RTSC-DVM: A Novel Methodology for Real-Time Siren Call to Halt Distracted Vehicle Mishaps

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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 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-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 all 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 all 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 all'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 all 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 all'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 all. 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 all'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 all proposed a non-intrusive system using the eyeclosure ratio as the input parameter. In Y.Liu et all'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 naive Bayes. Mika Sunagawa et all proposed a model that was accurately capable of sensing the entire range of stages of distraction, from weak to strong.

Monagi H. Alkinani et all 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 all 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 all., N. Hatami et all., and Z. Zhao et all.,'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 all 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 all suggested an electroencephalography-based sleepiness detection system (ESDS) with accuracy of 93.91%.Yaocong Hu et all submitted an state-of-the-art deep learning model framework which was a mixed hybrid of three dimensional conditional network model which was also generatively adversial and had a bilateral attention and reciprocal lengthy short-term memory network. It was proposed for robust recognition aimed at extracting short-term spatial-temporal features designed as a 3D encoder-decoder gene 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 all'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 METHODOLODY:- *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.

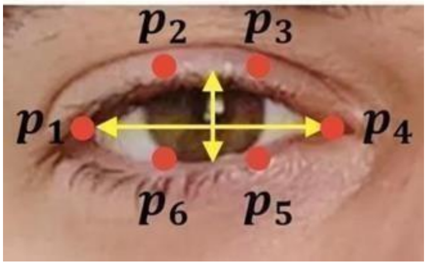


Fig 1: Eye Aspect Ratio Representation

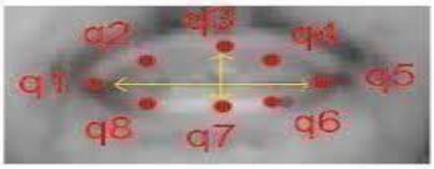
EAR(Eye Aspect Ratio): This is our preffered solution mode that uses a very basic calculation using the ratio of euclidean distances between the general points of the eyes' locations in 64-facial landmarks. It detects eye-blinks faster and it’s efficient, and easy to implement. The EAR for a single eye is calculated using this formula:

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

Fig 2: Eye Aspect Ratio Formula

If the EAR value is more that means the eye is open more widely.

MAR(Mouth Aspect Ratio):



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

Fig 3:Mouth Aspect Ratio

This is a solution that involves basic calculation using ratio of euclidean distances between the general points of the mouth location in 64-facial landmarks.

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: 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:-

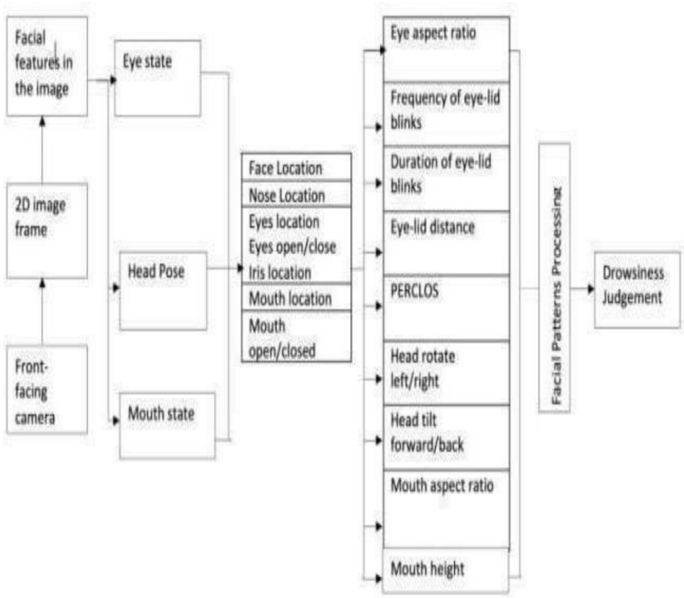


Fig 5: System Architecture for Drowsiness Judgment

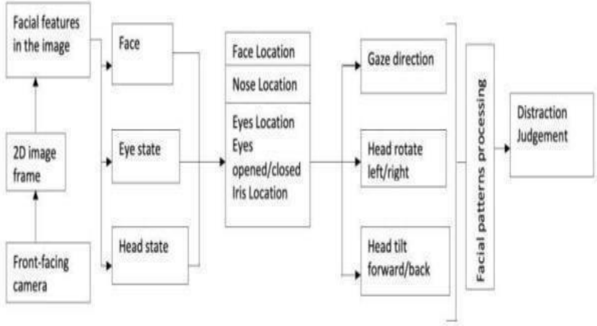


Fig 6: System Architecture for Distraction Judgment

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.

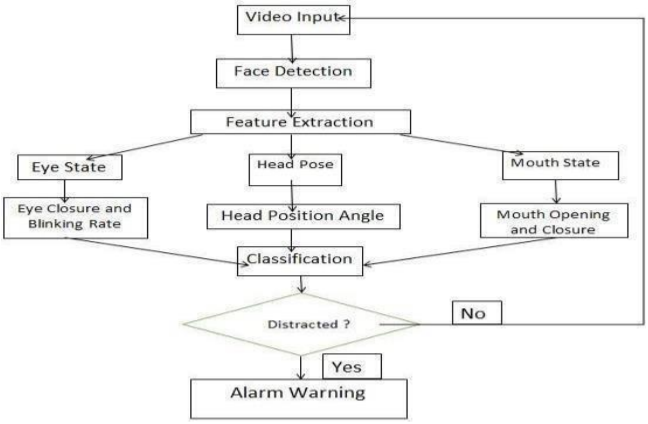


Fig 7: Workflow of our System

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.

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.

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.

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