A modified neural network model for Real-time Driver Drowsiness detection system

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Abstract: **-** World is running fast. With the speed of communication technology, there is a boom in the transportation industry also. The transportation vehicles are operating day and night to provide proper support of the need. This is really tiring for the transportation workers, especially the drivers who are driving the vehicle. A slight negligence of a driver may cause huge loss. The increasing number of road accidents are therefore a big concern. There is huge research going on to comfort the drivers and increase the security features of vehicles to avoid accidents. Here is this work, a model is proposed, which can efficiently detect driver drowsiness. The work mainly focused on building the learning model. A modified convolutional neural network is built to solve the purpose. The model trained with a dataset of 7000 images of open and closed eyes. For testing purposes, some real-time experiments are done by some volunteer drivers in different conditions, like gender, day, night, etc. the model is really good for daytime and if the driver is not wearing any glass. But with a glass in the eye and in night condition the system needs improvements.

Key-Words: Computer Vision, CNN, Drowsiness Detection, Machine Learning, face detection

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1. Introduction

With the advancement of various fields, the demand for transportation became high. To meet the demand, the vehicles are running day and night. This is really tiring for the transportation workers, especially the drivers who are driving the vehicle. A slight negligence of a driver may cause huge loss. The increasing number of road accidents are therefore a big concern. According to the road accident report published in the website of ministry of road transport and highways, Government of India, there were 366138 road accidents in India in the year 2020, as updates last till date [1]. One of the major causes is alertness of the driver, especially during night time. With the advancement of automated vehicle technology, the research is going on different aspects of safety too. The approach to detect driver drowsiness is one of them. Here we are in search of an automated system that can detect drowsiness and alert the driver. Machine learning is used in diversified areas like handwritten character recognition [3, 5, 7], medical image processing [2, 4, 6].

Here in this work, a neural network based model is proposed, which can efficiently detect driver drowsiness and alert the driver. The work mainly focused on building the learning model. A modified convolutional neural network is built to solve the purpose. The model trained with a dataset of 7000 images of open and closed eyes. For testing purposes, some real-time experiments are done by some volunteer drivers in different conditions, like gender, day, night, etc. the model is really good for daytime and if the driver is not wearing any glass. But with a glass in the eye and in night condition the system needs improvements.

2. Study of the Literature

Over the recent years, detection of driver fatigue has generated quite a lot of research interest and can be broadly classified into four categories [8]. The first category deals with methods based on physiological signals obtained from the driver, for example, electroencephalograph (EEG), electrocardiograph (ECG), and electrooculogram (EOG) signals [9, 10]. It has been shown that these methods have good predictive ability. However, obtaining clean datasets in this case offers considerable challenge in designing such methods [11, 12]. The second category relies on the behaviour of the driver such as decrease in the grip strength on the steering wheel or the lack of ability to control the steering wheel, both provide a measure for the driver's fatigue [13]. The departure of the vehicle from the intended trajectory, that is, deviation of the vehicle state can also be a good measure for the driver's fatigue and forms the foundation for the third category [14]. Finally, the driver's drowsiness can also be detection through physiological reactions from the driver, such as closed eye over a duration, which is the focus of the current work. The frame wise facial expression and their ratio is used for detecting the drowsiness in [15]. Another work based on facial expressions [16] claims 95.58% sensitivity and 100% accuracy for o-line detection with SVM classifier. Eye closure and yawning ratios is also used as facial expression, and classified through machine learning algorithm to detect drowsiness [17]. Considering eye as the only facial expression to detect sleepiness is sufficient and is established in many work [18, 19].

3. Proposed Methodology

3.1. The Overall System

The methodology adapted in the current work is shown in Fig. 1. The first stage consists of a webcam that captures the real-time video of the driver. It then locates the face as the first region of interest (ROI) from then the eye, which is the second region of interest. The second stage consists of a previously trained Convolutional Learning Model that is used to classify; the job of the classifier is to classify the state of the eyes as `open' or `close'. The final stage of the proposed system is to ring an alarm if the eyes are found close for some threshold value (3 seconds in this case).

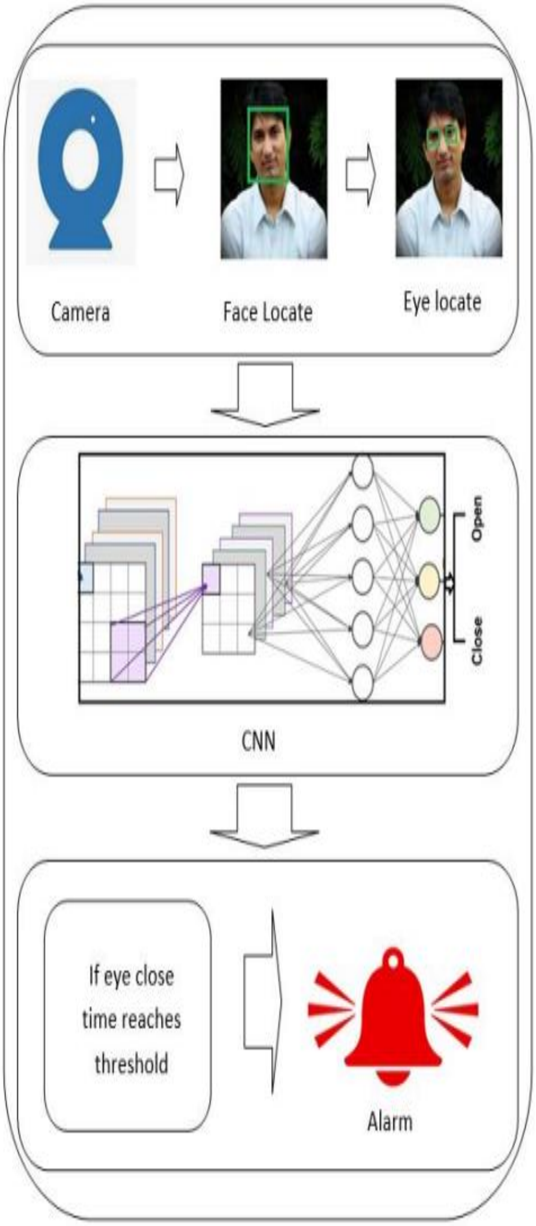

Figure 1: The Overall System

3.2. Pre-processing

Before producing the input, the image is converted to grayscale image and basic transformations- translation, rotation and scaling are applied. To translate the original coordinates (X, Y) to a new translated coordinate (X_t, Y_t) by the shift coordinate (Tx, Ty), the basic rule of translation is performed as follows-

$$[X_t] = [X] + [T_x]$$
$$[Y_t] = [Y] + [T_y] \quad (1)$$

To rotate the images from coordinate (X, Y) to the desired angle Θ with new coordinate (X_r, Y_r), the basic scaling technique is used as follows-

$$[X_r, Y_r] = [X, Y]\begin{bmatrix} cos\Theta & sin\Theta \\ -sin\Theta & cos\Theta \end{bmatrix}$$
for positive rotation

$$= [X, Y]\begin{bmatrix} cos\Theta & sin\Theta \\ -sin\Theta & cos\Theta \end{bmatrix} \quad (2)$$
for negative rotation

particular, the work- flow of our CNN model is as shown in Fig. 2.

The hidden layers consist of 3 Convolution layers, each activated with ReLU function to extract significant features from the input images to rectify the feature maps. Note that the ReLU activation function is as follows:

$$f(x) = max(0, x). \quad (4)$$

Each convolution layer is succeeded by a pooling layer that reduces the dimensionality of the feature map. Here, we have implemented a max pool operation in the pooling layer.

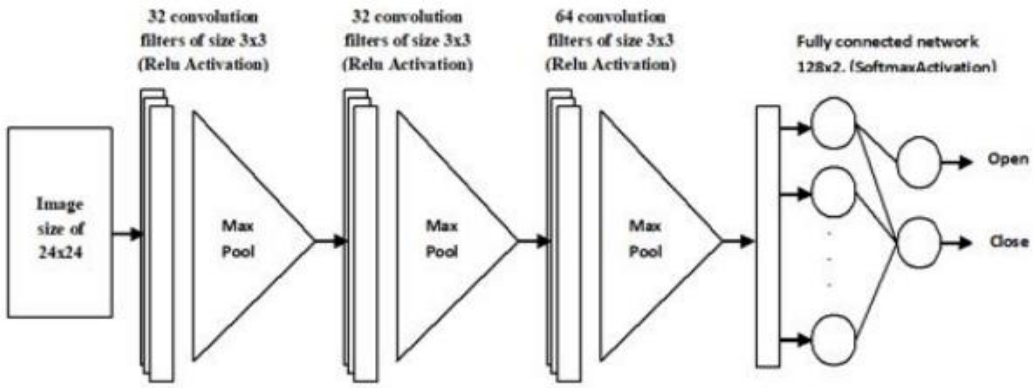

Figure 2: The neural network model

Scaling is achieved by multiplying the original coordinates (X, Y) with a scaling factor (S_x, S_y), which is calculated by comparing the desired input size and the given input image size. The desired coordinate points are (X_s, and Y_s) are calculated as follows

$$\begin{pmatrix} Xs \\ Ys \end{pmatrix} = \begin{pmatrix} X \\ Y \end{pmatrix}\begin{bmatrix} Sx & 0 \\ 0 & Sy \end{bmatrix} \quad (3)$$

Finally, the Input layer, the image matrix of size 24x24 is produced as input to the input layer of the model.

3.3. The Model

We now briefly explain the Convolutional Neural Network model, which we use here for classifying the images of the eye as open or closed. A CNN model is a feed-forward Neural Network which consists of the following layers: (i) Input layer, (ii) Hidden layers and an (iii) Output layer. The hidden layers consist of Convolution layers, activated with ReLU function and pooling layers. In

In the first convolution layer, the input data is convoluted with 32 filters of size 3x3 with a stride of 1. So it produces a matrix of 22x22 elements in output. Then a max pool layer with 2x2 filter and stride 2 is used to reduce the dimensionality of the matrix. Some dropouts are also used. In the same manner, another two convolutional layers with 32 and 64 filters are used. Then finally a flatten layer is used to prepare vector input for a fully connected network, which is activated using softmax activation.

The fully connected layer classifies the eye as open or close" based on the input feature map. The CNN model is first pre-trained with a set of 70,000 eye images, for classification. Then, in real-time, the same CNN model is used to classify the state of the eyes from the frames of the video, captured through the webcam.

4. Results and Discussion

4.1. Implementation

The implementation is done in a real time manner. It captures real time video frames through a camera and spots the eye as a region of interest. Using the help of a pre-trained CNN model it classifies if the eye is opened or closed and gives an alarm sound if the eye is found closed for a predefined threshold time (here 10 second in our case). A webcam is used to capture the image, then several python packages are used like OpenCV to detect the face and eye, Keras to build the model, TensorFlow as Keras used it as backend, and finally pygame to play alarm sound.

Table 1: observed output during trials

Driver	**Sex**	**No of trial**	**Success in Day with Glass**	**Success in Day without Glass**	**Success in Night with Glass**	**Success in Night without Glass**	**Total trial**	**Total Success**
D1	M	25	22	25	19	20	100	86
D2	M	25	24	25	19	21	100	89
D3	M	25	24	25	18	21	100	88
D4	M	25	21	25	19	21	100	86
D5	M	25	23	25	18	22	100	88
D6	M	25	22	25	16	22	100	85
D7	M	25	25	25	19	20	100	89
D8	F	25	25	25	18	21	100	89
D9	F	25	22	25	19	21	100	87
D10	F	25	24	25	16	21	100	86
Total		250	232	250	181	210	1000	873
%		--	92.8	100	72.4	84		87.3

4.2. Dataset

The CNN model is trained with a dataset with 70000 eye images, found in the website https://www.kaggle.com/datasets/serenaraju/yawn-eye-dataset-new. It consists of open and close eye images taken from different persons of both male and female gender. Various light conditions are also covered.

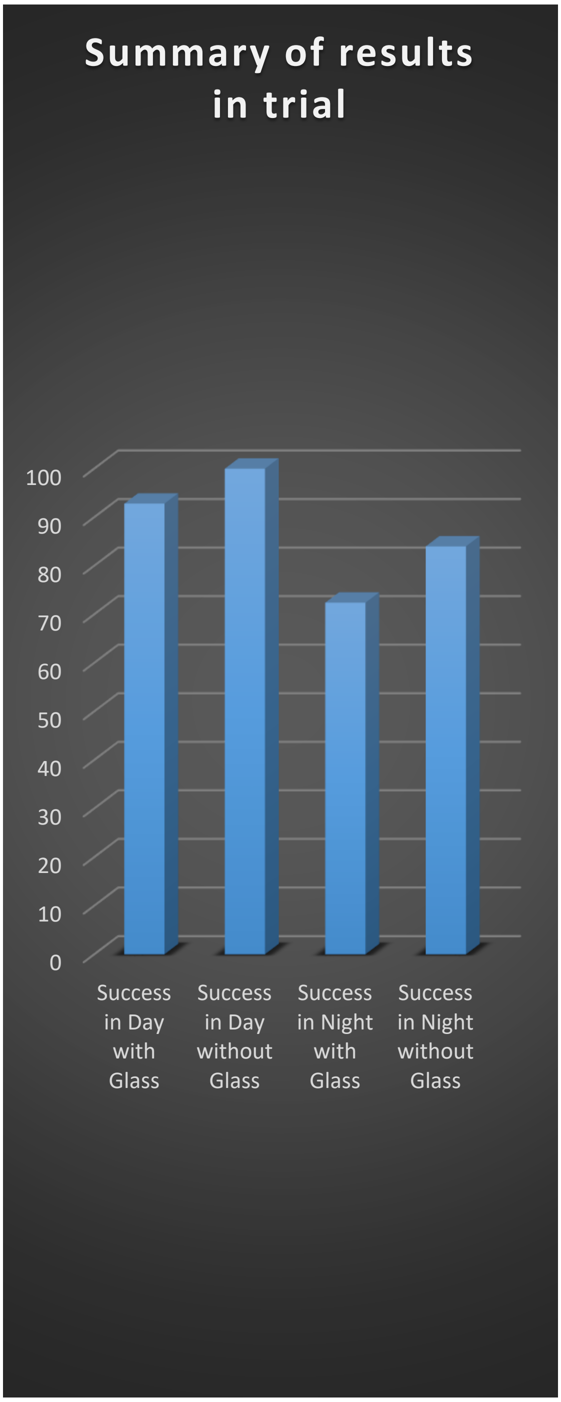

Figure 3: Summary of trials

4.3. Trials

A total of 1000 trials by 10 volunteer drivers (7 males and 3 females), is taken into consideration. The test is taken in day and night times and with or without glass. Fig. 3 shows the summary of the results. With a good light condition during day times, and if the driver is without glasses, the system shows an outstanding result of 100% accuracy. But, if the driver is wearing glasses, or the light condition is not appropriate during night times, the system seeks refinement. However, considering all scenarios for day and night, drivers with or without glasses, male and female, the overall accuracy is 87.9%, which is quite encouraging.

5. Conclusions

There are a huge number of road accidents recorded due to drowsiness of drivers. To overcome this, people are looking for an automated system which can detect and alert the driver if there is drowsiness. Here in this work one such approach is proposed. A simple architecture with a camera, a CNN trained with huge data set is used to detect the drowsiness. The camera captures the real time video; the system spots the face and finally the eyes as region of interest. Then the eye region is fed into the CNN, which is pre-trained to classify the eyes are closed or open. If the eyes are found close for 3 seconds at-a-stretch, the system rings an alarm, and the driver gets alert. The trials are showing outstanding result without a glass and day time. But when the light conditions are tough at night or the drive is with a glass, the system needs refinement, which is the focus of our future work.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.