DROWSINESS ALERT SYSTEM BY EMPLOYING FACIALFEATURES

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Abstract – **Drowsy driving is a significant contributor to road accidents and fatalities, prompting active research in the detection of driver fatigue. While conventional methods exist, they can be either intrusive or require expensive sensors and data handling. In response, this study develops a low-cost, real-time driver's drowsiness detection system using a webcam to record video and image processing techniques to detect the driver's face and compute facial landmarks. By analyzing the eye aspect ratio, mouth opening ratio, and nose length ratio, the system can detect drowsiness based on an adaptive thresholding algorithm. Additionally, offline machine learning algorithms can alert drivers when drowsiness is detected. This system aims to reduce accidents caused by driver fatigue by detecting special body and facial gestures, such as yawning and eye movements, and proposing a new method for detecting yawning based on changes in mouth geometricfeatures.**

Keywords- Drowsy driving, Driver fatigue, Real-time detection, Image processing, Yawningdetection.

I. INTRODUCTION

Drowsy driving is a serious problem that can lead to fatal accidents. Many drivers, such as truckers and bus drivers, are more susceptible to driver fatigue, especially when driving for long periods, such as during overnight shifts. Each year, numerous injuries and deaths occur due to fatigue- related road accidents. Therefore, detecting driver fatigue and its indication is a highly active area of research, as it has immense practical applicability. Detecting drowsiness in drivers can be achieved through three main types of methods: vehicle- based, behavioral-based, and physiological-based. In vehicle-based methods, various metrics such as steering wheel movement, accelerator or brake patterns, vehicle speed, lateral acceleration, and deviations from lane position are continuously monitored, and any abnormal changes in these values are considered as potential indicators of driverfatigue

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However, detecting driver fatigue requires more than just monitoring vehicle metrics. Driver fatigue not only impacts the alertness and response time ofthe driver, but it also increases the chances of being involved in car accidents. Analysis data from the National Highway Traffic Safety Administration (NHTSA)

suggests that drowsy driving is a contributing factor to 22-24% of car crashes, and that driving while drowsy results in a four- to six-times higher near-crash/crash risk relative to alertdrivers.
It is important to note that driver fatigue can lead to an ironic situation, as the driver may be too tired to realize their own level of drowsiness. Warning signs of driver fatigue can include daydreaming while on the road, driving over the center line, yawning, feeling impatient, feeling stiff, heavy eyes, and reacting slowly. In order to prevent road accidents, it is crucial to use assisting systems that monitor a driver's level ofvigilance and alert them in the case of drowsiness orinattention.

Various research works have been done to detect driver drowsiness based on body gestures such as eye motion detection and yawning detection. However, our approach is more robust against false detections and is more practical to implement. In our method, we use a low-cost, real-time driver's drowsiness detection system that is developed with acceptable accuracy.

II. LITERATURESURVEY

C. Alvarado et al.[1] (2021) proposed a method for driver drowsiness detection using a combination of head pose estimation, eye tracking, and heart rate variability. This method takes advantage of the different data sources to detect drowsiness and is more accurate and reliable.

H. Ye et al.[2] (2021) proposed a drowsiness detection method based on eye tracking and EEG signals. The major drawback is that the EEG signals needed electrodes to be attached to the scalp, which may not be suitable for all kinds of population.

S. De et al.[3](2021) developed a drowsiness detection system using a convolutional neural network and a Long Short-Term Memory (LSTM) network. This system was more convenient and user friendly but factors such as individual differences in brain activity affected the accuracy.

M. L. Wang et al.[4](2021) proposed a novel approach to drowsiness detection using a deep learning-based multi-sensor fusion method. This method made the system more complex andless scalable.

K. R. S. Sankar et al.[5] (2020) proposed a drowsiness detection system using a deep learning- based approach. The system used features extracted from EEG signals and a Random Forest classifier to detect drowsiness in drivers. This system solely focused on the EEG signals and did not consider other potential indicators for drowsiness detection.

M. A. Khan et al.[6] (2020) proposed a drowsiness detection system based on physiological signals. The system used an SVM classifier and multiple physiological signals, including ECG, respiration, and skin conductance, to detect drowsiness in drivers.

R. S. Bakshiet al.[7] (2020) proposed a drowsiness detection system based on facial expressions. The system used a convolutional neural network to classify the driver'sdrowsiness level based on facial expressions. The pros of this system includes that it uses a more non-invasiveapproach.

Y. Wang et al.[8] (2020) proposed a deep learning- based method for drowsiness detection using multiple sensors, including an EEG sensor and an EOG sensor. This method was more effective than the traditional machine learning methods.

Bhandari et al.[9] (2019) proposed a vision-based drowsiness detection system using a convolutional neural network (CNN).This system does not requireany physical contact with the driver. The drawback of this system is that it analyzes only the facial features.

Elbaihet al.[10] (2019) proposed a drowsiness detection system based on the analysis of electroencephalogram (EEG) signals. This system attains a relatively high accuracy. But the accuracy of the system is affected by the noise in the EEG signals.

Choudhary et al.[11] (2019) proposed a drowsiness detection system using a hybrid approach that combines both vision-based and physiological signals. This system requires both web cam and pulse oximeter which may not be available in all vehicles.

Gong et al.[12] (2019) proposed a system which uses headset for measuring the driver’s eye movement, thus making it more comfortable for the driver.

[13]Raj et al. (2019)proposed a drowsiness detection system using a hybrid approach that combines both vision-based and physiological signals. The reported accuracy may not be high enough for real worlddeployment.

Sun et al. [14] (2019) proposed a drowsiness detection system. based on the analysis of electrocardiogram (ECG) signals. This system uses adry ECG to measure the heart rate. This system is comfortable for the user.

Li et al.[15] (2020) proposed a drowsiness detection system using a convolutional neural network (CNN) and a long short-term memory. This system may not be effective in detecting the drowsiness when the driver is wearing spectacles, or the lighting is poor.

Xiao et al.[16] (2020) proposed a drowsiness detectionsystembasedonthe analysisof electroencephalogram (EEG) signals. The system may be considered intrusive as it involves wearing a deviceon thehead.

C. Zhang et al. [17](2021) developed a drowsiness detection system using a convolutional neural network and a Recurrent Neural Network (RNN). The disadvantage of the system is that the approach is intrusive in nature.

A. Imran et al.[18] (2021) proposed a deep learning- based drowsiness detection system using multiple sensors, including an EEG sensor and a camera. This allows for a more comprehensive analysis of the driver’s physiological state and behavior. Attention aware deep neural networks for drowsiness detection in driver monitoring by J.Li,

19]. Convolutional neural networks are used which allows the system automatically to learn the relevant features from raw data. A real-time, non-invasive system for driver drowsiness detection using EEG and eye-tracking signals proposed by A. Marcal

[20].Thissystem iseasytouse and comfortable for the drivers. The disadvantage of the system includes the fact that it is expensive to Implement.The detection of driver drowsiness has received significant attention in recent years due to its potential to reduce the number of accidents caused by fatigued drivers.

Ⅲ METHDOLOGY

This study aims to explore two approaches for detecting drowsiness: the physiological-level approach and the behavioral-based approach.

For the physiological level approach, we will use electrodes to obtain physiological signals, including pulse rate, heart rate, and brain activity information. We will use an electrocardiogram (ECG) to detect variations in heart rate and identify different conditions for drowsiness. Additionally, we will use the correlation between different signals, such as ECG, electroencephalogram (EEG), and electromyogram (EMG), to generate an output to determine whether the person is drowsy or not.

For the behavioral-based approach, we will use a camera to monitor the eye blinking frequency and head pose of a person. If any of these drowsiness symptoms are detected, the person will be alerted.

To evaluate the effectiveness of both approaches, we will conduct experiments in a controlled environment. Participants will be asked to stay awake for a specific period, and their physiological and behavioral data will be collected using the methods described above. We will then analyze the data to determine the accuracy of each approach in detecting drowsiness.

To ensure the reliability and validity of our results, we will recruit a diverse sample of participants and randomly assign them to different conditions. We will also use appropriatestatistical methods to analyze the data and control for potential confounding variables.

Overall, this methodology aims to provide a comprehensive and rigorous evaluation of two approaches for detecting drowsiness, which can have important implications for improving safety in various settings, including transportation and workplace environment.

IV. PROPOSED SYSTEM

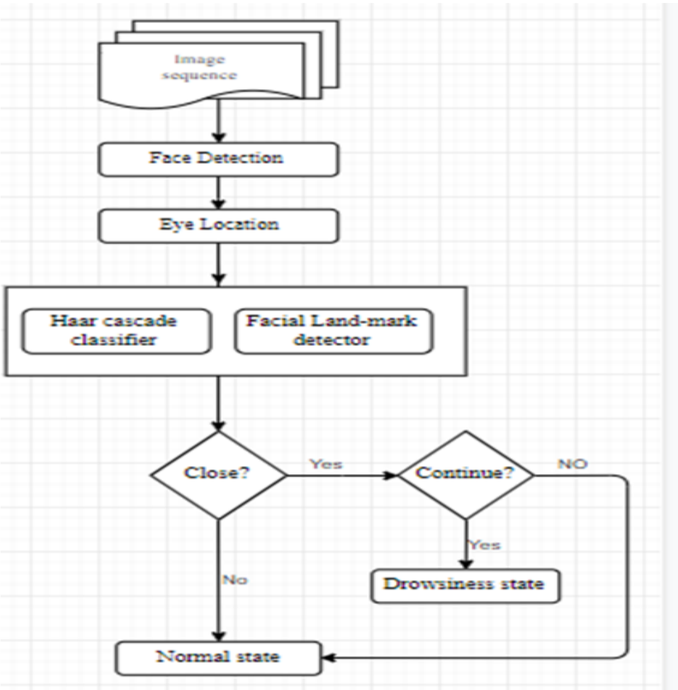

Figure1:Flowchart ofthe System

Face Detection:

Haar feature-based cascade classifiers are a popular method for object detection, particularly for face detection. It was proposed by Viola and Jones in 2001, and it involves a machine-learning approach that trains a cascade function using positive and negative images. The positive images are those that contain faces, while the negative images are those without faces. The algorithm extracts feature from these images using Haar-like features, which are similar to convolutional kernels. These features are obtained by subtracting the sum of pixels under the white rectangle from the sum of pixels under the black rectangle. There are several types of Haar-like features, such as edge features and line features, which are used to identify differentfacial features.Figure 2 represents five haar like features and example is shown in Figure 3.

Figure 2

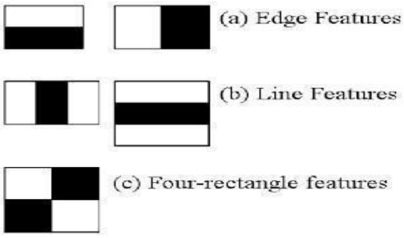

Figure 3

For real-time face detection, a cascaded Adaboost classifier that utilizes Haar-like features is often used. The process involves segmenting the compensated image into multiple rectangular areas, which can be positioned and scaled within the original image. Haar-like features are efficient for facial feature differentiation, as they can be calculated based on the difference of pixel values within rectangle areas. The features can be represented by the composition of black-and-white regions. A cascaded Adaboost classifier is a robust classifier that combines multiple weak classifiers, each trained by the Adaboost algorithm. By passing candidate samples through this classifier, the face region can be detected, and most face samples can pass through while non-face samples can be rejected.

Eye Detection:

Facial landmark prediction is a technique we have implemented in our system for eye detection. These landmarks are used to identify and represent significant areas of the face, including the eyes, eyebrows, nose, mouth, and jawline. Facial landmarks have proven useful for a variety of applications, such as face alignment, blink detection, head pose estimation, and face swapping. The process of detecting facial landmarks involves two steps: first, localizing the face within the image, which is achieved through the Haar feature-based cascade classifiers discussed in the face detection step of our algorithm. The second step involves identifying key facial structures within the face's region of interest (ROI). Various facial landmark detectors can achieve this, but they all aim to label and locate critical facial regions such as the mouth, eyebrows, eyes, and nose. The dlib library includes a facial landmark detector that implements the One Millisecond Face Alignment with an Ensemble of Regression Trees paper by Kazemi and Sullivan (2014).

The method we're discussing starts by using a training set of labeled facial landmarks, where specific regions surrounding each facial structure are manually labeled with (x, y)-coordinates. Additionally, prior probabilities are used to determine the distance between pairs of input pixels. The pre-trained facial landmark detector included in the dlib library estimates the location of 68 (x, y)-coordinates that correspond to facial structures on the face.The indexes of the 68 coordinates can be visualized on Figure 4 below.

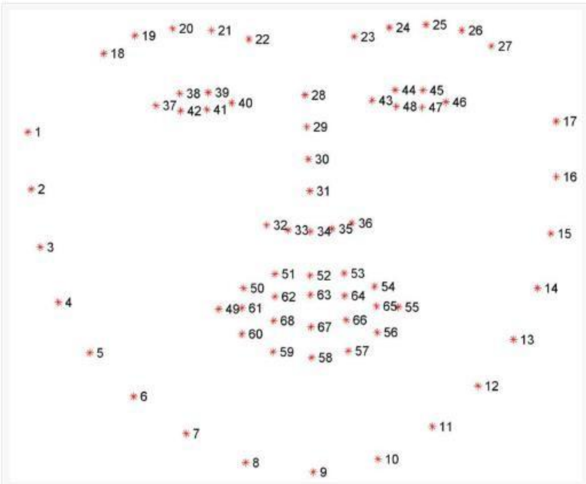

Fig.4: Visualizing the 68 facial landmark coordinates.

To identify and extract the eye regions, we utilize facial landmark indices [36, 42] for the right eye and [42, 48] for the left eye. These annotations are included in the 68-point iBUG 300-W dataset, which the dlib facial landmark predictor was trained on. It's worth noting that alternative facial landmark detectors are available, such as the 194-point model that can be trained on the HELEN dataset. Regardless of the dataset used, the dlib framework can be applied to train a shape predictor on the input training data.

Recognition of Eye's State:

The eye area can be estimated in multiple ways, such as using optical flow, sparse tracking, frame-to-frame intensity differencing, and adaptive thresholding. Once the eye area is estimated, the state of the eyes can be inferred by various methods, such as correlation matching with open and closed eye templates, horizontal or vertical image intensity projection over the eye region, and parametric model fitting to find the eyelids or active shape models. However, these methods often impose strict requirements on the setup, image resolution, illumination, and motion dynamics, making them sensitive and limiting their performance. To address this issue, a simple but efficient algorithm is proposed to detect eye blinks by using a recent facial landmark detector. The algorithm derives a single scalar quantity reflecting the level of eye-opening from the landmarks and employs an SVM classifier to find eye blinks based on a per-frame sequence of eye-opening estimates. The SVM classifier is trained on examples of blinking and non-blinking patterns.

Eye Aspect Ratio Calculation:

The eye landmarks are detected for each frame in the video and the eye aspect ratio (EAR), which is the ratio of the height to width of the eye, is calculated.

$$EAR = = \frac{\|p2 - p6\| + \|p3 - p5\|}{2\|p1- p4\|} \text{eq (1)}$$

To calculate the Eye Aspect Ratio (EAR), the eye landmarks are first detected for each video frame. The EAR is computed by taking the ratio between the height and width of the eye, using a formula that involves the 2D landmark locations. The EAR is generally consistent when the eye is open but decreases towards zero when the eye is closing. It is somewhat insensitive to head pose and individual differences. The aspect ratio of the open eye has a small variance among individuals and is fully invariant to uniform scaling and in-plane rotation of the face. Since blinking typically involves both eyes at the same time, the EAR for both eyes is averaged.

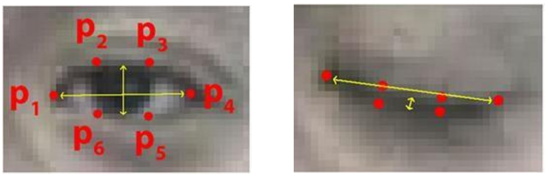

Figure6: Open and closed eye with landmark

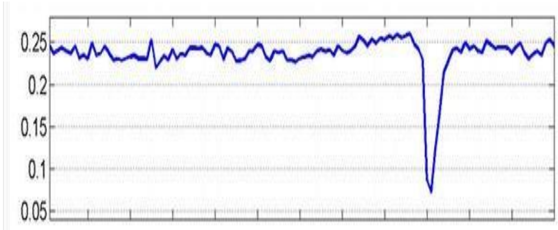

Fig.7 EAR for single blink

Eye State Determination:

Finally, the decision for the eye state is made based on the EAR calculated in the previous step. If the distance is zero or is close to zero, the eye state is classified as “closed” otherwise the eye state is identified as “open”.

Drowsiness Detection:

The final step of the algorithm is to determine if the person is drowsy based on a pre-set condition for drowsiness. Typically, the average blink duration for a person is between 100-400 milliseconds. Therefore, if a person is drowsy, their eye closure duration should be longer than this interval. The algorithm sets a time frame of 5 seconds and checks if the eyes remain closed for this duration. If the eyes are closed for five seconds or more, the algorithm detects drowsiness and triggers an alert to notify the user.

V. CONCLUSION

The above methods propose a real-time eye blink detection algorithm that utilizes Haar feature-based cascade classifiers and regression-based facial landmark detectors to accurately estimate eye openness in positive face images. The algorithm's precision and robustness were quantitatively demonstrated through various tests, showing that it can reliably detect eye blinks in low-quality images and in-the-wild scenarios. The results suggest that this approach can be useful in various applications, such as driver monitoring systems, human-computer interaction, and medical diagnosis. Overall, the proposed algorithm presents a significant contribution to the field of computer vision and could pave the way for future research on eye blink detection in real-time scenarios.

VI. REFERENCES

[1] C. Alvarado et al. (2021) proposed a method for driver drowsiness detection using a combination of head pose estimation, eye tracking, and heart ratevariability.

[2] H. Ye et al. (2021) proposed a drowsiness detection method based on eye tracking and EEG signals.

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[12] Gong et al. (2019) proposed a drowsiness detection system based on the analysis of electrooculogram (EOG)signals.

[13] Raj et al. (2019) proposed a drowsiness detection system using a hybrid approach that combines both vision-based andphysiologicalsignals.

[14] Sun et al. (2019) proposed a drowsiness detection system based on the analysis of electrocardiogram (ECG)signals.

[15] Li et al. (2020) proposed a drowsiness detection system using a convolutional neural network (CNN) and a long short-term memory(LSTM)network.

[16] Xiao et al. (2020) proposed a drowsiness detection system based on the analysis of electroencephalogram (EEG)signals.

[17] C. Zhang et al. (2021) developed a drowsinessdetection system using a convolutional neural network and a Recurrent Neural Network(RNN).

[18] A. Imran et al. (2021) proposed a deep learning-based drowsiness detection system using multiple sensors, including an EEG sensor and acamera.

[19] Attention-aware deep neural networks for drowsiness detection in driver monitoring by J. Li, C. Wang, Y. Lin, and H. Li.

[20] A real-time, non-invasive system for driver drowsiness detection using EEG and eye-tracking signals by A. Marcal, G.F. Pedreira and P.G.Pires.