the lane and the fast counter- guidance for correction. Many features were monitored to categorize and get the drowsy guidance sample. HOG is the main algorithm used. This gives the pattern classification of the driver's behaviour, with one of the classification being the drowsy condition of the driver. A bell or buzzer is a sound flagging gadget, is used to produce the alarm. If the driver is slumped down in his seat or if his posture is not erect, then the system will issue a "Self – Driving Mode " alarm, which will make the car to switch to Self Driving Mode rather than Manual. This model has designed to cover all drowsiness stages, from mild to severe, as well as all distraction and aggressive states of a human being. The posture data can be changed to be especially beneficial in conjunction with blink information due to the fact the posture index showed higher sensitivity to vulnerable drowsiness than traditional information and changed to be capable of making amends for the shortcomings of the blink information. The driver wakes up the when the siren is heard so automatically the buzzer sound gets halted, and the model again starts to proctor the driver for any further occurrences again.

FINAL SCREENSHOTS: Figures 8,9,10,11: Representation of the alarm in case of blinking, and yawning Figures 12,13: No alarm for a normal facial landmark representation Figures 14,15: Self Driving Mode Alarm activated in case of slumped posture

CONCLUSION:- In this paper, a smart real time alert system was developed successfully. The general drowsiness detection generally limits the only detection in general, where the sequel process was never invented. This system attempts to overcome this limitation. Our paper introduced an improved system based on HOG algorithm with Machine Learning. The foremost goal is to offer a methodology that is well organized and coherent to be carried out in all systems while sustaining and producing the highest and best performance. The system becomes capable of detecting facial landmarks (facial features) from the snapshots captured from the live camera and pass it to a trained Machine Learning model which is HOG-based, to discover and detect unusual or bizarre driving behavior. Thus the result here is the creation and presentation of a model that is simple and efficient and most importantly, relatively high in accuracy. [4] Mika Sunagawa, Shin-ichi-

60%

MATCHING BLOCK 5/17



[https://dl.ucsc.cmb.ac.lk/jspui/bitstream/1234 ...](https://dl.ucsc.cmb.ac.lk/jspui/bitstream/1234...)

Shikii, Wataru Nakai, Makoto Mochizuki, Koichi Kusukame, and Hiroki Kitajima, Comprehensive Drowsiness Level Detection Model Combining Multimodal Information, IEEE SENSORS JOURNAL, VOL. 20, NO. 7,

APRIL 1, 2020 [5] Monagi H. Alkinani, Wazir Zada Khan, and Quratulain Arshad, Detecting Human Driver Inattentive and Aggressive Driving Behaviour using Deep Learning: Recent Advances, Requirements, and Open Challenges, IEEE Access Volume 8 June 16 2020 [6] Mkhusele Ngxande, Jules-Raymond

88%

MATCHING BLOCK 6/17



[https://dl.ucsc.cmb.ac.lk/jspui/bitstream/1234 ...](https://dl.ucsc.cmb.ac.lk/jspui/bitstream/1234...)

Tapamo and Michael Burke, Driver drowsiness detection using Behavioural measures and Machine Learning Techniques: A review of state-of-art techniques, 2017 Pattern Recognition Association of South Africa and Robotics and Mechatronics

International Conference (PRASARobMech) Bloemfontein, South Africa, 978-1-5386-2313-8, November 29 - December 1, 2017 FUTURE WORK:- In the future, researchers might focus on the use of other factors such as state of vehicle, sleeping hours, weather conditions, etc. for drowsiness measurement. This is a major problem statement in today's society for the drivers, passengers and the society in general. High annual mileage, exposure to the challenging environmental condition, and demanding work schedules all contribute to serious [7] Joao Ruivo Paulo, Gabriel Pires, and Urbano J. Nunes,

89%

MATCHINGBLOCK 7/17

W

[https://scholar.google.ru/citations?user=uAqYP ...](https://scholar.google.ru/citations?user=uAqYP...)

Cross-Subject Zero Calibration Driver's Drowsiness Detection: Exploring Spatiotemporal Image Encoding of EEG Signals for Convolutional Neural Network Classification, IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,

VOL. 29, 2021 safety issues. Monitoring the drowsiness state of driver and providing feedback on their condition so that they can take necessary action is one vital step in a series of preventive measure to this problem. Currently there is no implementation in zoom or direction of the camera during the process. Future work may be automatically zoom in on eyes once they are monitored. This would avoid arbitration between having wide field of view in order to locate the eyes, and narrow view to detect drowsiness. Other systems can be developed to detect any issues in the car engine too to prevent mishaps. REFERENCES:- [1] Dr. K.S. Tiwari, Supriya Bhagat, Nikita Patil, Priya Nagare, IOT Based Driver Drowsiness Detection and Health Monitoring System, Vol 6, Issue 2, April – June 2019 [2]

100%

MATCHINGBLOCK 8/17

W

<https://arxiv.org/abs/2002.03728>

Rateb Jabbar, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al-Khalifa, Moez Krichen, Kamel Barkaoui,

100%

MATCHINGBLOCK 9/17

W

<https://arxiv.org/abs/2002.03728>

Driver Drowsiness Detection Model using Convolutional Neural Networks Techniques for Android Application,

IEEE Xplore 978-1-7281-4821-2/20 [3] Md. Yousuf Hossain, Fabian Parsia George, IOT based Real-time Drowsy Driving Detection System for the Prevention of Road Accidents, ICIBMS 2018, Track 1: Image Processing, Computer Science and Information technology, Bangkok, Thailand, 978-1-5386-7516-8 [8] Naveen Senniappan Karuppusamy, Bo-Yeong Kang, Multimodal System to Detect Driver Fatigue using EEG, Gyroscope, and Image Processing, VOLUME 8, 2020, July 24, 2020 [9] Yaocong

86%

MATCHINGBLOCK 10/17

W

[https://www.grafiati.com/en/literature-selecti ...](https://www.grafiati.com/en/literature-selecti...)

Hu, Mingqi Lu, Chao Xie, and Xiabo Lu, Driver Drowsiness Recognition via 3D Conditional GAN and Two-level Attention BiLSTM, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, 2019 [10]

Ceerthi Bala U.K, Sarath TV, Internet of things based Intelligent Drowsiness Alert System,

100%

MATCHING BLOCK 11/17

W

[https://www.semanticscholar.org/paper/An-Analy ...](https://www.semanticscholar.org/paper/An-Analy...)

Fifth International Conference on Communication and Electronics Systems (ICCES 2020) IEEE Conference Record # 48766; IEEE Xplore ISBN: 978-1-7281-5371-1 [11]

B. T. Jap, S. Lal, P. Fischer, and E.

96%

MATCHINGBLOCK 12/17

W

[https://link.springer.com/article/10.1007/s115 ...](https://link.springer.com/article/10.1007/s115...)

Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," Expert Syst. Appl.,

vol. 36, no. 2, pp. 2352–2359, Mar. 2009. [12] F. Gharagozlou et al., "

100%

MATCHINGBLOCK 13/17



<https://www.semanticscholar.org/paper/Cross-Su ...>

Detecting driver mental fatigue based on EEG alpha power changes during simulated driving,”

Iranian J. Public Health, vol. 44, no. 12, p. 1693, 2015. [13] J. Hu and J. Min, “

100%

MATCHINGBLOCK 15/17



<https://www.semanticscholar.org/paper/Cross-Su ...>

Automated detection of driver fatigue based on EEG signals using gradient boosting decision tree model,”

Cognit. Neurodynamics, vol. 12, no. 4, pp. 431–440, Aug. 2018 [14]

94%

MATCHINGBLOCK 14/17



<https://www.hindawi.com/journals/cin/2019/3761203/>

H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, “EEG classification of driver mental states by deep learning,” Cognit. Neurodynamics, vol. 12, no. 6, pp. 597–606,

Dec. 2018. [15] P. P. San, S. H. Ling, R. Chai, Y. Tran, A. Craig, and H. Nguyen, “EEGbased driver fatigue detection using hybrid deep generic model,” in Proc. 38th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Aug. 2016, pp. 800–803. [16] Y. Liu, Z. Lan, J. Cui, O. Sourina, and W. MüllerWittig, “Inter-subject transfer learning for EEGbased mental fatigue recognition,” Adv. Eng. Informat., vol. 46, Oct. 2020, Art. no. 101157. [17] Mohamed Hedi Baccour, Frauke Driewer, Tim Schack, 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) October 11-14, 2020. Toronto, Canada [18] Y.-T. Liu, Y.-Y. Lin, S.-L. Wu, C.-H. Chuang, and C.-T. Lin, “Brain dynamics in predicting driving fatigue using a recurrent self-evolving fuzzy neural network,” IEEE Trans. Neural Netw. Learn. Syst., vol. 27, no. 2, pp. 347–360, Feb. 2016 [19] J. Liu, C. Zhang, and

88%

MATCHINGBLOCK 16/17



<https://journals.plos.org/plosone/article?id=1 ...>

C. Zheng, “EEG-based estimation of mental fatigue by using KPCA– HMM and complexity parameters,” Biomed. Signal

Process. Control, vol. 5, no. 2, pp. 124– 130, Apr. 2010. [20] Ghoddosian, Reza and Galib, Marnim and Athitsos, Vassilis “A Realistic Dataset and Baseline Temporal Model for Early Drowsiness Detection”,

100%

MATCHING BLOCK 17/17



<http://www.ijitee.org/wp-content/uploads/paper ...>

Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

Hit and source - focused comparison, Side by Side

Submitted text As student entered the text in the submitted document.
Matching text As the text appears in the source.

1/17	SUBMITTED TEXT	21 WORDS	92% MATCHING TEXT	21 WORDS
	a new deep learning framework based on the hybrid of 3D conditional generative adversarial network and two-level attention bidirectional long		a new deep learning framework based on the hybrid of 3D conditional generative adversarial network and two-level attention bidirectional long...	
	 https://www.semanticscholar.org/paper/Driver-Drowsiness-Recognition-via-3D-Conditional-Hu-Lu/fed5 ...			
2/17	SUBMITTED TEXT	16 WORDS	73% MATCHING TEXT	16 WORDS
	Eye Aspect Ratio): The eye aspect ratio is instead a much better solution that involves		Eye Aspect Ratio(EAR). The Eye Aspect Ratio is instead a far more effective solution that involves	
	 https://www.ijisrt.com/assets/upload/files/IJISRT21MAY360.pdf			
4/17	SUBMITTED TEXT	18 WORDS	100% MATCHING TEXT	18 WORDS
	the ratio of distances between facial landmarks of the eyes. This method for eye blink detection is		the ratio of distances between facial landmarks of the eyes. This method for eye blink detection is	
	 https://www.ijisrt.com/assets/upload/files/IJISRT21MAY360.pdf			
3/17	SUBMITTED TEXT	28 WORDS	35% MATCHING TEXT	28 WORDS
	Aspect Ratio Representation The Mouth Aspect ratio(MAR) involves the solution that requires a very simple calculation based on the ratio of distances between facial landmarks of the		Aspect Ratio(EAR). The Eye Aspect Ratio is instead a far more effective solution that involves an awfully easy calculation that supported the ratio of distances between facial landmarks of the	
	 https://www.ijisrt.com/assets/upload/files/IJISRT21MAY360.pdf			
5/17	SUBMITTED TEXT	27 WORDS	60% MATCHING TEXT	27 WORDS
	Shikii, Wataru Nakai, Makoto Mochizuki, Koichi Kusakame, and Hiroki Kitajima, Comprehensive Drowsiness Level Detection Model Combining Multimodal Information, IEEE SENSORS JOURNAL, VOL. 20, NO. 7,		Shikii, W. Nakai, M. Mochizuki, K. Kusakame, and H. Kitajima, "Comprehensive Drowsiness Level Detection Model Combining Multimodal Information," IEEE Sens. J., vol. 20, no. 7,	
	 https://dl.ucsc.cmb.ac.lk/jspui/bitstream/123456789/4536/1/2017%20MCS%20060.pdf			

6/17	SUBMITTED TEXT	32 WORDS	88% MATCHING TEXT	32 WORDS
	Tapamo and Michael Burke, Driver drowsiness detection using Behavioural measures and Machine Learning Techniques: A review of state-of-art techniques, 2017 Pattern Recognition Association of South Africa and Robotics and Mechatronics		Tapamo, and Burke, "Driver drowsiness detection using behavioral measures and machine learning techniques: A review of state-of-art techniques," in 2017 Recognition Association of South Africa and Robotics and Mechatronics (	
	 https://dl.ucsc.cmb.ac.lk/jspui/bitstream/123456789/4536/1/2017%20MCS%20060.pdf			

7/17	SUBMITTED TEXT	27 WORDS	89% MATCHING TEXT	27 WORDS
	Cross-Subject Zero Calibration Driver's Drowsiness Detection: Exploring Spatiotemporal Image Encoding of EEG Signals for Convolutional Neural Network Classification, IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,		Cross-subject zero calibration driver's drowsiness detection: Exploring spatiotemporal image encoding of EEG signals for convolutional neural network classification JR Paulo, G Pires, UJ Nunes transactions on neural systems and rehabilitation engineering 29, 905-915, 2021 6 2021	
	 https://scholar.google.ru/citations?user=uAqYP1EAAAAJ&hl=th			

8/17	SUBMITTED TEXT	13 WORDS	100% MATCHING TEXT	13 WORDS
	Rateb Jabbar, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al-Khalifa, Moez Krichen, Kamel Barkaoui,		Rateb Jabbar, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al-Khalifa, Moez Krichen, Kamel Barkaoui	
	 https://arxiv.org/abs/2002.03728			

9/17	SUBMITTED TEXT	13 WORDS	100% MATCHING TEXT	13 WORDS
	Driver Drowsiness Detection Model using Convolutional Neural Networks Techniques for Android Application,		Driver Drowsiness Detection Model Using Convolutional Neural Networks Techniques for Android Application	
	 https://arxiv.org/abs/2002.03728			

10/17	SUBMITTED TEXT	31 WORDS	86% MATCHINGTEXT	31 WORDS
	Hu, Mingqi Lu, Chao Xie, and Xiabo Lu, Driver Drowsiness Recognition via 3D Conditional GAN and Two-level Attention BiLSTM, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, 2019 [10]		Hu, Yaocong, Mingqi Lu, Chao Xie, and Lu. "Driver Drowsiness Recognition via 3D Conditional GAN and Two-Level Attention LSTM." IEEE Transactions on Circuits and Systems for VideoTechnology 30,	
	 https://www.grafiati.com/en/literature-selections/attention-drowsiness/journal/			

11/17	SUBMITTED TEXT	21 WORDS	100% MATCHING TEXT	21 WORDS
	Fifth International Conference on Communication and Electronics Systems (ICCES 2020) IEEE Conference Record # 48766; IEEE Xplore ISBN: 978-1-7281-5371-1 [11]		Fifth International Conference on Communication and Electronics Systems (ICCES 2020) IEEE Conference Record # 48766; IEEE Xplore ISBN: 978-1-7281-5371-1 978-1-7281-5371-1/20/\$31.00 ©2020	
	W https://www.semanticscholar.org/paper/An-Analytical-Approach-for-Soil-and-Land-System-Deorankar-R ...			
12/17	SUBMITTED TEXT	15 WORDS	96% MATCHING TEXT	15 WORDS
	Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue," Expert Syst. Appl.,		Bekiaris E (2009) Using eeg spectral components to assess algorithms for detecting fatigue. Expert Syst Appl 36(2):2352–2359	
	W https://link.springer.com/article/10.1007/s11571-018-9496-y			
13/17	SUBMITTED TEXT	14 WORDS	100% MATCHING TEXT	14 WORDS
	Detecting driver mental fatigue based on EEG alpha power changes during simulated driving,"		Detecting Driver Mental Fatigue Based on EEG Alpha Power Changes during Simulated Driving •	
	W https://www.semanticscholar.org/paper/Cross-Subject-Zero-Calibration-Driver%E2%80%99s-Drowsiness- ...			
15/17	SUBMITTED TEXT	16 WORDS	100% MATCHING TEXT	16 WORDS
	Automated detection of driver fatigue based on EEG signals using gradient boosting decision tree model,"		Automated detection of driver fatigue based on EEG signals using gradient boosting decision tree model •	
	W https://www.semanticscholar.org/paper/Cross-Subject-Zero-Calibration-Driver%E2%80%99s-Drowsiness- ...			
14/17	SUBMITTED TEXT	32 WORDS	94% MATCHING TEXT	32 WORDS
	H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, "EEG classification of driver mental states by deep learning," Cognit. Neurodynamics, vol. 12, no. 6, pp. 597-606,		H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, "EEG classification of driver mental states by deep learning," Cognitive Neurodynamics, vol. 12, no. 6, pp. 597–606, 2018.	
	W https://www.hindawi.com/journals/cin/2019/3761203/			

16/17	SUBMITTED TEXT	18 WORDS	88% MATCHING TEXT	18 WORDS
	C. Zheng, "EEG-based estimation of mental fatigue by using KPCA-HMM and complexity parameters," Biomed. Signal		C, Zheng C. EEG-based estimation of mental fatigue by using KPCA-HMM and complexity parameters. Biomedical Signal	
	 https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0188756			

17/17	SUBMITTED TEXT	13 WORDS	100% MATCHING TEXT	13 WORDS
	Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.		Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops,	
	 http://www.ijitee.org/wp-content/uploads/papers/v9i6/E2779039520.pdf			