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Driver Drowsiness and Intoxication Detection System

Sinchana Hegde[1], Pranav Mahajan[2]

1Department of Information Science and Engineering, R.V College Of Engineering , Banglore, India
sinchanarh.is18@rvce.edu.in
[2]Department of Information Science and Engineering, R.V College of Engineering, Banglore, India
pranavmahajan.is18@rvce.edu.in

Abstract

Driver drowsiness detection is a technology which alerts drivers if he/she is getting drowsy and prevents road accidents.In this paper an efficient way to detect driver drowsiness system is developed to ensure safety of drivers on the road .The falling sleep state of the driver acts as the sign of drowsiness and to achieve high accuracy and fastness Convolutional Neural Networks[1] (CNN) is used. The system developed here identified key attributes of drowsiness such as eye closure, yawning, and fatigue in drivers .The system also detected intoxication using pupil movements. Alert was generated based on eye detections and warnings on drowsiness were given based on yawning and pupil movement tracking for intoxication.

Keywords—Drowsiness, Deep learning, Convolutional neural network, Intoxication, OpenCV, Dlib, Pupil, Iris

1 INTRODUCTION

In recent decades automobiles have become a vital part of human life, they have considerably made our day-to-day activities more convenient, but there are some negative effects that come along with these benefits. According to published reports from the World Health Organization (WHO), traffic accidents leads to top 10 deaths in the world.In these accidents, fatigue of driving caused approximately 20% −30%[1] of traffic accidents .According to the above statistics it is evident that fatigued driving has caused lot of traffic accidents.So it's necessary to alert the driver while he is drowsy to avoid accidents.

Vehicle based , Signal based , and Behavioural based these are three main categories to detect drowsiness of the driver . Vehicle based methods detect drowsiness of the driver from vehicle situations such as steering wheel angle, acceleration, lateral position. Signal based methods detect drowsiness from psychophysiological parameters(ECG ,EEG) etc.

Lastly Behavioural methods, this evaluates the drowsiness in real time with less expensive materials than other methods.In this paper behavioural based method is used to detect drowsiness. The problem statement behind the project is to reduce the risk of automobile accidents by implementing a system which could detect the fatigue in the driver through his/her facial features to alert the driver while driving.

Additionally, to detect alcohol intoxication using facial features of the driver as alcohol intoxication can also lead to major accidents.The industrial relevance of the project is as it can be used to build a certain embedded system which can fit in automobiles to detect the drowsiness in the driver which in turn can alert the driver based upon drowsiness detected and can prevent certain major accidents.

II. RELATED WORKS

In this section, several relevant and well-known papers are studied to understand what the present systems offer and how they operate. Authors in [1] published paper which was based on early detection of driver drowsiness . To differentiate between the alert state and drowsy state of a driver ensemble machine learning is used. Several machine learning algorithms were used to identify differences between the alert and drowsy state of driver. 78.7% accuracy obtained with the help of random forest algorithm. Limitations in above study was that number of participants was less, and all were males in their 20s.
In the same year another paper based on real-Time driver drowsiness detection is published [2] to detect the drowsiness of the driver. Authors made use of convolutional neural network to detect drowsiness and alert is generated if the system detects the eye closure continuously for more than 15 successive images. Gaps identified -authors had not considered yawning detection and alcohol intoxication, which are the features of drowsiness.

Furthermore another paper was published [3] For motive force drowsiness detection based totally on eye country. This categorized the origin of the eye that is drowsy or non drowsy and indicators with an alarm whilst the kingdom of the eye is drowsy. Viola-jones[3] detection set of rules is used to discover face and eye regions.Authors in[4] published paper on detection of driver fatigue symptoms using transfer learning .In this paper, transfer learning(AlexNet) and convolutional neural networks[4] were used to detect driver fatigue features. Presented technique did not consider assessment of the real level of fatigue caused mostly by sleep deprivation that can seriously effect drivers.For detecting alcohol intoxication paper was published [5] which gave Comprehensive review on different datasets related to alcohol intoxication detection .This paper gave the idea of how the DIF dataset is created and what features can be used to detect alcohol using faces.Dataset made is still not 100 percent accurate to detect intoxication through faces and it needs to be enlarged more.

In the same year another paper was published[6] which Used feature extraction , color analysis, correlation based feature selection, ML classification and random forest to create a model, but this system had limited dataset, coarse classification, higher system requirements and internet access from smartphones. Another paper on alcohol intoxication was[7] to track facial intoxication in form of facial temperature map. Authors used IR images to reflect alcohol intoxication and used K-means clustering for optimal distribution of pixels and evolutionary computing optimization. limitation of this research was the model built had robustness and sensitivity issues in predicting as well as limited dataset availability.

Authors in[8] proposed a method on detection of alcohol intoxication which presents different approaches for identifying alcohol intoxication . Overall 80% success rate is achieved for separate method .The gap identified was that limited dataset availability and accuracy concerns in models related to technique used.

III. ARCHITECTURE

In the current study, the deep neural network architecture actualized is convolutional neural network[8] (CNN). It is a special type of deep neural network[8] which is mainly for image processing and classification . CNN model architecture in the present study is shown in figure1.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 143, 143, 256)     7168
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 71, 71, 256)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 69, 69, 128)       295040
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 34, 34, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 64)        73792
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 14, 14, 32)        18464
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 7, 7, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 1568)              0
_________________________________________________________________
dropout (Dropout)            (None, 1568)              0
_________________________________________________________________
dense (Dense)                (None, 64)                100416
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 260
=================================================================
Total params: 495,140
Trainable params: 495,140
Non-trainable params: 0
```

Figure 1: Architecture of CNN

The output layer contains Softmax as an activation function. SoftMax[8] function is used to calculate probability distribution of the classes. In all other layers Relu is an activation function. To improve the firmness of the neural network batch normalization is used.

IV. DATASET

This section discusses the dataset used for training in the model.The datasets used in the model are MRL-EYE Dataset available on kaggle. This helps to train the model and to detect closed eyes, open eyes. Eye dataset is prepared for classification tasks containing single eye images which were captured in various lighting conditions.Yawning and intoxication, no dataset is required as it will use Dlib and OpenCV in real time based mathematical calculations of finding Region of Interest from the images given to it in real time.

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A. Data Preprocessing

In the first step Images belonging to open and closed categories are read and converted to grayscale .These images are then resized to (24,24) to work with the model. After preprocessing these images are saved.The images in the training set are randomly shuffled and features,labels are separated.All the images are normalized.For yawning and intoxication part, Dlib library along with OpenCV is used inorder to preprocess image in the real time to detect the features related to mouth positions, lip positions, distance between lips, and pupil movements

B. Data Visualization

Input image is taken and eye region is extracted and then converted to grayscale. .

Input image:

Figure2: Input Image[9]

From figure 2 eye region is extracted . After getting region of interest(ROI) we converted that in to grayscale so it can be fed into a model for training.

Figure 3: Closed eye

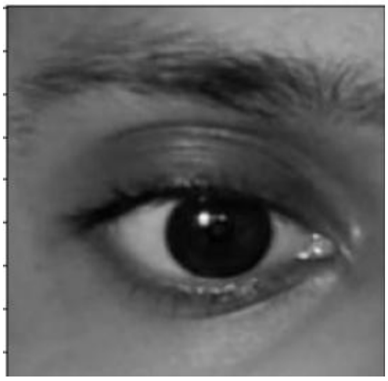

Figure 4: Open eye

V. METHODOLOGY

Region of Interest Selection

This section includes the selection of the region of interest for the eye detection , yawn and intoxication detection. For finding eyes, first we estimated headbox area ,Viola and Jones algorithm[11] is used for frontal face detection and facial landmarks analysis is done using Dlib. This method reduces the time of computation for detection to a considerable amount. Front eyes part of the camera must be decided on because it contains more data and decreases the mistake rate in the version. To reap this end result, the algorithm computes the distance between the distant left and distant right of the left and the proper eyes and compares them to pick out for locating the greater distance for cropping criteria. The eye distance intended for our undertaking is proven in determine 5. The set of rules used, unearths eye landmarks from the figure 5, measures the absolute distance between point 37 and 40, 43 and 46, and selects the most important distance as the front of the camera. For yawn detection , lips landmarks are initially detected , distance between the point 50 , point 54 ,point 61 and point 65 are calculated for the upper lips, similarly distance between the point 65, point 69, point 56 and point 60 are calculated for the bottom lips. For the upper lips and lower lips detected , the mean is calculated for both which will be later used for real time detection of the yawning based on some threshold distance between upper lips and lower lips. For pupil and iris detection , we used the eyes detected earlier in the model and extracted the features related to pupil from it. We feed the eye image to a function which will binarize the eye frame based on the threshold value used and will return the frame with a single element representing the pupil. Then we detected the iris in real time and calculated its position by calculating the centroid.

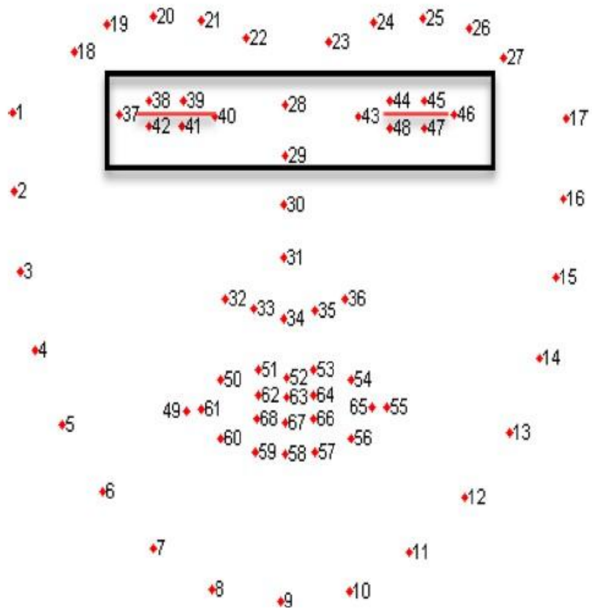

Figure 5: Facial Landmarks [10]

A.Taking Image Required as Input from a Camera

For taking pictures as input from a digital camera, Opencv is employed. so to access the webcam, we create an endless loop that can hold the whole frame.

B.Detect Facial Features in Image and Create Region of Interest (ROI)

To get a face feature in an image, we first convert the image to grayscale as the [8]OpenCV object detection algorithm captures gray images as input. We used a haar cascade classifier to find the face. Face detection is done using face.detectMultiScale (gray). Returns the acquisition list with x coordinate, y coordinate, and coordinates of height, the width of the object's boundary box.

C.Detecting eye region from ROI and input it to the classifier

The equal method we used to get face is now used to get eyes. First, we set the [8]cascade partition via eye to l_eye and r_eye respectively and then eyes were detected the usage of left_eye = leye.Detectmultiscale (gray). After this we've most effective extracted eye statistics from the total picture. That is accomplished by using eliminating the eye-catching container and extracting the eye photograph from the body with this code. The same technique is used to gain the right eye.

D.Classification

We used CNN segmentation/classifiers to predict eye condition. Before uploading our image to a model, we have done some tasks because the model requires the right size to start with. First, we changed the color image to gray. After that, we measured the image into 24 * 24 pixels as our model was trained in 24 * 24 pixel images. We have set our details for the best combination r_eye = r_eye / 255 (All values will be between 0-1). increase the feed size in our divider. We uploaded our model and predicted each eye with our model.If the prediction value is 1 it means the eyes are open, if the predictive value is 0 at that time, it says the eyes are closed.

E.Calculate Score to detect Drowsiness

Points/Score are actually a price we often want to guarantee no matter when someone closes their eyes for a long time. Therefore, when each unit of the eye area is closed, we tend to continue to increase points and when the eye area is open, we tend to reduce points. The limit is set for example if the school becomes larger than fifteen which means that the area of the human eye area is closed for an extended period. This usually happens after we sound the alarm.

F. Yawn and Intoxication Detection

The lip distance was calculated initially while determining the region of interest, based on that lip distance determined, if the distance between the upper lip and lower lip is more than lets say 25, then it will count as a yawn and this warned the driver of drowsiness and correspondingly, count of yawn during the interval is calculated. For intoxication detection the pupil is detected while determining the region of interest, if the pupil are stagnant for let's say about 10 seconds, then it noted as intoxicated and driver warned of intoxication.

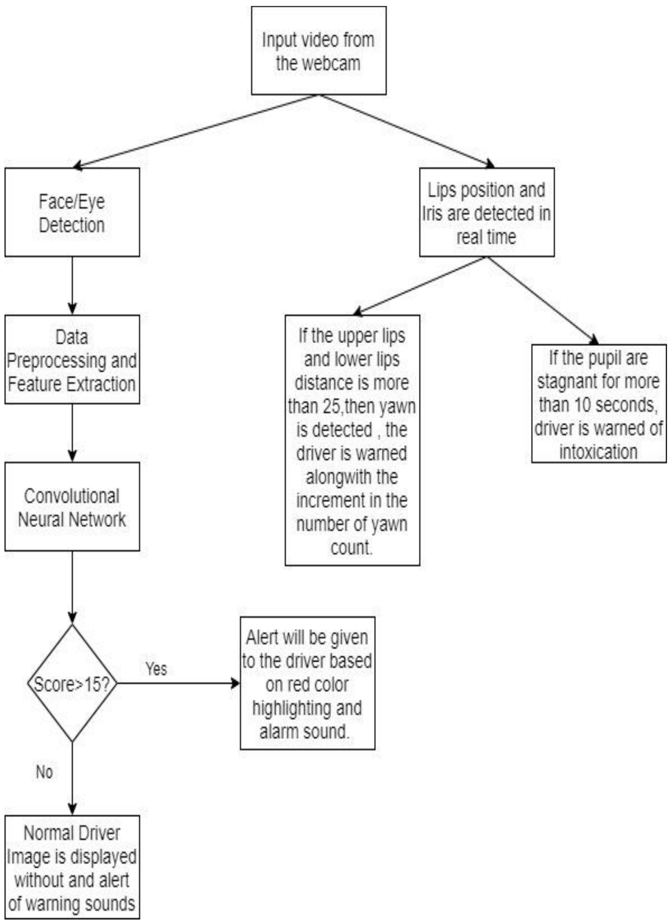

Figure 6: Proposed Workflow

VI. RESULT AND ANALYSIS

With the above mentioned CNN based model we achieved an accuracy of about 92%, the model was trained on CNN as mentioned above and 10 epochs were done to train the model, the model of tested based on different learning rates and with different optimizers and correspondingly we found accuracies related to each and selected the best one out of it. The model was validated for overfitting using the history of the model. The model shows training accuracy of over 92% and validation accuracy of 93%, as there is not much difference between their values, this shows the model was free from overfitting as shown in graph in figure 7.

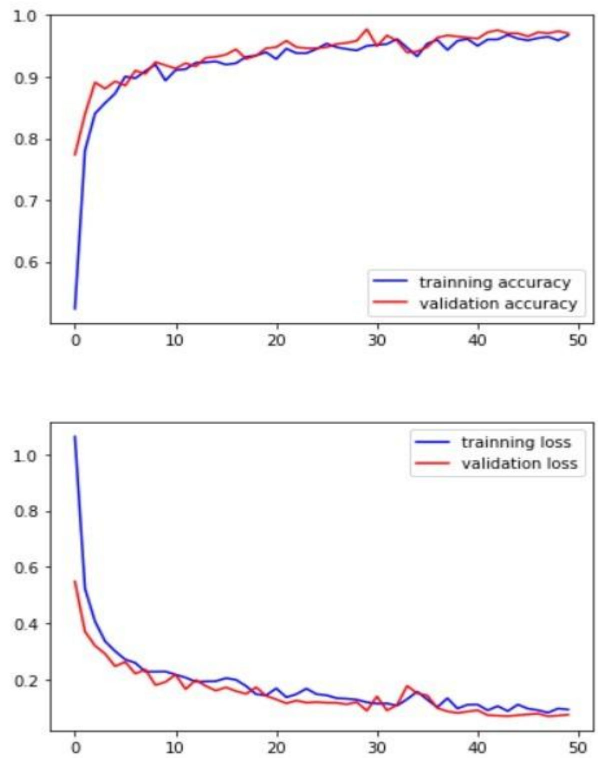

Figure 7: Accuracy Graph

We selected the relevant features for the model by calculating F-Score for each feature in our model.F-Score is calculated using the differences between features and variations within each feature. A high F rating usually means that a factor is more important than a factor with a lower F-score. We counted the F-Scores of the feature and the following plot was obtained as shown in the figure 8.

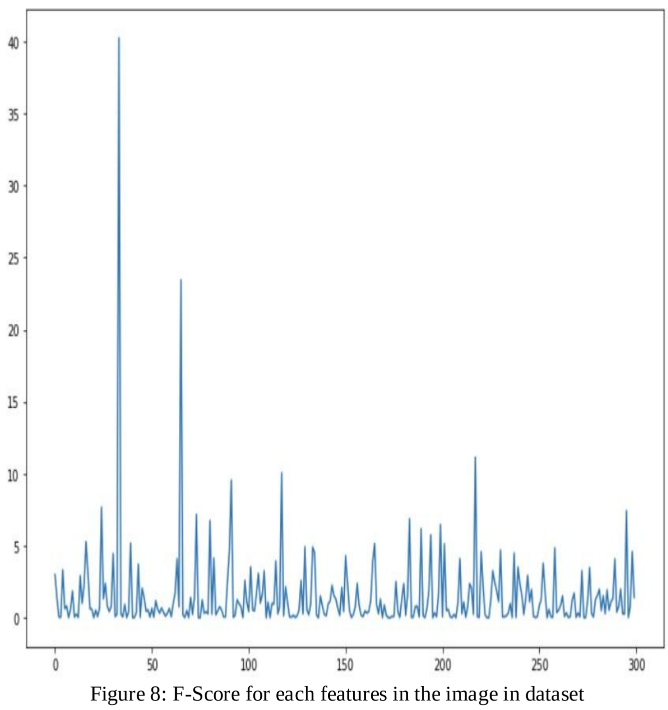

Figure 8: F-Score for each features in the image in dataset

The model was also validated and hyper parameter tuning was done with different learning rates and with two different optimizers as shown in the table 1**,** So based on accuracy best learning and optimizer was chosen to implement the model.

Table 1: Parameter Tuning

Learning rate	Optimizers	Accuracy
0.0001	SGD ADAM	60.89 66.77
0.001	SGD ADAM	85.02 92.16
0.01	SGD ADAM	61.19 73.65
0.1	SGD ADAM	59.96 62.17

During the test phase,captured frames of video with the camera device and alert via alarm when the model predicts the state of continuous drowsiness. Vertical images are used for training but during the test independent of the keys are removed from the continuous video and tested for professional still images.

VII. CONCLUSION

Sleep deprivation aka drowsiness plays an important role in safe driving and averting street injuries and this paper proposes a new manner to save you accidents from drowsiness. Consequently, within the first step of the program, this system takes a standalone broadcast, and in the pre-training unit, key factors are used to achieve the roi, wherein case the attention place is selected, and the unit used selects the attention in the front of the digital camera item. Extracted part of images were input to the model to train. If the model finds the eye closed with more than 15 consecutive images, an alarm is sounded. Otherwise, it considers it as normal blinking.The system also detected alcohol intoxication using pupil movements. Alert will be generated based on eye detections and warnings on drowsiness will be given based on yawning and pupil movement tracking for intoxication.

In the future, a different level of drowsiness will be investigated without limitation because the boundaries between the various drowsiness levels are very small, and it can be a daunting task and we can use [9]transfer learning to improve system performance.

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