IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

DRIVER DROWSINESS DETECTION USING MACHINE LEARNING WITH VISUAL BEHAVIOUR

Shikha Pachouly[1], Neha Bhondve[#], Ashutosh Dalvi[#], Vinit Dhande[#], Neerav Bhamare[#]

[1]Assitsant Professor, Department of Computer Engineering, AISSMS-COE, Pune.
[#] B.E. Student, Department of Computer Engineering, AISSMS-COE, Pune.

Abstract**:** A person while driving a vehicle - if does not have proper sleep or rest, is more inclined to fall asleep which may cause a traffic accident. This is why a system is required which will detect the drowsiness of the driver. Recently, in research and development, machine learning methods have been used to predict a driver's conditions. Those conditions can be used as information that will improve road safety. A driver's condition can be estimated by basic characteristics age, gender and driving experience. Also, driver's driving behaviours, facial expressions, bio-signals can prove helpful in the estimation. Machine Learning has brought progression in video processing which enables images to be analysed with accuracy. In this paper, we proposed a method for detecting drowsiness by using convolution neural network model over position of eyes and extracting detailed features of the mouth using OpenCV and Dlib to count the yawning.

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

I. INTRODUCTION

Driving while being drowsy has become one of the major reasons of causing road accidents. Drivers who drive at night or for a long distance without resting are more prone to get involved in an accident. Large amount of fatal injuries and deaths occur because of this reason. Hence, it has become an active area of research. .

Various systems exist for this purpose which makes use of physiological features, behavioural patterns and vehicle-based features. Physiological features considered here are Electroencephalogram (EEG), Electrooculogram (EOG), Electrocardiogram (ECG), heartbeat, pulse rate etc. Behavioural patterns considered here are visual behaviours of drive like eye blinking, eye closing, yawning, head bending etc. Vehicle based features are metrics like wheel movement, acceleration, vehicle speed, brake pattern, deviation from lane pattern etc. Most of these methods are time consuming and expensive. In this system, we propose an alternate system which uses images for detection of drowsiness using machine learning.

II. RELATED WORK

The percentage of road accidents occurred due to distraction of driver tops the list. Among many reasons of distraction of driver, sleepiness, tiredness induced drowsiness is most probable reason. Researches have been done to to detect drowsiness with the help of vehicular, behavioural and biological. For solution, various systems have been proposed using with vehicular components, bio-signalling technologies, machine learning and computer vision.

One approach is to decide the condition of driver by its facial expressions is proposed by Kyong Hee Lee et al[1]. it has been shown that the drowsiness level of a driver can be determined by extracting its facial features. Video dataset from NTHU-DDD has been used to test the methods. Head pose, eye blinks and mouth status are the features considered. The angle of driver's head, helps find head yaw and pitch angle. PERCLOS is implemented for eye blinks. Action unit from FACS is used to monitor yawning. The face is detected on the screen and parameters of all other detected features like yawn, blinks, head yaw and pitch angle are shown on the screen. A threshold is set for all the attributes. If parameter value exceeds the threshold value, drowsiness is said to be detected.

Second approach includes behavioural measures and machine learning techniques to develop a system. The system is proposed by Mkhuseli Ngxande et al. [8] Machine learning techniques like support vector machine, convolutional neural network and hidden markov model are used for behavioural measures like eye blinks, yawns and head movements. All three machine learning approaches are applied and results are tabulated. Method with support vector machine approach gives highest accuracy but with high cost, similar to hidden markov model, with accuracy just next to support vector mechanism. Method with convolutional neural network gives good accuracy with lesser cost. They have also listed various publicly available datasets for drowsiness detection practices.

Another approach by Ashish Kumar et al. in [2] also consider visual behaviours viz. eyes, mouth and nose. Face is detected using histogram of oriented gradients and linear support vector machine. The detection algorithm is applied on frames of 2D images extracted from video. After the detection, facial landmarks are marked with the help of landmark points. Feature extraction is implemented for classification. Nose Length Ratio (NLR), Eye Aspect Ratio (EAR), Mouth Opening Ratio (MOR) are calculated. When values of these parameters go beyond threshold, driver is classified as drowsy. The system generates accurate results with generated system data.

Many researchers have followed visual behaviours with machine learning for implementing the drowsiness detection system. Other researched systems include bio-signalling equipment or vehicular components, without any collaborative use of machine learning algorithms. Machine algorithms like Bayesian classifier, Support Vector Machine (SVM), Hidden Markov Model (HMM), Convolutional Neural Network (CNN) have been used. All of the methods give good accuracy for different facial features; methods support vector machine, hidden markov model, Bayesian classifier cost more than convolutional neural network in training. Bigger the model grows, bigger the cost and computational requirements grow.

III. THE PROPOSED SYSTEM

The block diagram of the proposed driver drowsiness detection system has been depicted in Fig 1. At first, the real-time video is recorded using a webcam. The camera will be positioned in front of the driver to capture the frontal face image. The frames are extracted from video to obtain 2-D images. Face is detected in the frames using Haar-Adaboost face detection method. After detecting the face, facial landmarks like positions of eye, nose and mouth are marked on the images. From the facial landmarks, position of eyes and mouth are quantified. Using these extracted features and machine learning methods, a decision is obtained about the drowsiness of the driver. Convolution neural network is applied for classification of eyes, which detects drowsiness of driver by considering blinking of eyes. As an additional attribute to the system, feature extraction method is used for calculating mouth opening ratio, which also helps to decide if the driver is easy. If drowsiness is detected, an alarm will be sent to the driver to alert him/her. The details of each block are discussed in further sections.

For the purpose of training the model to detect the open or closed eyes , a dataset of eyes from Media Research Lab is used.[6] The dataset contains images of eyes of males and females, eyes closed and open, with and without glasses, with low reflection, high reflection and no reflection.

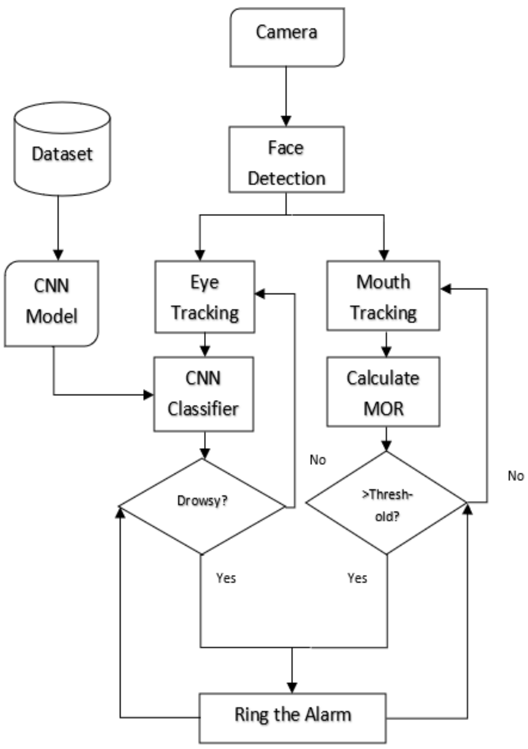

Figure 1. Block Diagram of proposed drowsiness detection system

3.1 Face Detection and Facial Landmark Marking

The Haar-Adaboost based face detection scheme is applied to the proposed system. OpenCV functions are used to train the face detector. For training, Face images with different angles, different brightness, wearing glasses, and not wearing glasses are fed. After training, the obtained face classifier can detect the facial sizes, which are ranged from 240x240 to 320x320 pixels.[3] Functions from dlib libraries are used to incorporate the detection in real-time. Functions shape_predictor and get_frontal_face_detection is applied for real-time face detection. We used Python 3.8.2 and imported libraries of OpenCV 4.2.0 and Dlib 19.19. These libraries can also be applied for face morphing or swapping functions. The OpenCV library provides a previously trained classifier for the face or the eyes as well as a detector. The following figure, Fig 2, in [2] shows the landmark points of mouth, left eye, right and nose.

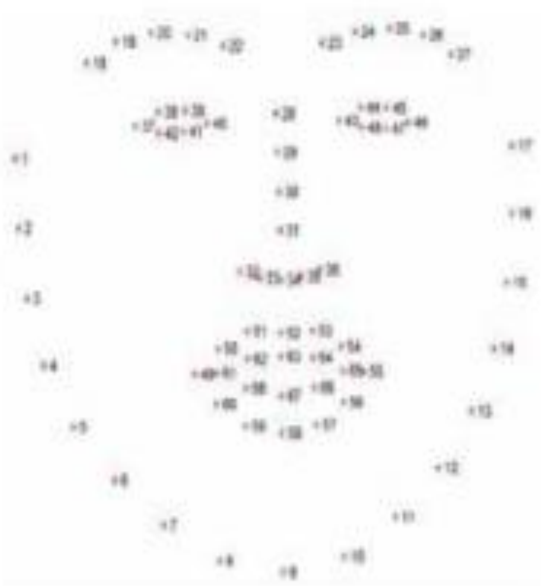

Figure 2. The 68 facial landmark points from the iBUG 300-W dataset [1]

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.[2] The sum of square error loss is optimized using gradient boosting learning. Using this method, the boundary points of eyes and mouth are marked and the number of points for eye and mouth are given in Table I.

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

Table I: Facial landmark points

3.2 Classification of Eyes by Convolutional Neural Network (CNN)

Convolutional neural network (CNN) is used in the proposed system for detection of driver drowsiness. CNN have layers like convolutional layers, pooling (max, min and average) layers, ReLU layer and fully connected layer. Convolution layer is having kernels (filters) and each kernel having width, depth and height.[8]

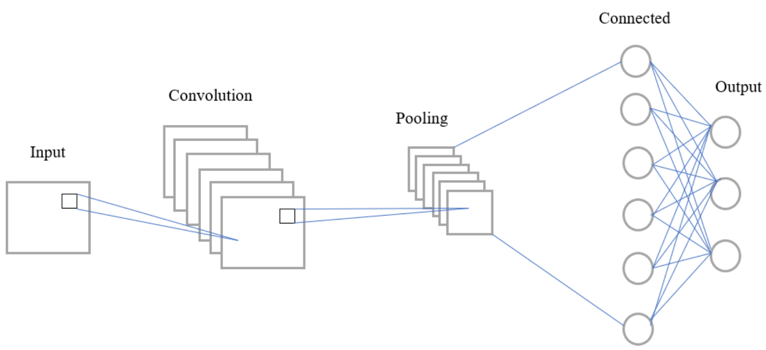

Figure 3. CNN Architecture

The input images are seen as two-dimensional matrices by the convolutional layers. The number of nodes is 32 in first and second layer and 64 in the third layer. The filter matrix of 3x3 is used in all these convolutional layers. This layer produces the feature maps as a result of calculating the scalar product between the kernels and local regions of image. CNN uses pooling layers (Max or Average) to minimize the size of the feature maps to speed up calculations. In this layer, input image is divided into different regions then operations are performed on each region. In Max Pooling, a maximum value is selected for each region and places it in the corresponding place in the output. ReLU (Rectified Linear Units) is a non-linear layer.[9] The Rectifier linear unit (ReLu) is used as an activation function as it does prompt evaluation and does not saturate, it also provides non-linearity to activations. The ReLU layer applies the max function on all the values in the input data and changes all the negative values to zero. The following equation shows the ReLU activation function.

$$f(x)=\max(0, x) \tag{1}$$

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 activations which are used for classification

A Max Pooling layer is used after this layer. Max pooling method is used to choose best features. It does sub-sampling of each output. After three convolution layers, a flatten layer is used to flatten the output. After the convolutional, ReLU, and max-pooling layers in the third convolutional layer, the outputs from all the activations are joined in a fully connected layer. The classification model is trained for left and right eye. Image of each eye is selected from the original image. This can be achieved by extracting the boundary box of the eye. The scores from both the networks are used to obtain the class labels.

$$Score = \frac{ScoreL+ScoreR}{3} \tag{2}$$

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

The real-time video is examined continuously for drowsiness. If eyes are labelled as closed for more than 15 times, the alarm starts beeping. The convolutional neural network model is trained with a network of 15 epochs and with default batch size of 32. The accuracy and robustness of convolutional neural network are better than many standard machine learning algorithms.

3.3 Yawning Detection

Yawning is an unconscious behaviour which is evident of tiredness and sleepiness. One method used to detect mild fatigue is to study the yawning behaviour of a driver [9]. As an indicator of fatigue, yawning is estimated as to stretching of the mouth in the action unit of the Facial Action Coding System.[1]. Because yawning is characterized by a slow and wide opening of the mouth, detecting the sides of the mouth and measuring the size and shape of the mouth is necessary to identify a yawn.

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

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

As defined, it increases rapidly when mouth opens due to yawning and remains at high value for a while due to yawn and again decreases towards zero rapidly. As yawn is one of the characteristics of drowsiness, MOR gives a measure regarding driver drowsiness. This functionality is used as an additional functionality in the proposed system, along with convolutional neural network.

IV. RESULT AND DISCUSSION

The method is applied to several eyes images and the results are obtained. The result of these tests is positive if the algorithm detects closed eys as closed and open eye as open.
In order to evaluate the performance of our method we applied it to some closed and open images. The result that the method/system gives by applying it on closed blood cells is shown in Figure 3. The figure shows that the system indicates that the eye is closed.

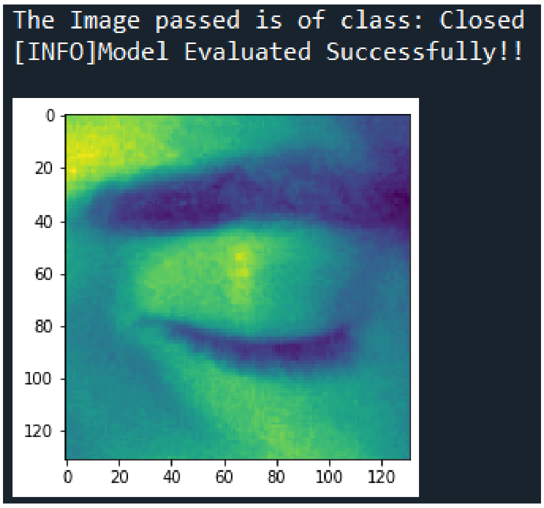

Figure 4. Closed eye successfully being detected closed.

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 is open.

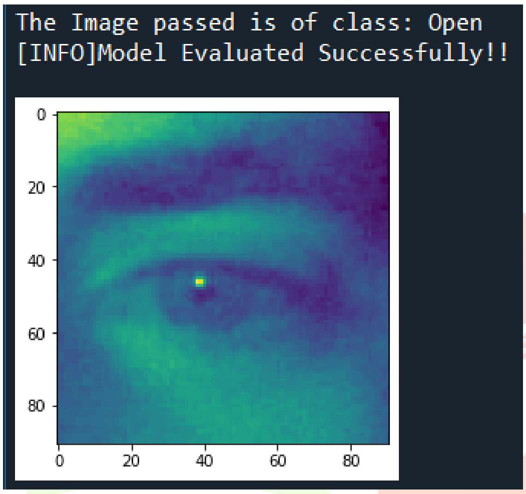

Figure 5. Open eye successfully being detected open.

In some cases, the method indicated that the result is open while the eye is closed and vice-versa. This result could be caused to effect of light and its reflection. Table II shows the performance metrics of the system. In Table II, Precision, Recall value and F1- Score have given. In Table III, the classification accuracy on training and test dataset has listed. In Table IV, confusion matrix has listed for analysis and study purpose.

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
Trainig 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.

V. CONCLUSION

In order to detect a driver's drowsiness, facial features, eyes and mouth were identified on the video of an individual driving. Convolutional neural network was implemented to classify eyes as open or closed. Drowsiness was determined on the basis of frequency of closed eyes. Using OpenCV and Dlib in Python, frequency of yawning was examined. An alarm was set to ring after the detection to alert the driver. There will be limitations concerning the detection of drivers' conditions and facial expressions due to factors like darkness, light reflection, obstructions by drivers' hands and wearing of sunglasses. Convolutional neural gives better performance and facial extraction method accompanies it, as an additional drowsiness detection technique which is often used with other facial extraction methods.

VI. ACKNOWLEDGEMENT

We would like to thank Prof. Shikha Pachouly Ma'am, under whose guidance we were able to fulfil our research and project idea. We would also like to thank the department of computer engineering at AISSMS College of Engineering for their support and guidance.

VII. REFERENCES

[1] Kyong Hee Lee, Whui Kim, Hyun Kyun Choi, Byung Tae Jang, "A Study on Feature Extraction Methods Used to Estimate a Driver's Level of Drowsiness", International Conference on Advanced Communications Technology (ICACT), 2019.

[2] Ashish Kumar, Rusha Patra, "Driver Drowsiness Monitoring System using Visual Behaviour and Machine Learning", IEEE Conference, 2018.

[3] Cyun-Yi Lin, Paul Chang, Alan Wang, Chih-Peng Fan, "Machine Learning and Gradient Statistics Based Real-Time Driver Drowsiness Detection", 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW).

[4] Ching-Hua Weng, Ying-Hsiu Lai, Shang-Hong Lai, "Driver Drowsiness Detection via a Hierarchical Temporal Deep Belief Network", In Asian Conference on Computer Vision Workshop on Driver Drowsiness Detection from Video, Taipei, Taiwan, Nov. 2016

[5] Anjith George, Aurobinda Routray, "Real-time Eye Gaze Direction Classification Using Convolutional Neural Network", IEEE, 2016.

[6] Media Research Lab, http://mrl.cs.vsb.cz/, 2018.

[7] Venkata Rami Reddy Chirra, Srinivasulu Reddy Uyyala, Venkata Krishna Kishore Kolli, "Deep CNN: A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State", Revue d'Intelligence Artificielle Vol. 33, No. 6, December, 2019, pp. 461-466.

[8] Mkhuseli Ngxande, Jules-Raymond Tapamo, Michael Burke, "Driver drowsiness detection using Behavioral measures and machine learning techniques: A review of state-of-art techniques", 2017 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech).

[9] T. Vogelpohla, M. Kühn, T. Hummel, M. Vollrath, "Asleep at the automated wheel—Sleepiness and fatigue during highly automated driving", https://doi.org/10.1016/j.aap.2018.03.013, Accident Analysis and Prevention, 2018.

[10] Xuan-Phung Huynh, "Detection of driver drowsiness using 3D deep neural network and semi-supervised gradient boosting machine", in Asian Conference on Computer Vision Workshop, 2016

[11] A. George and A. Routray, "Real-time Eye Gaze Direction Classification Using Convolutional Neural Network," Int. Conf. Signal Process. Commun., pp. 1–5, 2016