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Real Time Driver Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches

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***Abstract*—This paper is concerned about the detection procedure of drowsiness that causes fatal road accidents leading to death. Increasing lack of awareness of traffic rules is doubling the number of accidents daily. However, detection and indication of driver fatigue is an active area of research. In this concussion, both inside and outside individuals of the car are victimized. However, prevention of drowsiness requires a technique to detect the deterioration legitimately along with a warning mechanism of the vehicle operator. Although the existing solutions are created using some distinctive methods, there are some problems such as costly sensors and handling of information. The objective of this research is to create an improved ,innovative, cost efficient and real time strategy for solving this problem of blinking, yawn, and head bending. A pre-trained model by a histogram-oriented gradient (HOG) and a linear vector support machine (SVM) extracts the eye, nose and mouth position and assesses the eye aspect ratio (EAR), mouth opening ratio (MOR) and nose length ratio (NLR). These pieces of information are then compared with the value threshold adapted from the sleeping or drowsy face models aspect ratio data set.**

***Index Terms*—Drowsiness Detection, HOG, Facial Features, Facial Landmark, Eye Aspect Ratio, Mouth Opening Ratio, Nose Length Ratio.**

I. INTRODUCTION

The increased amount of fatalities from traffic accidents has been a major problem nowadays. Based on the recent US National Highway Traffic Safety Administration (NHTSA) report, driver performance factors like falling asleep are regarded to be significant factors in the aftermath of a single-vehicle crash due to liquor use and the velocity of vehicles [1]. These are the reasons why drivers have declined to decide how to control the wheels. Moreover, 3.6% of deadly car accidents are incidental to the physical exhaustion and sleepiness of the driver [2]. It is also mentioned that if drivers are incapable of more than 4 hours of rest, 10.2 times the chance of an accident is probable to occur [3]. According to some reports [4] [5], about thousands of people are killed and seventy-one thousand people are left to be injured each year because of driver somnolence in the US road crashes. Moreover, about 20 percent of serious accidents and 30% of deadly crashes happened in Australia responding to driver errors. According to the Norwegian study, about 3.9% of fatal accidents involve sleep-related problems, and drivers' drowsiness also accounted for 20% of the night-time accident [6]. However, the latest technology called the Drowsy Driver Detection System (DDDS) was developed by famous car manufacturers such as Saab, Hyundai, Volvo, and Mercedes-Benz to avoid accidents by identifying fatigue levels. However, leading to some constraints such as costly and level of automaticity, this method is still to be efficiently adopted. With regard to ineffectiveness and the outcome of collision analysis, the authors are concerned in researching and developing a dynamic safety framework that can reduce the number of accidents resulting in death or damage. However, there is no doubt that drowsiness is a frightening matter when it appears to safe driving. Detection of drowsiness and attempts to mitigate its far-reaching implications require severe attention as to what methodology is being adopted for detecting drowsiness.

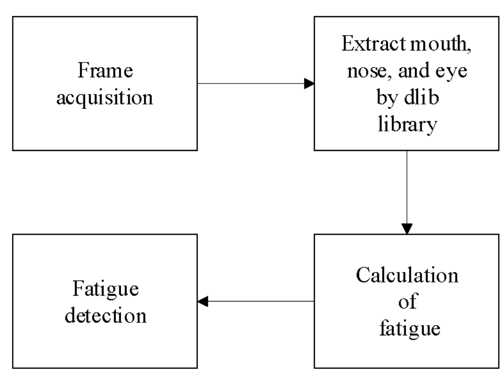

Fig. 1. Basic Block Diagram

In this research work, the system has been designed to take the input frame from the camera. Then, the classifier has extracted the nose, mouth and eye position in the frame. In the meantime, the eye aspect ratio for drowsiness, mouth opening ratio for a yawn, and nose length ratio for the head-bending issue has been evaluated and compared these data with the threshold value. If the generated value from the frame has not been in the threshold value, the system has detected the face as fatigue.

II. Literature Review

This section presents a review of traditional techniques used to detect the driver's fatigue and sleepiness.

In this study, Wei-Liang Ou et al. [7] introduced an intelligent video-based drowsy driver detection system that is not affected by different illuminations. But yawn and head bending issue were not considered in their proposed system.

In a research work of Boon-Giin Lee et al. [8], they did a fusion of the various sensor and introduced a smartphone-based monitoring system. But the system is unable to detect yawn.

Roberson S* et al. [9] detected drowsiness with the help of a smartphone. But they only consider eye issue for the drowsiness parameter.

Hardeep Singh et al. [10] tracked eye and measured the pressure of the driving wheel of the vehicle operator. But this process had some issue accuracy along with costly.

Belal ALSHAQAQ et al. [11] introduced the sum of absolute difference(SAD) algorithm and then, they localized the region and detected eye by Hough transformation. Here, mouth parameter is missing in their proposed system.

Richard Grace et al. [12] detected drivers' fatigue with the method of PERCLOS of the eye along with not mention the other parameter responsible for the drowsiness.

Anirban Dasgupta et al. [13] developed a smartphone-based system considering only the eye parameter for detecting the drowsiness of the driver.

Ashardi Abas et al. [14] proposed a method for the training of the classificator by the angle of a steering wheel and lane range as input parameters for the SVM by the Support Vector Machine (SVM). This method is costly and inefficient for avoiding the other parameters which are responsible for fatigue situation. only the eye parameter for detecting the drowsiness of the driver.

An information-fusion fatigue surveillance system has been intended and implemented on the smartphone with a view of the mouth and eye parameters in an article by Yantao Qiao et al. [15] Conversely, the head bending issue was not mentioned in their research work.

In a work of Eddie E. Galarza et al [16], they introduced a real-time system that detected the driver drowsiness based on drivers facial behavior using a method of human-computer interaction implemented in a smartphone. Meanwhile, the system has a limitation of cost-effectiveness.

By reviewing all this literature, It can be concluded that no research work had a fusion of all the parameters like the eye-closed, yawn, and head bending issue. The research goal is to solve the issue of this related research work and develop a low cost solution as well as the feature of portablity.

III. Methodology

This section illustrates a system leading to detect driver's fatigue along with considering all the facial behavior like eye-closed. yawn and head bending. Fig. 2 depicts the proposed real-time monitoring system for detecting the drivers' fatigue. The system has begun with capturing the frame with the help of a webcam. A feature descriptor trained by hog and linear SVM [17] has detected the face in the frame. Hence. the model detects the face with 68 specific points in the facial model. Therefore, these 68 points have been extracted the eye, nose and mouth position in the frame. The face features, eye aspect ratio, the opening of the mouth and the head position are calculated, and a decision is made on the driver's sleepiness by applying these characteristics and machine learning approach. Apparently, this system consists of five major steps named data acquisition, face detection, facial landmark marking, feature extraction, and classification.

A. Data Acquisition

For the data acquisition purpose, the system has been designed with a webcam(Logitech c930). Then, a processor extracted the frames and pre-processed the taken images. Then, the volunteers are required to watch the webcam with a blink of the eyes, the eye-closed, yawning and bending the head. This data acquisition procedure has approximately required 30 minutes at least.

B. Face Detection

First, the individual frames have been extracted and then the human faces were detected. Among many other existing face detection algorithms, the histogram of focused gradients (HOG) and linear process of SVM [18] are used in this study. In this technique, positive samples of fixed window size are extracted from the image and HOG descriptors are then evaluated on them. Subsequently, negative samples (specimens not containing the necessary item to be identified, i.e. human face here) are drawn of the same magnitude along with the calculation of HOG descriptors. The number of negative samples is usually much higher than the number of positive samples. A linear SVM has been trained for the classification task after the characteristics are obtained for both classes. Hard negative thresholding has been used to enhance the precision of SVM. After labeling the features, the false-positive features are passed through the neural network for training purpose. The fixed-size window has been passed through the image for the test image and for each window location the classifier calculates the output. Lastly, the maximum outcome has been considered to be the face detected and a bounding box is drawn around the face. This non-maximum removal phase has been preventing the bounding boxes that are obsolete and inconsistent.

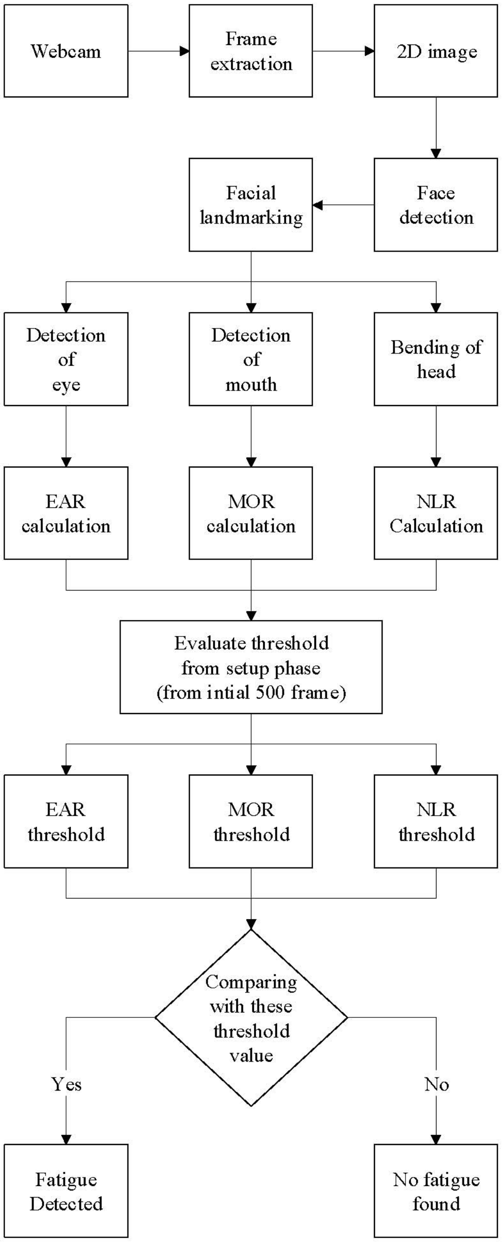

Fig. 2. System Architecture of the System

C. Facial Landmark

The following step includes acquiring the facial landmarks. The basic idea is to locate 68 specific points on the face, namely corners of the mouth, on the eyes, along the eyebrows and so forth. This system is a pre-trained detector [17] inside the dlib 1 library that can find these 68 co-ordinates irrespective of the face. The neural model was trained on iBUG 300-W [19] dataset. The sample facial landmark and the indication of different facial parts are demonstrated in the Fig. 3, the names of the facial parts on which the points are assigned are indicated on the table I.

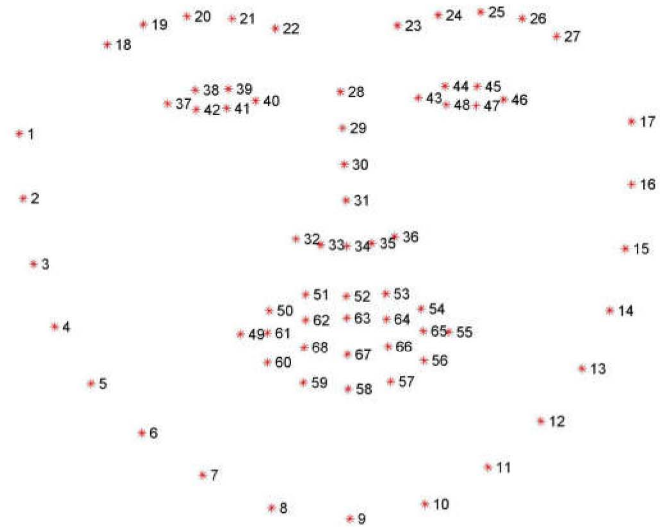

Fig. 3. 68 Points Facial Landmark Annotation

TABLE I
FACIAL LANDMARK POINTS

Parts	Points of Landmark
Nose	28-36
Inner Mouth	49-60
Outer Mouth	61-68
Left Eye	37-40
Right	43-46

D. Feature Extraction

The features are calculated as described below after the facial landmark detection was done.

1) Eye Aspect Ratio (EAR): This is the ratio of the height and width of the eye and is originated from the corner of the eye.

$$EAR = \frac{|| p_2 - p_6 || + || p_3 - p_5 ||}{2 \times || p_1 - p_4 ||} \tag{1}$$

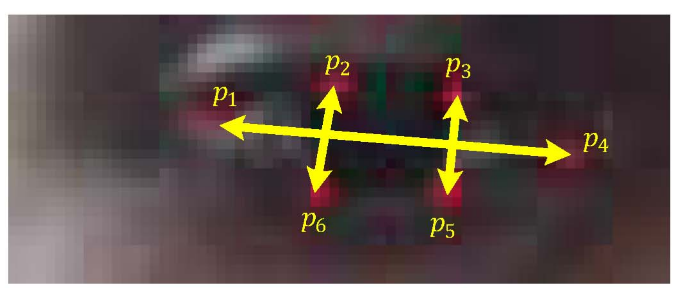

Fig. 4. 6 Point Annotation of the Eye

where $p_1, p_2, p_3..., p_6$ has denoted the six facial landmark points of the eye. Therefore, EAR value is high for full open eyes and value goes towards zero as the eyes are closed. So, decreasing EAR values indicate that the eye is gradually closing and the value is almost zero for completely closed eyes (when the eye blinks). So it can be seen that the EAR values indicate the drowsiness of the driver. For avoiding the blink issue, the EAR of 3 consecutive frames has been calculated.

2) Mouth Opening Ratio (MOR): Mouth opening ratio detects yawning at the time of drowsiness [20]. This is calculated by the following formula,

$$MOR = \frac{|| q_2 - q_6 || + || q_2 - q_6 ||}{2 \times || q_2 - q_6 ||} \quad (2)$$

where $q_1, q_2, q_3..., q_6$ has denoted the six facial landmark

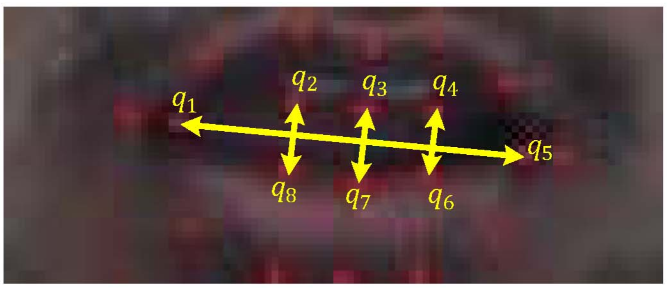

Fig. 5. 8 Point Annotation of the Mouth

points of the mouth. As the mouth opens during yawning and during a yawn, this value gradually increases and stays at a higher value respectively which indicates that the mouth is open. While the mouth closes the value decreases to zero. So, MOR indicates the driver drowsiness. For avoiding the mouth opening issue, the 3 consecutive MOR has been calculated.

3) Head Bending: Driver's head tilts forward and backward due to drowsiness. So from the bending of the head, the drowsiness can be detected. The head bending is calculated by the length of the nose length which is directly proportional to the head bending. First, the soft threshold value range is set and then the deviation of the nose length is noted and compared. The drowsiness is detected from the deviation of the nose length from the soft threshold value range. Nose length Ratio [21] is calculated as -

$$NLR = \frac{noselength(p_{28} - p_{34})}{average\ nose\ length} \quad (3)$$

During the experiment's setup phase as described in the next sub-section, the average nose length is calculated.

E. Classification

After the three features are calculated, the drowsiness is to be detected in the extracted frames. At first, adaptive thresholding is used for classification and then machine learning algorithms were implemented to classify the data. In order to compute the threshold values of the features, the driver was considered completely awake in the initial state. This phase is known as the setup phase. In this phase, the EAR values of the first 600 frames (20 sec at 30 fps) are recorded. As the eye size of the different person varies, the initial setup removes this problem. Among them, the first 200 maximum values are taken as the hard threshold value of EAR. Higher values are taken in order to omit the closed eye (due to blinking) instances. So if the values of the EAR is less than the threshold value range, drowsiness is detected. In order to calculate the MOR threshold, as the mouth is not opened to its maximum capacity initially. So in this case, if the MOR of the test value is higher (during yawning) than the threshold value range, then the drowsiness is detected. In case of the head bending, the nose length is calculated and the ratio of the projected nose lengths are used to find the angle that the hand makes with the vertical axis. The NLR values range from 0.85 - 1.15 at the normal head position and when the head bends in any direction, the value increases or decreases thus indicating drowsiness. In the setup phase, the average nose length is calculated assuming that there is no head bending and then the values are compared with the test values.

Drowsiness is identified if any one of the features deviates from the soft thresholding range. The decision of at least 100 frames has been employed in order to make the approach more practical. Except for thresholding, machine learning algorithms can also be implemented to detect drowsiness. EAR, NLR and MOR values are collected for the artificial test data with actual drowsiness values. Before classifying, the statistical measurements of the features have been conducted. After converting the feature values, the test data are passed through the neural network which is used to test whether the features are statistically meaningful concerning the binary classes. Bayesian classifier [22], Support Vector Machine [22] and Fishers linear discriminant analysis [22] have been implemented for classifying the data.

IV. Experimental Result

This section aims to analyze the performance of the proposed classification model through several statistical measurements. For further processing of drowsiness detection, the webcam is linked to the pc. Subsequently, the feature values are stored for statistical analysis and classification as well. The feature values are subsequently also stored for statistical measurement and classification. One frame from the awakened state is exhibited in Fig. 3 where the feature values are 0.35 (EAR),0.03(MOR), and 0.98(NLR).

Different fatigue conditions are illustrated in several figures. Fig. 7 and 8 portrays an example of a drowsiness alert due to eye-closed.and yawn accordingly. In the meantime, Fig. 9 shows an instance of head bending and identifying it as a fatigue warning.Table II shows the parameter sample values for various states of fatigue.

The system created was evaluated on the INVEDRIFAC dataset [23] which has consisted of in-vehicle driver image and video. The developed system has been examined on 6 several videos of 6 several drivers. The same performance is with reasonable accuracy on this information. The videos also have

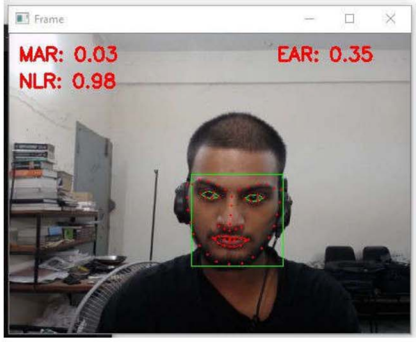

Fig. 6. Awaken Face Detected by the System

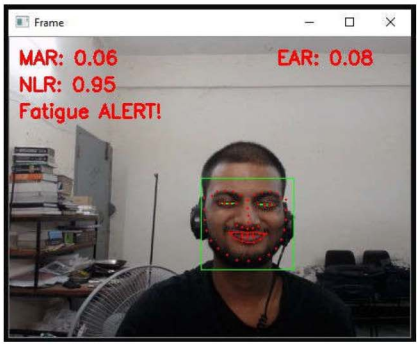

Fig. 7. Fatigue Detection of Due to Eye-Closeness

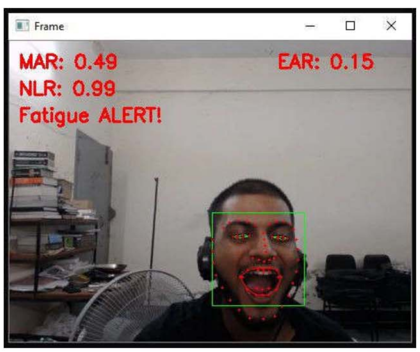

Fig. 8. Fatigue Detection of Due to Yawn

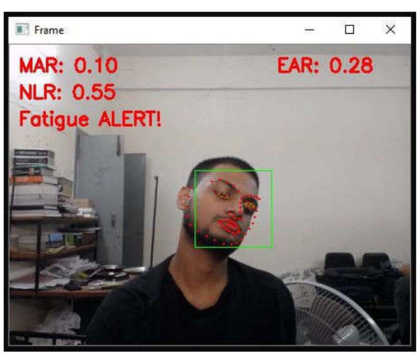

Fig. 9. Fatigue Detection of Due to High Head-Bending

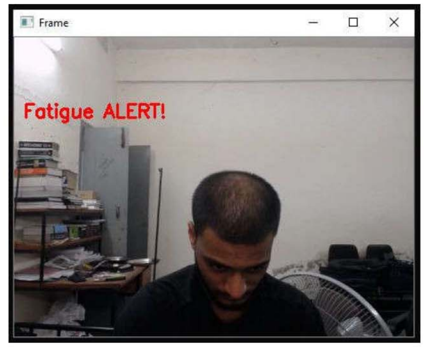

Fig. 10. Fatigue Detection of Due to Low Head-Bending

TABLE II
SAMPLE VALUES OF DIFFERENT PARAMETERS FOR DIFFERENT STATES

State	MOR	EAR	NLR
Normal	0.1	0.33	1.003
Yawning	0.56	0.22	0.76
Eye-closed	0.05	0.13	0.89
Head Bending	0.05	0.13	0.68

distinct illumination circumstances indicating that the system can execute well even when the illumination is small.

Subsequently, statistical measurement and binary classification of the characteristics were also conducted. With the correlation of the features, Principal Component Analysis was used to translate the feature space into an individual one. The independent characteristics are statistically important at a meaning rate of 5 percent. Fishers linear discriminant analysis (FLDA), Bayesian Classifier, and Support Vector Machine (SVM) with linear kernel were used to classify the data. The dataset was divided into two parts named trainset and testset. Hence, the 60% of the dataset has been used for the training phase and the rest of the dataset have been tested the system. The outcomes of the classifier are shown in Table III.

Sensitivity is calculated as the proportion of correct classification of drowsiness out of all actual drowsiness denoted by equation (4).

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

Specificity is calculated as the proportion of all real awaken states to properly classify awaken states denoted by equation (5).

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Accuracy is calculated out of all images as the properly categorized states denoted by equation (6).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{6}$$

In the meantime, Bayes's specificity is quite small at 58 percent. This may be owing to the mistake of approximating the measurements of probabilities. Because of the small specificity, the warning may sound when there is no real somnolence. The driver may be disturbed by this.

TABLE III
SAMPLE

Method	Sensitivity	Specificity	Accuracy
Bayesian Classifier	0.969	0.572	0.857
FLDA	0.899	1	0.933
SVM	0.946	1	0.964

V. CONCLUSION

A low-cost, real-time driver drowsiness surveillance system relying on visual behavior along with machine learning approach has been introduced in this research work. However, From the streaming video recorded by a webcam, facial conduct characteristics such as eye aspect ratio, mouth closing ratio, and nose length ratio are calculated. In the meantime, to identify driver drowsiness in real time, an automated thresholding method has been created. Hence, the system has been performed with the artificial data produced correctly. The feature values are then stored and algorithms for machine learning have been used for classification. FLDA, Bayesian classifier, and SVM have been implemented here. FLDA and SVM have been noted to outperform Bayesian classification. The SVM and FLDA sensitivity are accordingly 0.948 and 0.896, while both specificities are 1 in the statistical measurement. As SVM and FLDA have provided better accuracy, work will be brought out to execute them in the developed method to perform the classification (i.e., drowsiness detection) online. The system will also be applied in hardware to enable its mobilityto the vehicle system, and driver pilot studies will be performed to validate the system created. To sup up, the system has been able to present a detection system of a driver drowsiness based on facial expression.

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