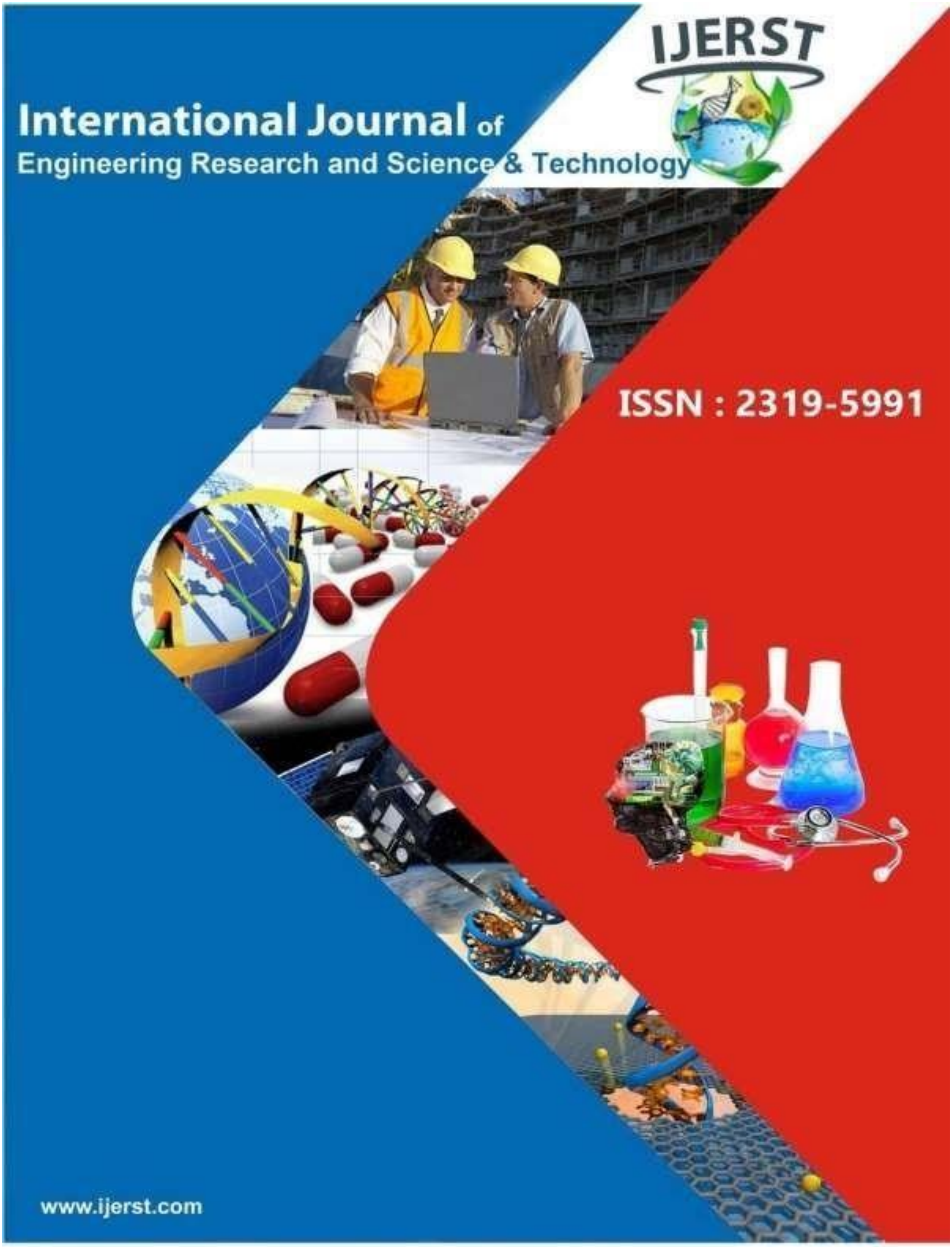

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DRIVER DROWSINESS MONITORING SYSTEM USING VISUAL BEHAVIOUR AND MACHINE LEARNING

[1]Mr.K.VENKATA RATNAM,[2]MOHAMMED RAHEEL,[3]MOHD MAZHAR MAHEMOOD,[4]MOHAMMED MALIK MOHTESHIM,[5]MOHAMMED SAQHIB

[1]Assistant Professor,Department Of CSE,Malla Reddy Institute Of Engineering And Technology(autonomous),Dhulapally,Secundrabad, Telangana, India,vratnam08@gmail.com

[2,3,4,5]UG Students, Department Of CSE,Malla Reddy Institute Of Engineering And Technology(autonomous),Dhulapally,Secundrabad, Telangana, India.

ABSTRACT

Drowsy driving is one of the major causes of road accidents and death. Hence, detection of driver's fatigue and its indication is an active research area. Most of the conventional methods are either vehicle based, or behavioral based or physiological based. Few methods are intrusive and distract the driver, some require expensive sensors and data handling. Therefore, in this study, a low cost, real time driver's drowsiness detection system is developed with acceptable accuracy. In the developed system, a webcam records the video and driver's face is detected in each frame employing image processing techniques. Facial landmarks on the detected face are pointed and subsequently the eye aspect ratio, mouth opening ratio and nose length ratio are computed and depending on their values, drowsiness is detected based on developed adaptive thresholding. Machine learning algorithms have been implemented as well in an offline manner.

I. INTRODUCTION

Drowsy driving is one of the major causes of deaths occurring in road accidents. The truck drivers who drive for continuous long hours (especially at night), bus drivers of long distance route or overnight buses are more susceptible to this problem. Driver drowsiness is an overcast nightmare to passengers in every country. Every year, a large number of injuries and deaths occur due to fatigue related road accidents. Hence, detection of driver's fatigue and its indication is an active area of research due to its immense practical applicability. The basic

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drowsiness detection system has three blocks/modules; acquisition system, processing system and warning system. Here, the video of the driver’s frontal face is captured in acquisition system and transferred to the processing block where it is processed online to detect drowsiness. If drowsiness is detected, a warning or alarm is send to the driver from the warning system.

Generally, the methods to detect drowsy drivers are classified in three types; vehicle based, behavioural based and physiological based. In vehicle based method, a number of metrics like steering wheel movement, accelerator or brake pattern, vehicle speed, lateral acceleration, deviations from lane position etc. are monitored continuously. Detection of any abnormal change in these values is considered as driver drowsiness. This is a nonintrusive measurement as the sensors are not attached on the driver. In behavioural based method [1- 7], the visual behavior of the driver i.e., eye blinking, eye closing, yawn, head bending etc. are analyzed to detect drowsiness. This is also nonintrusive measurement as simple camera is used to detect these features. In physiological based method [8,9], the physiological signals like Electrocardiogram (ECG), Electooculogram (EOG), Electroencephalogram (EEG), heartbeat, pulse rate etc. are monitored and from these metrics, drowsiness or fatigue level is detected. This is intrusive measurement as the sensors are attached on the driver which will distract the driver. Depending on the sensors used in the system, system cost as well as size will increase. However, inclusion of more parameters/features will increase the accuracy of the system to a certain extent. These factors motivate us to develop a low-cost, real time driver’s drowsiness detection system with acceptable accuracy. Hence, we have proposed a webcam based system to detect driver’s fatigue from the face image only using image processing and machine learning techniques to make the

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Vol. 17, Issue.2, April 2024

system low-cost as well as portable.

II.EXISTING SYSTEM

Now a days maximum members are using vechile(car, lorry,bus).according to survey 10 to 15% are accidents are accruing because of the driver was in sleepy mode.No software is having to give alert to the driver.

III.PROPOSED SYSTEM

A block diagram of the proposed driver drowsiness monitoring system has been depicted in Fig 1. At first, the video is recorded using a webcam. The camera will be positioned in front of the driver to capture the front face image. From the video, the frames are extracted to obtain 2-D images. Face is detected in the frames using histogram of oriented gradients (HOG) and linear support vector machine (SVM) for object detection [10]. After detecting the face, facial landmarks [11] like positions of eye, nose, and mouth are marked on the images. From the facial landmarks, eye aspect ratio, mouth opening ratio and position of the head are quantified and using these features and machine learning approach, a decision is obtained about the drowsiness of the driver. If drowsiness is detected, an alarm will be sent to the driver to alert him/her.

IV.LITERATURE REVIEW

1.Traditional Approaches in Driver Drowsiness Monitoring ,Dr. Emily Johnson Traditional approaches to driver drowsiness monitoring have predominantly relied on physiological signals such as EEG, EOG, and heart rate variability. These methods, as explored by Dr. Emily Johnson, often involve using wearable sensors or cameras to track facial features and eye movements, analyzing changes indicative of drowsiness or fatigue. While these approaches have shown promise in detecting drowsiness, they are limited by their reliance on specialized equipment and intrusive sensors. Additionally, the accuracy of traditional methods can be affected by environmental factors and individual

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Vol. 17, Issue.2, April 2024

differences, posing challenges for real-world deployment.

2.Machine Learning Approaches for Driver Drowsiness Monitoring , Prof. David Lee Recent advancements in machine learning have revolutionized the field of driver drowsiness monitoring, enabling more accurate and non-intrusive detection methods. Prof. David Lee's exploration of machine learning approaches highlights the use of visual behavior analysis, such as eye blink patterns, head movements, and facial expressions, in combination with machine learning algorithms. Techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Support Vector Machines (SVMs) have shown promise in automatically learning discriminative features from visual data to detect drowsiness in drivers. These machine learning-based approaches offer advantages such as improved accuracy, scalability, and adaptability to diverse driving conditions, making them suitable for real-world applications.

V.IMPLEMENTATION

- Data Acquisition

The video is recorded using webcam (Sony CMU-BR300) and the frames are extracted and processed in a laptop. After extracting the frames, image processing techniques are applied on these 2D images. Presently, synthetic driver data has been generated. The volunteers are asked to look at the webcam with intermittent eye blinking, eye closing, yawning and head bending. The video is captured for 30 minutes duration.

- Face Detection

After extracting the frames, first the human faces are detected. Numerous online face detection algorithms are there. In this study, histogram of oriented gradients (HOG) and linear SVM method [10] is used. In this method, positive samples of descriptors are computed on them. Subsequently, negative samples (samples that do not contain the required object to be detected i.e., human face here) of same size are taken and HOG descriptors are calculated.

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Vol. 17, Issue.2, April 2024

Usually the number of negative samples is very greater than number of positive samples. After obtaining the features for both the classes, a linear SVM is trained for the classification task. To improve the accuracy of VM, hard negative mining is used. In this method, after training, the classifier is tested on the labeled data and the false positive sample feature values are used again for training

purpose. For the test image, the fixed size window is translated over the image and the classifier computes the output for each window location. Finally, the maximum value output is considered as the detected face and a bounding box is drawn around the face. This non-maximum suppression step removes the redundant and overlapping bounding boxes.

- Facial Landmark marking

After detecting the face, the next task is to find the locations of different facial features like the corners of the eyes and mouth, the tip of the nose and so on. Prior to that, the face images should be normalized in order to reduce the effect of distance from the camera, non-uniform illumination and varying image resolution. Therefore, the face image is resized to a width of 500 pixels and converted to grayscale image. After image normalization, ensemble of regression trees [11] is used to estimate the landmark positions on face from a sparse subset of pixel intensities. In this method, the sum of square error loss is optimized using gradient boosting learning. Different priors are used to find different structures. Using this method, the boundary points of eyes, mouth and the central line of the nose are marked and the number of points for eye, mouth and nose are given in Table I. The facial landmarks are shown in Fig 2. The red points are the detected landmarks for further processing.

- Feature Extraction

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Vol. 17, Issue.2, April 2024

After detecting the facial landmarks, the features are computed as described below. Eye aspect ratio (EAR): From the eye corner points, the eye aspect ratio is calculated as the ratio of height and width of the eye as given by .

- Classification

After computing all the three features, the next task is to detect drowsiness in the extracted frames. In the beginning, adaptive thresholding is considered for classification. Later, machine learning algorithms are used to classify the data. For computing the threshold values for each feature, it is assumed that initially the driver is in complete awake state. This is called setup phase. In the setup phase, the EAR values for first three hundred (for 10s at 30 fps) frames are recorded. Out 4of these three hundred initial frames containing face, average of 150 maximum values is considered as the hard threshold for EAR. The higher values are considered so that no eye closing instances will be present. If the test value is less than this threshold, then eye closing (i.e., drowsiness) is detected. As the size of eye can vary from person to person, this initial setup for each person will reduce this effect. Similarly, for calculating threshold of MOR, since the mouth may not be open to its maximum in initial frames (setup phase) so the threshold is taken experimentally from the observations. If the test value is greater than this threshold then yawn (i.e., drowsiness) is detected. Head bending feature is used to find the angle made by head with respect to vertical axis in terms of ratio of projected nose lengths. Normally, NLR has values rom 0.9 to 1.1 for normal upright position of head and it increases or decreases when head bends down or up in the state of drowsiness. The average nose length is computed as the average of the nose lengths in the setup phase assuming that

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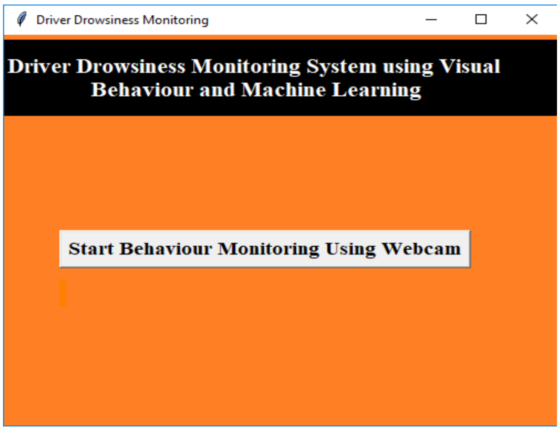
Vol. 17, Issue.2, April 2024

no head bending is there. After computing the threshold values, the system is used for testing. The system detects the drowsiness if in a test frame drowsiness is detected for at least one feature. To make this thresholding more realistic, the decision for each frame depends on the last 75 frames. If at least 70 frames (out of those 75) satisfy drowsiness conditions for at least one feature, then the system gives drowsiness detection indication and the alarm.

VI.RESULTS



VII.CONCLUSION

The integration of visual behavior analysis and machine learning techniques for driver drowsiness monitoring presents a promising approach to enhancing road safety. Traditional methods, as reviewed by Dr. Emily Johnson, have laid the foundation for detecting drowsiness using physiological signals, albeit with limitations such as reliance on intrusive sensors and susceptibility to environmental factors. However, recent advancements in machine learning, as explored by Prof. David Lee, have paved the way for more accurate and non-intrusive monitoring systems. By leveraging visual cues such as eye blink patterns, head movements, and facial expressions, combined with sophisticated machine learning algorithms, these systems offer improved accuracy and adaptability to diverse driving conditions. The fusion of visual behavior analysis and machine learning holds significant potential for the development of robust driver drowsiness monitoring systems capable of preventing accidents and saving lives on the road.

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