

AN INTEGRATED APPROACH FOR DRIVER'S DROWSINESS DETECTION

[1]Dr. Panhalkar Archana R, [2]Bhosale Rajkumar S.

Department of Computer Engineering, Amrutvahini College of Engineering, Sangamner– 422605, India

Department of Information Technology, Amrutvahini College of Engineering, Sangamner – 422605, India

archana10bhosale@rediffmail.com, bhos_raj@rediffmail.com

Abstract— Driver's ability to control the vehicles is reduced when they are sleepy or exhausted. The main reason of the rising number of traffic fatalities and accidents is falling asleep while driving. Driving in drowsy state is therefore considered to be the most active field of research. A ninety grated strategy that depends on the EAR and MAR calculations as well as the eye and mouth closure status (PERCLOS) is proposed in this paper. This aids in determining whether the mouth is open or closed, or when driver is yawning. Using this approach, a camera is installed on the dashboard of the car to continuously take video of the face of the driver. After that, these video frame shares analyzed to see if the driver appears sleepy or not. Real-time testing was conducted for the proposed system.

Keywords— Eye aspect ratio (EAR), facial landmark, Mouth aspect ratio (MAR), Haar cascade, dlib68.

A. INTRODUCTION

In the context of international road safety, driver sleepiness, also known as "drowsy driving," poses a complicated and multidimensional dilemma. It is a ubiquitous risk that is defined by a condition of reduced awareness and mental capacity while operating a vehicle, resulting from things like exhaustion, lack of sleep, or even side effects from medications. This pernicious ailment greatly increases the likelihood of car crashes, injuries, and fatalities; thus, prompt action and creative remedies are required. The realization that sleepy driving plays a significant role in traffic accidents has led to increased attempts in technology and research to lessen the effects of this behavior. To efficiently detect and address driver drowsiness in real-time circumstances, a variety of approaches have been investigated, ranging from physiological monitoring to behavioral analysis and technological solutions.

Moreover, the dynamic character of sleepiness and its capacity to intensify quickly highlight the significance of preventative actions and quick reaction mechanisms. Integrating cutting-edge technologies, such as computer vision, machine learning provides promise or enhancing the precision and effectiveness of drowsiness detection systems.

. These systems use real-time analysis of driving behavior, eye movements, and face features to deliver time ly alerts and actions to protect road users and prevent accidents. Not with standing not worthy advancements, obstacles persist in attaining extensive integration and endorsement of these technologies, encompassing concerns pertaining to confidentiality, dependability, and economy of scale. Therefore, to advance the development and implementation of complete solutions for preventing driver sleepiness and guaranteeing safer road environments globally, a coordinated and cooperative effort involving stakeholders from multiple sectors is required.

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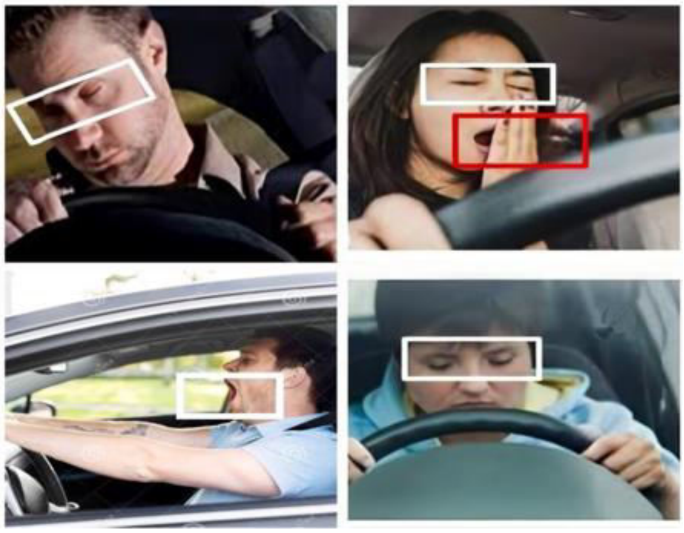

Fig1.Samples of Drivers Sleepy Condition While Driving Vehicle

3,081 accidents occurred in 2015 as a result of driver drowsiness sleep deprivation, or illness. 3,383 persons were hurt and 706 individuals lost their lives as a result of these accidents [18]. Automation simplifies people's busy lives while yet providing excellent services in a faster and safer method. Even though many organizations are already investing heavily in the subject, evaluating a driver's level of fatigue remains a difficult problem. Therefore, for real-time applications, an automated and effective system based on driver state prediction and sleepiness detection must be implemented.

Ocular measurements have also been established in several studies to be a potential means of detecting sleepiness. These methods frequently employ computer vision techniques to check the state of the driver's eyes. Many studies use the proportion of closed eyelids as a measure of tiredness too. Various metrics include blink rate and duration of ocular closure. Among those different approaches, monitoring the driver's eye condition along with yawning is the most effective and least invasive method. This yields the most accurate and dependable accident rate prevention results. For this the high computation and high execution speed required [13].

B. **Literature Survey**

The technique that Rajanikanth Aluvalu, M. P. Kantipudi, Ketan Kotecha, and J. R. Saini, V. Uma Maheswari, Krishna K. Chennam suggested uses the eye closure status (PERCLOS), also known as the facial spec ratio (FAR), to provide an integrated approach to closing one's eyes and yawning. Common hand gestures like nodding and covering one's lip swith one hand are recognized by this method[1].H. U. Khan, A. Ismail, M. Ramzan, M.Ilyas, S.M. AwanandA. Mahmood review explores drowsiness detection systems, emphasizing physiological parameters' accuracy. Hybrid approaches combining physiological vehicular, and behavioral measures prove effective. Among supervised learning techniques, SVM stands out for accuracy, though not ideal for large datasets. The review highlights the need for integrated methods to enhance overall performance in drowsiness detection [4].J. Mayand C. bald win distinguishing between active (SR) and passive (TR) driver fatigue is crucial for targeted countermeasures. Technologies like increased automation benefit TR active fatigue;

while interactive tools help mitigate TR passive fatigue. SR fatigue, linked to circadian rhythm and sleep deprivation, may be less responsive to countermeasures. Effective strategies for SR fatigue include naps and caffeine. Crash prevention technologies are beneficial for both SR and TR fatigue. Future research should focus on tailored countermeasures and integrated fatigue-detection technologies [5].

The issue with changing lighting and various driver postures was handled by B. Cheng, W. Zhangand Y. Lin. Six measurements, including PERCLOS and CV of the eyes, were included in addition to Fisher's linear discriminate function for enhanced categorization. Using customized characteristics and models at the alert Drivers phase is advised to increase identification rates [2]. The research by W.-Y. Chungan d B.-
G. Lee suggested that the driver's state may be dynamically evaluated using a Bayesian network in an Android phone fatigue monitoring system by fusing information. The study demonstrates the value of utilizing a variety of information sources, including facial expressions, to enhance the effectiveness of drowsiness detection [3]. Ruei. C. Wu, Chin. T. Lin, W. H. Chao, Sheng. F. Liang, T. P and Yu-jie Chen, and Jung suggests a VR-based driving environment sleepiness estimate approach based on EEG that uses ICA, power-spectrum analysis, and linear regression. The study shows stable correlations between people across sessions and reveals a consistent association between driving performance variations and the log sub band power ICA/EEG spectrum. By applying linear regression on 10 sub band log power spectra near -bands of two ICA components, the approach achieves good accuracy. This method provides a non-invasive way to track cognitive processes in situations when attention is crucial, and it is particularly useful for applications with few EEG channels [6].

Y. Xu, Y. Cui, and D. Wu suggested FWET method completely does away with the necessity for calibration by integrating feature weighting (FW) with ensemble training (ET). Tests demonstrate the usefulness of both FW and ET, and their combination improves generalization capabilities. Future research seeks to adapt FWET tomany areas beyond driver sleepiness detection. Plug-and-play applications can benefit from its convenience since it does not require calibration data from fresh participants [7]. Y. Zhang, Y. Jiang, D. Wu, C. Lin, and C.-T. Lin, created offline transfer regression model that requires little subject-specific calibration data to estimate driver drowsiness from EEG signals. To maintain consistency across many viewpoints, the model has been expanded to an online and multi-view context, encompassing elements from both the source and target domains. Future research aims to overcome constraints despite the promising performance, such as improving the simultaneous fixation of four parameters for increased accuracy and fine-tuning sample weighting in the target domain [8]. Various researches used decision tree for problem solving [12-15].

M. J. Khan, M. Asjid. Tanveer, Noman Naseer, M. J. Qureshi and Keum-shik Hong used functional near-infrared spectroscopy and deep learning algorithms, this study explored the possibility of sleepiness detection for a passive brain-computer interface. A deep neural network with four windows (0-1, 0-3, 0-5, and 0-10) was utilized to identify driver sleepiness. Additionally, we employed convolutional neural network with an accuracy of 99.3µ on the functional brain maps. This network allowed us to identify thirteen unique channels that are particularly active during sleepiness, as well as a newly identifies area comprised of the channels with the greatest classification accuracy [9]. S. Ganesan and M. Kahlon used a good algorithm for detecting sleepiness examines real-time video from a camera to determine if the driver's eyes are open or closed. When three or more consecutive open or closed eye states are identified, the driver is alerted to the possibility of drowsiness. Although the system can accept spectacles, it may not be accurate in different lighting situations or driving postures. By overcoming these obstacles, combining data from other components like the gas pedal and steering wheel, and applying self-learning capabilities at startup, future improvements hope to increase robustness [10].

C. Haar Cascade Algorithm

Haar Cascade can be implemented using below steps:

1. Pre-processing:

To reduce computational complexity, convert the input image to gray scale, as face identification does not need color information.

2. Haar feature selection:

Rectangular filters called Haar-like features are employed in face recognition; in the training phase, these features—which include edges, corners, and lines—are chosen based on their capacity to discriminate between faces and non-faces.

3. Integral image calculation:

Compute the integral image of the gray scale image, which is a fast way to find the sum of all the pixel values in a rectangle region, for faster feature calculation.

4. Ada boost Training:

Utilize the Ada boost (Adaptive Boosting) technique to train a series of classifiers. A sequence of weak classifiers, or straightforward decision functions based on Haar-like characteristics, make up each classifier. The best weak classifier that properly classifies the majority of the training data is chosen iteratively by Ada boost.

5. Cascading Classifier:

Assemble the trained classifiers in to a cascade, with each stage advancing to the next by filtering a ways significant percentage of negative samples, or non- face regions. This improves computational performance and lowers false positives.

6. Sliding window detection:

Place a fixed-size window across the grayscale image, then apply the classifier cascade at each location. A region is categorized as a face if it successfully completes every step of the cascade.

D. Methodology

Systems for detecting drowsiness are essential for improving traffic safety and averting collisions. The proposed system is meant to forecast driver drowsiness and recognize different signs of drowsiness. These include spotting yawning, open mouths, and closed eyelids. The system crops and isolates the driver's face from a camera image by using the Haar Cascade

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Face Detection Algorithm. Then, it recognizes the mouth and eyes in the face area, which are used as inputs for the HAAR algorithm. By using an algorithm to categorize different states of drowsiness, accidents can be avoided in real time.

The proposed system involves the following steps:

Video capturing:

Driver's face is captured via web camera to extract video frames. this video frames input is pass to further processing for detection of drowsiness.

A. **Face detection:**

Utilize a facial recognition technique to identify and retrieve the driver's face from the obtained pictures. Numerous face identification algorithms exist, including deep learning-based techniques like convolutional neural networks and Haar cascades. In proposed system, haar cascade algorithm is used to detect face.

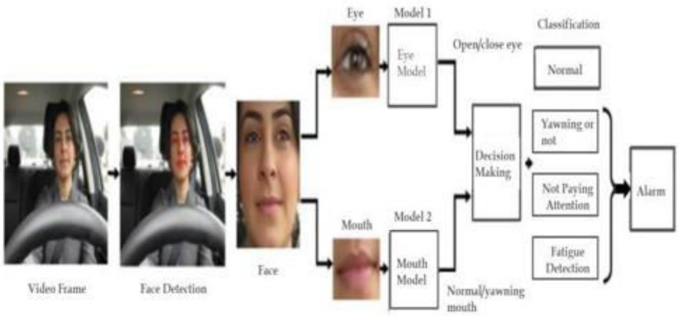

Fig.2. System Architecture For Drivers Drowsiness Detection

B. Measurement of eye mouth Status:

Analyzing intricate problems such as expression recognition requires the ability to identify prominent features on the face. This procedure makes it possible for different programs to exploit particular feature statuses for additional processing. Automated face landmarking is a novel technique that effectively identifies salient distinctions for building suitable models. This technique computes crucial metrics such as the mouth aspect ratio and eye aspect ratio by labeling facial landmarks using the dlib68 point model. These factors are essential for determining how well the mouth and eyes are doing. EAR and MAR are computed once face landmarks are recognized, offering important information about the condition of facial features.

Equation to find status of eye:

EAR=||v-z||+w-y||/2||u-x||……… Eqn(1)

The Eye Aspect Ratio calculates the ratio of distances between particular spots on the eye. Closed eyes are suggested by a lower EAR value, whilst wide eyes are indicated by a larger value.

For the proposed system, the threshold range of EAR taken is mentioned in table1.

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Fig3.Facial Landmarks

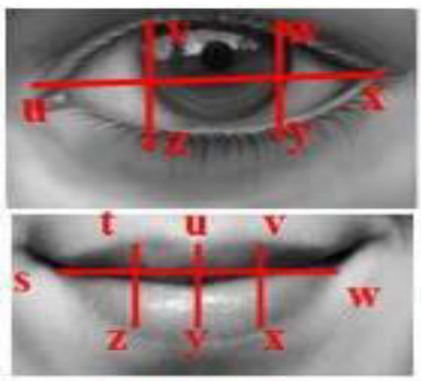

Fig4.dlib68L and mark Illustration for MAR and EAR

Equation to find status of mouth:

MAR=||t-z||+||u-y||+||v-x||/3||s-w||……Eqn(2)

MAR, on the other hand, is a tool used to detect mouth opening and closure. It does this by measuring the ratio of distances between sites surrounding the mouth. One can interpret an open mouth as having a greater MAR value and a closed mouth as having a lower value.

Table1: Threshold range for EAR

Range	Status
<0.25	Low(Drowsy)
0.25–0.30	Normal

Table2: Threshold range for MAR

Range	Status
0–15	Normal
>15	High (Yawning state)

C. Drow siness alert:

The threshold values successfully identify the state of driver whether driver is drowsy or not. If drowsiness detected then driver get alerted through alarm buzz until he comes in alert state.

E. Result analysis

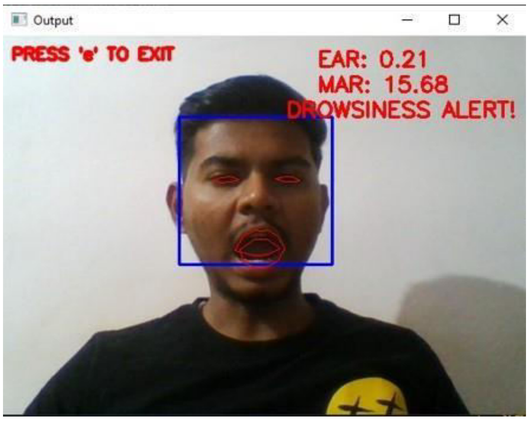

Fig5.Yawning Detection

As shown in fig5 threshold of MAR is greater than15.which is successfully detecting the yawning movement of driver. After detection of yawning the driver get alerted using alarm.

Fig6.Close Eye Detection

As shown in fig.6 threshold of EAR is lesser than 0.25. Which is successfully detecting the closing of eye of driver. After detection of eye lid closure the driver get alerted using alarm.

F. CONCLUSION

Major reason behind the road accidents is drivers drowsy condition. So, to avoid the rate of accidents caused by drowsiness, there should be alerting system to alert the driver. The proposed system able to successfully detect the drowsiness. The primary issue with the framework is its inability to extract the useful information from the cropped and sliced images from the video frame. A number of indicators, including closed eye lids and a no pen mouth when yawning, have been used by the planned study to identify the driver's drowsiness. EAR and MAR techniques were employed to extract features. Haar cascade gives more accuracy for face detection. Enhancing the presented work may also be accomplished by utilizing CNN and classification algorithms, as well as by concentrating on extracting additional features utilizing a variety of feature extraction approaches.

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