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DRIVER DROWSINESS DETECTION USING HAAR-ADABOOST BASED FACE DETECTION SCHEME WITH VISUAL BEHAVIOUR

[1]Prem Nisha. G, [2]R. Saranya

[#]Assistant Professors, Department of Computer Science and Engineering, Amrita College of Engineering and Technology, Anna University, Chennai, India.

***Abstract*:** If a person does not sleep well or rest while driving, it is easy to fall asleep, which can lead to a car accident. Therefore, there is a need for a system that can catch a drowsy driver. Recently, machine learning has been used in research and development to predict the state of the drive. These events can be used as information to improve road safety. A driver's status can be predicted by important characteristics such as age, gender and driving style. The driver's driving behaviour, facial expressions and biosignatures also contribute to the prediction. Machine learning has led to advances in video processing, allowing images to be analysed accurately. In this paper, we propose a method for analysing fatigue using a convolutional neural network model of eye position and use OpenCV and Dlib to extract subjects' detailed features of the mouth to count yawns.

Index Terms- **Machine Learning, Features Extraction, Drowsiness Detection, Blinking, Yawning.**

I. INTRODUCTION

Drowsy driving has become a major cause of car accidents. Drivers who drive at night or travel long distances without rest are more likely to have an accident. Because of this, many people were injured and died. Therefore, it has become an active research area. There are many systems that use physical, behavioral and vehicle features for this purpose. The physical properties required here are electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), heart rate, pulse rate, etc. The behavioral patterns discussed here are blinking, eye closing, yawning, staring, etc. while driving. visual behaviors. Features include wheel movement, acceleration, vehicle speed, braking pattern, off road departure, etc. Many of these processes are time consuming and expensive. In this system, we would like to have another method that uses images to detect fatigue through machine learning.

II. RELATED WORK

The percentage of road accidents caused by driver distraction tops the list. Among the many causes of driver crashes, fatigue, fatigue from fatigue is the most common cause. Many studies have been conducted to explore fatigue with the use of tools, behavioral and biological services. To solve this problem, many systems use automotive components, bio-signal technology, machine learning and computer vision.

A method by Kyong Hee Lee et al. It turns out that it is possible to determine how long a driver slept by removing his face. Image data from NTHU-DDD was used to test this method. Head posture, blinking, and mouth posture are considered characteristic. The angle of the driver's head helps determine the yaw and pitch angle.PERCLOS is used for flashing. The FACS unit is used to monitor yawning. The face is detected on the screen and displayed on the screen without all other perceptions such as yawning, winking, head yawning and voice angle. Timing for each character. If the parameter value exceeds the threshold, drowsiness is said to be detected.

The second approach includes behavioral testing and machine learning techniques to improve the system. This system was proposed by Mkhuseli Ngxande et al. [8] Machine learning techniques such as support vector machines, convolutional neural networks, and latent Markov models are used to measure behaviours such as blinking, yawning, and head movement. Use all three machine learning methods and evaluate the results. The support vector machine method has the highest accuracy, but similar to the latent Markov model, it is costly and the accuracy is second only to the support vector machine. Convolutional neural network methods provide high accuracy at low cost. They also gathered a lot of information that is publicly available through the search.

Another approach by Ashish Kumar et al. Visual behaviour is also covered in [2], ie. Eyes, mouth and nose. Identify faces using histograms of direction gradients and linear support vector machines. The detection algorithm is applied to 2D image frames extracted from movies. After detection, facial features are marked with the help of landmarks. Feature extraction is used for classification. Calculate the nose length ratio (NLR), eye ratio (EAR), mouth ratio (MOR). When the value of these parameters exceeds the threshold, the drive is classified as fatigue. The system uses the generated data to produce accurate results.

Many researchers use machine learning to monitor visual behaviour in search of sleep. Other topics include bio signalling devices or vehicle devices without the cooperation of machine learning algorithms. Machine algorithms such as Bayesian classifiers, support vector machines (SVM), hidden Markov models (HMM), and convolutional neural networks (CNN) are used. Each method has good accuracy for different facial features; Methods Supporting Vector Machines, Extended Markov Models, Bayesian Classifiers are more expensive than Convolutional Neural Networks. The larger the sample, the higher the cost and computational need.

III. THE PROPOSED SYSTEM

The block diagram of the drowsiness detection system while driving is shown in Figure 1. First record live video with webcam. The camera will be placed in front of the driver to capture the front view. Extract frames from video to get 2D images. Detect faces in frames using the Haar-Adaboost face detection method. When a face is detected, facial features such as the position of the eyes, nose and mouth are marked on the image. The position of the eyes and mouth can be evaluated according to facial symptoms. Using feature extraction and machine learning techniques, a decision can be made about the drowsy driver. Convolutional Neural Networks for eye classification to detect a drowsy driver considering blinks. As an additional feature of the system, the feature extraction method is used to calculate the mouth opening rate, which also helps determine if the driver is comfortable. If sleep is detected, an alert is sent to the driver to alert him. Details of each block are discussed in the next section.

The Media Research Lab Eyes dataset was used to train the model to detect open or closed eyes. [6] This file contains images of male and female eyes closed and open, with and without glasses, low angle, high angle and non-angle.

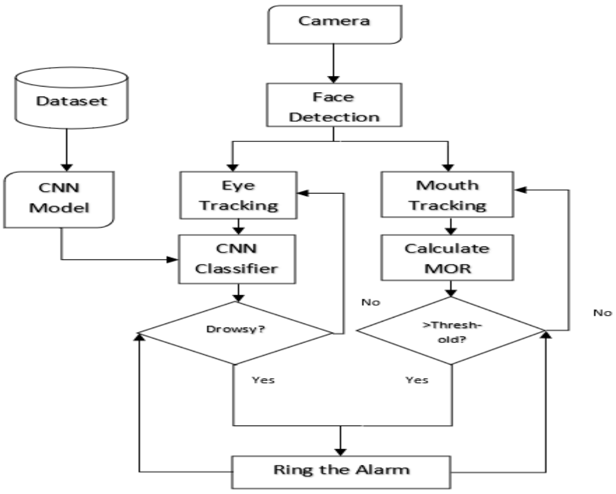
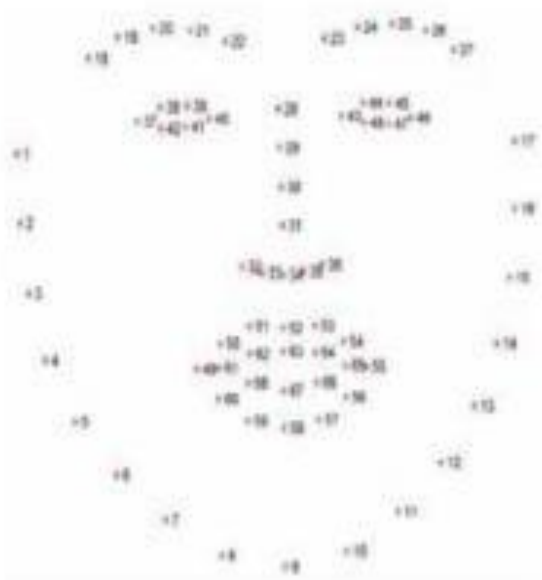


Figure 1. Block Diagram of proposed drowsiness detection system

3.1. Face Detection and Facial Landmark Marking

A face detection scheme based on Haar-Adaboost is used for the proposed operation. OpenCV functions are used to train the face detector. Access to face images from different angles, with different brightness, with and without glasses, for education. The face classifier that emerged after the training can identify face sizes from 240x240 to 320x320 pixels. [3] Functions in the dlib library for real-time integration detection. The shape predictor and get_frontal_face_detection functions are used for real face detection. We are using Python 3.8.2 and importing the OpenCV 4.2 library.0 and Dlib 19.19. This library can be used for face swapping or swapping operations. The OpenCV library provides pre-learning face or eye segmentation and measurement. Figure 2 in [2] below shows the mouth, left eye, right eye, and nose region.

Figure 2. The 68 facial landmark points from the iBUG 300-W dataset [1]



After detecting the face, the task is to determine the face's eye corners, mouth corners, nose, etc. to find the different parts. Prior to this, facial images must be normalized to reduce distance from the camera, uneven illumination, and differences in image resolution. [2] used gradient enhancing learning to optimize the sum of the squared error loss. Using this model to draw the boundary between the eyes and mouth, the details of the eyes and mouth are shown in Table 1.

Parts	Landmark Points
Mouth	[13-24]
Right Eye	[1-6]
Left Eye	[7-12]

3.2. Classification of Eyes by Convolutional Neural Network (CNN)

The proposed method uses a convolutional neural network (CNN) to detect driver drowsiness. CNN consists of layers such as convolution layers, pooling (maximum, minimum, and average) layers, ReLU layers, and all layers. Convolutional layers have cores (filters), and each core has width, depth, and height. [8]

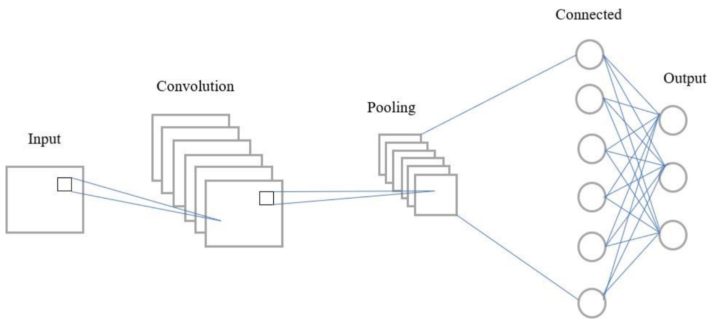


Figure 3. CNN Architecture

The input image is treated as a two-dimensional matrix by a convolutional layer. The number of nodes in the first and second layers is 32, and the number of nodes in the third layer is 64. All these convolutional methods use a 3x3 filter matrix. This layer creates a unique map by calculating the scalar product of the kernel and the region of the map. CNNs use layers (maximum or average) to reduce the size of the map to speed up computation. In this process, the input image is divided into different regions and then operations are performed on each region. In maximum pooling, the maximum value is selected for each region and placed in the corresponding position in the output. ReLU (Rectified Linear Unit) is a non-linear unit. [9] A rectifier linear unit (ReLu) is used as the activation function because it makes the test and does not saturate, it also gives non-linearity to the activation. A ReLU layer applies the max function to all values in the input data and replaces all negative values with zero.

$$f(x)=\max(0, x) \qquad (1)$$

where, x is the input and f(x) the output after the ReLU unit. The fully-connected layers used to produce class scores from the activationswhich are used for classification.

This level is based on the max join level. The maximal combination method is used to select the best features. Subsamples each output. After the 3 folded layers, a smoothing layer is used to flatten the output. The max pooling layer of the convolutional layer, the ReLU layer, and the outputs of all activations after the third convolutional layer are combined into a fully connected layer. Classification models are trained on left and right. Images for each eye were selected from original images. This can be done by removing the blindfold box. Scores from both networks are used to grade lectures.

$$Score = \frac{ScoreL+ScoreR}{3} \qquad (2)$$

where, ScoreL and ScoreR denote the scores obtained from left and right eyes respectively. The class can be found out as the label withmaximum probability.

Live video ensures regular sleep. An alarm will sound if you close your eyes more than 15 times. The CNN model was trained using a 15-cycle network with a default burst size of 32. Convolutional neural networks are more accurate and powerful than many machine learning algorithms.

3.3. Yawning Detection

Live video provides regular sleep. If the eyes are closed more than 15 times, the alarm will sound. The convolutional neural network model was trained using a 15period network with a default batch size of 32. Convolutional neural networks are more accurate and po werful than many machine learning algorithms.

Mouth opening ratio (MOR): Mouth opening ratio detects yawning during drowsiness. It is calculated as

$$MOR= \frac{(P15-P23)+(P16-P22)+(P17-P21)}{3(P19-P13)}$$

By definition, it increases very quickly when the mouth opens due to yawning, stays high for the duration of the yawn, and then quickly drops back to zero. Since yawning is a feature of sleepiness, the MOR provides a measure of the driver's sleepiness. This function is used together with the convolutional neural network as an additional function in the proposed system.

III. RESULT AND DISCUSSION

The method is used for many photo sales and results. The results of these tests are good if the algorithm detects closed eyes and open eyes when opened. To test the effectiveness of our method, we apply it to some indoor and outdoor images. Results from this method/system applied to blood cells are shown in FIG. 3. The system diagram shows that the eyes are closed.

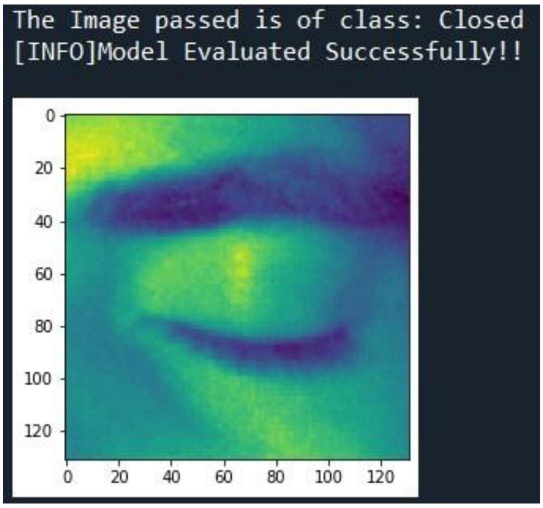


Figure 4. Closed eye successfully being detected closed.

The result that the method/system gives by applying it to open eye images is shown in Figure 4. The figure shows that the system indicates that the eye

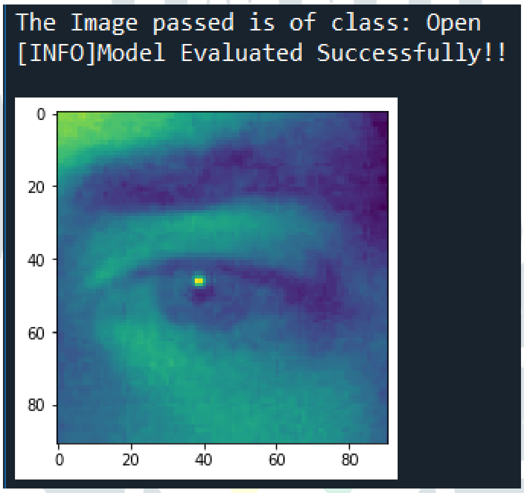


Figure 5. Open eye successfully being detected open.

Sometimes teaching takes place with eyes open and eyes closed, and vice versa. This phenomenon can be caused by the influence and reflection of light. Table II shows the performance of the system. Precision, Recall values and F1-Score are given in Table II. Table III lists the classification accuracy of the training and test data. The confusion matrix is listed in Table IV for analysis and research purposes.

State	Precision	Recall	F1-Score
Closed	0.95	0.95	0.95
Open	0.93	0.93	0.93

TABLE II: Result of applying the system to the dataset.

Method of Evaluation	Accuracy
Training Accuracy	98.1
Test Accuracy	94

TABLE III: Classification accuracy on training and test dataset.

State	Predicted Closed	Predicted Open
Actual Closed	410	22
Actual Open	21	411

TABLE IV: Confusion matrix.

IV. CONCLUSION

Identify faces, eyes, and mouths in driving images to diagnose drowsy drivers. A convolutional neural network is used to classify eyes as open or closed. Fatigue is determined by how often you close your eyes. Controlling yawn rate using Python's OpenCV and Dlib. When detected, a siren sounds to alert the driver. Detects driver status and expression, darkness, lighting conditions, driver hiding places, wearing sunglasses, etc. may be limited by factors. Convolutional neural networks offer better performance and face removal methods interact with them as a way to detect additional fatigue and are often used in conjunction with other face removal methods.

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