Driver Drowsiness Monitoring System using Visual Behaviour and Machine Learning

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Abstract - Drowsy driving is one of the leading causes of traffic accidents and fatalities. As a result, detecting and indicating driver weariness is an important research field. The majority of traditional techniques are vehicle-based, behavioral-based, or physiological-based. Some approaches are invasive and distract the driver, while others necessitate the use of pricey sensors and data processing. As a result, a low-cost, real-time driver sleepiness detection system with adequate accuracy is built in this work. A webcam records the video in the created system, and image processing algorithms are used to determine the driver's face in each frame. Facial landmarks on the detected face are identified, and the eye aspect ratio, mouth opening ratio, and nose length ratio are computed, and drowsiness is determined based on their values, drowsiness is identified thanks to the adaptive thresholding that has been established. Offline implementation of machine learning algorithms is also possible. Support Vector Machine-based classification has a sensitivity of 95.58 percent and a specificity of 100 percent.

Indexed Terms- Smart Contracts, Ethereum, Web3.js, Truffle-framework.

I. INTRODUCTION

Drowsy driving is one of the leading causes of fatalities in car accidents. Truck drivers that travel for lengthy periods of time (especially at night), long-distance bus drivers, and overnight bus drivers are more vulnerable to this condition. Passengers in every country face the nightmare of drowsy drivers. Fatigue-related traffic accidents result in a substantial number of injuries and deaths each year. As a result, due to its wide practical application, detecting and indicating driver weariness is a hot topic of research. The acquisition system, processing system, and warning system are the three blocks/modules of the basic sleepiness detection system. The driver's frontal face video is acquired in the acquisition system and transported to the processing block, where it is processed drowsiness can be detected online. The driver receives a warning or alarm from the warning system if drowsiness is detected. In general, there are three sorts of approaches for detecting drowsy drivers: vehicle-based, behavioral-based, and physiological-based.

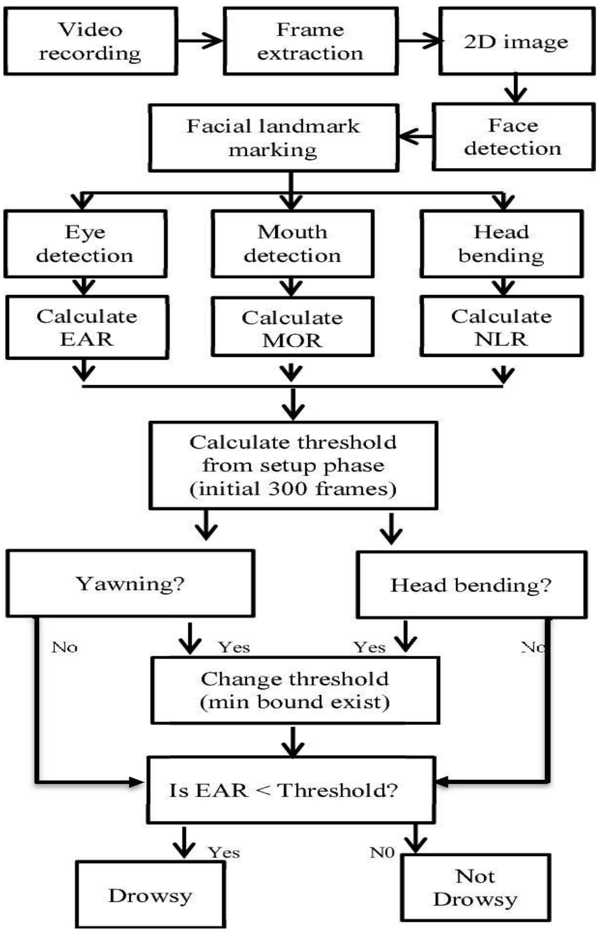
A range of parameters such as steering wheel movement, accelerator or brake pattern, vehicle speed, lateral acceleration, deviations from lane position, and so on are continuously monitored in the vehicle-based method. Driver drowsiness is defined as the detection of any abnormal change in these parameters. Because the sensors are not linked to the driver, this is a nonintrusive measurement. To detect drowsiness, behavioral based methods [1- 7] assess the driver's visual behavior, such as eye blinking, eye closing, yawn, head bending, and so on. This is also a non-intrusive measurement because the features are detected using a simple camera. Physiological signals such as electrocardiogram (ECG), electrooculogram (EOG), electroencephalogram (EEG), heartbeat, pulse rate, and others are tracked in physiological-based methods [8,9], and drowsiness or exhaustion levels are determined using these metrics. Because the sensors are linked to the driver, this is an intrusive measurement that will disturb the driver. The cost and size of the system will grow depending on the sensors used.

However, including more parameters/features will improve the system's accuracy to some amount. These things encourage us to take design a low-cost, accurate real-time sleepiness detection system for drivers. As a result, we've presented a webcam-based system that uses image processing and machine learning techniques to identify driver fatigue from a face image, making the device both low-cost and portable.

II. THE PROPOSED SYSTEM AND COMPUTATION OF PARAMETERS

Figure 1 shows a block diagram of the proposed driver drowsiness monitoring system. The footage is first recorded with a webcam. To capture the driver's front face image, the camera will be positioned in front of him. The frames are taken from the movie to create 2-D pictures. The histogram of oriented gradients (HOG) and linear support vector machine (SVM) for object detection are used to recognize faces in the frames [10]. Facial landmarks [11], such as the positions of the eye, nose, and mouth, are marked on the images once the face has been detected. Eye aspect ratio, mouth opening ratio, and head posture are all calculated from facial cues, and a conclusion about tiredness is made utilizing these features and a machine learning approach the driver's position If drowsiness is detected, an alarm will be sounded to notify the driver. The following sections go into the specifics of each block.

Fig. 1 The block diagram of the proposed drowsiness detection system



A. Data Acquisition

A webcam is used to record the video, and the frames are retrieved and processed on a laptop. Image processing techniques are performed to these 2D images after the frames have been extracted. Synthetic driver data has been generated at this time. The participants are invited to look at the webcam while blinking, closing their eyes, yawning, and bending their heads. The footage was recorded for 30 minutes.

B. Face Recognition

The human faces are first discovered after the frames have been extracted. There is a plethora of online face detection techniques available. The histogram of oriented gradients (HOG) and linear SVM algorithm [10] are employed in this investigation. Positive samples of a fixed window size are extracted from the images and HOG descriptors are computed on them in this method. The HOG descriptors are then generated using negative samples (samples that do not contain the needed object to be detected, in this case, a human face). In most cases, the number of negative samples much outnumbers the number of positive samples. A linear SVM is trained for the classification job after the characteristics for both classes are obtained. Hard negative mining is used to improve the accuracy of SVM. In this strategy, the classifier is evaluated with labelled data after training, and the false positive sample feature values are used for training again. The fixed-size window is translated over the image for the test image, and the classifier computes the output for each window point. Finally, the maximum value produced is used to identify the detected face, which is surrounded by a bounding box. The redundant and overlapping bounding boxes are removed in this non-maximum suppression stage.

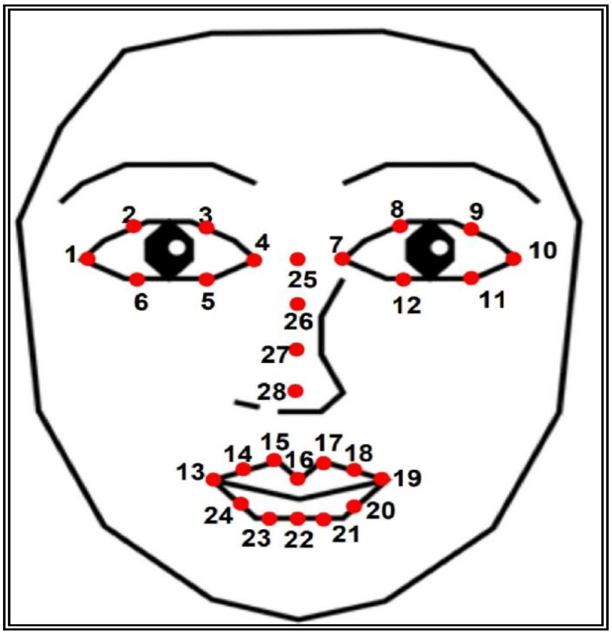
C. Facial Landmark marking

Following the detection of the face, the following step is to locate various facial features such as the corners of the eyes and mouth, the tip of the nose, and so on. Prior to that, the facial images should be normalized to eliminate the effects of camera distance, non-uniform illumination, and changing image resolution. As a result, the facial image is shrunk to 500 pixels wide and turned to grayscale. After picture normalization, a sparse subset of pixel intensities is employed to estimate landmark positions on the face using an ensemble of regression trees [11]. The sum of square error loss is improved using gradient boosting learning in this method. To find distinct structures, different priors are employed. Using this technique, the boundaries of the eyes, mouth, and Centre line of the nose are delineated, and the number of points for each are listed in Table I. Figure 2 depicts the facial landmarks. The red spots are the detected landmarks that will be processed further.

Table I: Facial landmark Points

Parts	**Landmark Points**
Mouth	[13-24]
Right eye	[1-6]
Left eye	[7-12]
Nose	[25-28]

Fig. 2 The facial landmark points



D. Feature Extraction

The features are computed after the facial landmarks have been detected, as stated below.

EAR (eye aspect ratio): The eye aspect ratio is computed from the eye corner points as the ratio of the eye's height and width as stated by

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

where pi represents point marked as i in facial landmark and (pi − pj) is the distance between points marked as i and j. Therefore, when the eyes are fully open, EAR is high value and as the eyes are closed, EAR value goes towards zero. Thus, monotonically decreasing EAR values indicate gradually closing eyes and it's almost zero for completely closed eyes (eye blink). Consequently, EAR values indicate the drowsiness of the driver as eye blinks occur due to drowsiness.

Mouth opening ratio (MOR): Mouth opening ratio is a drowsiness-related yawning detection metric. It is determined in the same way as EAR.

$$MOR = \frac{(p_{15} - p_{23}) + (p_{16} - p_{22}) + (p_{17} - p_{21})}{3(p_{19} - p_{13})}$$

As defined, it rapidly climbs when the mouth opens owing to yawning, stays at that high value for a long due to the yawn (indicating that the mouth is open), and then swiftly declines to zero. Because yawning is one of the symptoms of tiredness, MOR provides a measure of driver drowsiness.

Head Bending: Drowsiness causes the driver's head to tilt (forward or backward) with regard to the vertical axis. Drowsiness in the driver can thus be diagnosed based on the head bending angle. Because the projected length of the nose on the camera focus plane is proportional to the bending, it can be used to calculate head bending. In typical circumstances, our nose forms an acute angle with the camera's focal plane. As the head travels vertically up, the angle increases, and as the head moves down, the angle decreases. As a result, the ratio of nose length to average nose length while awake is a measure of head bending, and if the number falls within a certain range, it reflects both head bending and tiredness. From the nose length is computed and determined using facial landmarks.

The average nose length is computed during the setup phaseof the experiment as described in the next sub-section.

$$NLR = \frac{nose\ length(p_{28} - p_{25})}{average\ nose\ length}$$

III. Results and Discussion

With the generated data, the proposed system was constructed and tested. The webcam is connected to the laptop so that the video streaming can be further processed and classified online. The feature values are then saved for statistical analysis and categorization purposes. Figure 3 depicts a frame from the usual or awake state. This frame's feature values are as follows:

EAR = 0.30, MOR = 0.24, NLR = 0.97

Fig. 3 Normal or awake state with facial landmarks

Fig. 4 Drowsiness detected by the system due to eye closing

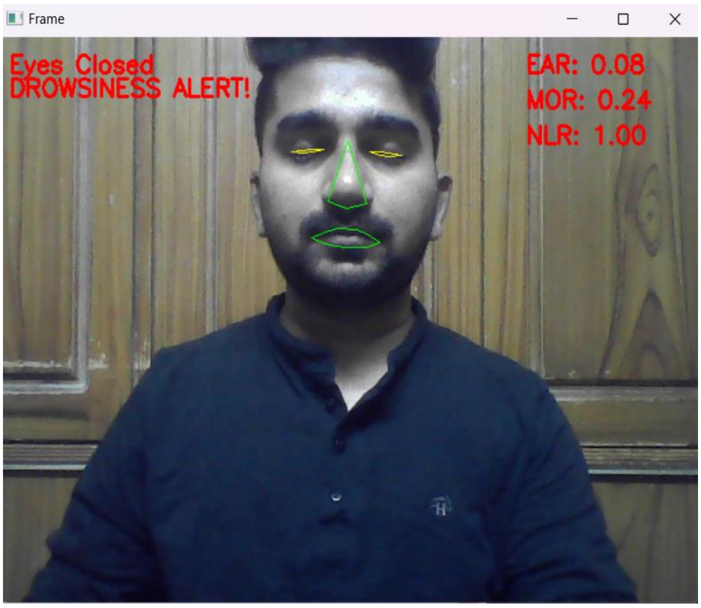


Fig. 5 Drowsiness detected by the system due to head bending

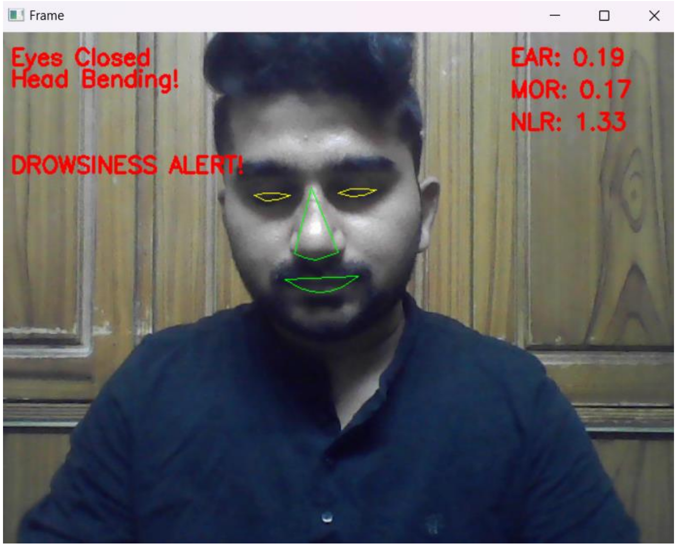
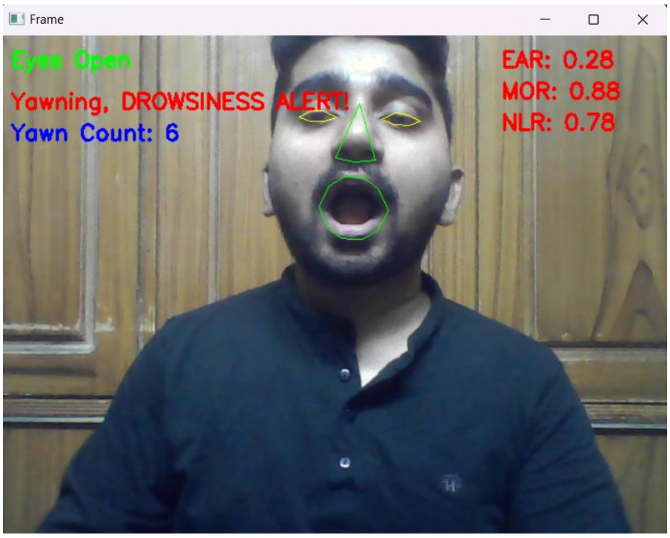


Fig. 6 Drowsiness detected by the system due to yawning



IV. CONCLUSION

Based on ocular behaviour and machine learning, a low-cost, real-time driver sleepiness monitoring system is proposed in this work. From the streaming video collected by a camera, visual behaviour features such as eye aspect ratio, mouth opening ratio, and nose length ratio are computed. To identify driver tiredness in real time, an adaptive thresholding technique has been devised. With the generated synthetic data, the built system works perfectly. Following that, the feature values are saved, and machine learning methods are employed to classify the data.

A pilot study on drivers will be conducted to validate the developed system, which will be implemented in hardware to make it portable for automotive systems.

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