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Real-Time Drowsiness Detection

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Abstract: The human body requires nearly 7 to 8 hours of sleep. But due to work stress it is lacking. Due to a lack of sleep and irregular sleep cycles, humans tend to feel drowsy at any time of the day. Hence with these poor work-life timings, people may find it difficult to perform tasks such as driving that require mental and physical health and well-being. Sleepless driving can cause problems and therefore it is necessary to be awake while driving. Due to the drowsiness of drivers, accidents are caused which kill thousands of people worldwide every year. Therefore there is a need for a sleep sensor application to help prevent such accidents and save lives. In this regard, we propose a system based on neural networks (CNN) and a Haar cascade classifier with a user interface to deal with the problem. In this research we aim to develop a prototype "Real-time drowsiness detection system". The system monitors the driver's eyes and rings the alarm while he is drowsy. This system is object oriented, which is built using OpenCV library in python where the images are gathered from the webcam and fed into a Haar based algorithm which will detect face and eyes and later a CNN model which will predict whether the person’s eyes are ‘Open’ or ‘Closed’. A web application for this model with a user interface and also a CSV file to store the details of the user is developed. Experiments were conducted to test the effectiveness of the proposed method in comparison to other methods. The empirical results show that the proposed method using deep learning techniques can achieve a high accuracy of 98.5%. This study provides a solution to prevent automobile accidents due to drowsiness.

Keywords: Deep Learning, Convolutional Neural Network (CNN), Haarcascade, Keras, Drowsiness detection, Eye’s detection

I. INTRODUCTION

Driver fatigue has been the main issue for countless mishaps due to tiredness, tedious road conditions, and unfavorable climate situations [1]. Every year, the National Highway Traffic Safety Administration (NHTSA) and the World Health Organization (WHO) have reported that around 1.35 million people die due to vehicle accidents worldwide. Generally, road accidents mostly occur due to inadequate way of driving [2]. These situations arise if the driver is addicted to alcohol or in drowsiness [3]. The maximum types of lethal accidents are recognised as a severe factor of tiredness of the driver. When drivers fall asleep, the control over the vehicle is lost [4]. There is a need to design smart or intelligent vehicle system through advanced technology [5]. This paper implements a mechanism to alert the driver on the condition of drowsiness. The camera monitors the driver’s eyes and if drowsiness is detected then an alarm is raised. Also the time and details of the driver are stored in a csv file. The system uses a Haar classifier along with CNN as the CNN limits the degree of light variation, given that sudden changes cause the entire background to be recognized as an element, whereas the Haar classifiers continue to recognize objects [6].

II. RELATED WORKS

Drowsiness while driving often leads to car crashes and accidents. Many people die in traffic accidents each year as a result of driving fatigue caused by poor sleep, alcoholism, drug and alcohol abuse, heat or alcohol. Car manufacturers [7] such as Tesla, Mercedes-Benz, and others have a variety of driving assistance features such as diversion alerts, emergency braking systems, variable cruise control, and assistance guidance. These new techniques have helped drivers to avoid collisions. At the same time, most of these technologies are patented and restricted to high-end vehicles. Many sleep detection methods have been developed in the past. Based on the vehicle base, drowsiness detection procedures are performed to monitor route changes, steering wheel rotation, speed, and pressure on the accelerator pedal. These methods include the measurement of the driver's physical symptoms [8], vehicle-based performance tests [9], and recorded behavior [10]. The bio-signal measurement method has shown a very high ability to detect driver drowsiness between these strategies: unlike the other two methods, it only depends on the driver's condition. Based on behaviors such as blindfolds, yawning, and head position, sleep recognition procedures require a camera. Another step is based on physiological diagnostic procedures that work by monitoring fatigue to correlate between their physical symptoms such as the EOG and ECG[11,12]. The limit of sleep dripping procedures using the lifestyle is that the diver needs to contain

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electrodes in its body [11]. There is a major limitation based on the identification of vehicle-based drowsiness [12], such as the tendency to have power connected to drivers and vehicles, and road conditions. There are many strategies outlined in different books that have some limitations and a few benefits. The purpose of this study is to propose a cost-effective procedure for diagnosing divers' drowsiness while driving. To create a drowsy detector system, CNN architecture along with the Haar based algorithm has been used.

III. PROPOSED WORK

A. Methodology adopted in the proposed system

(1) Haar face detection algorithm is used to detect the faces and the images are given as input to Haar eye detection algorithm

(2) Once the face is detected, Haar eye detection algorithm is used to extract the eye region from the facial images and given as input to CNN.

(3) A CNN with four convolution layers is used to extract deep features and those features are passed to the fully connected layer.

(4) Soft max layer in CNN classify the images into closed or open images.

(5) A Web application is built with the help of flask framework.

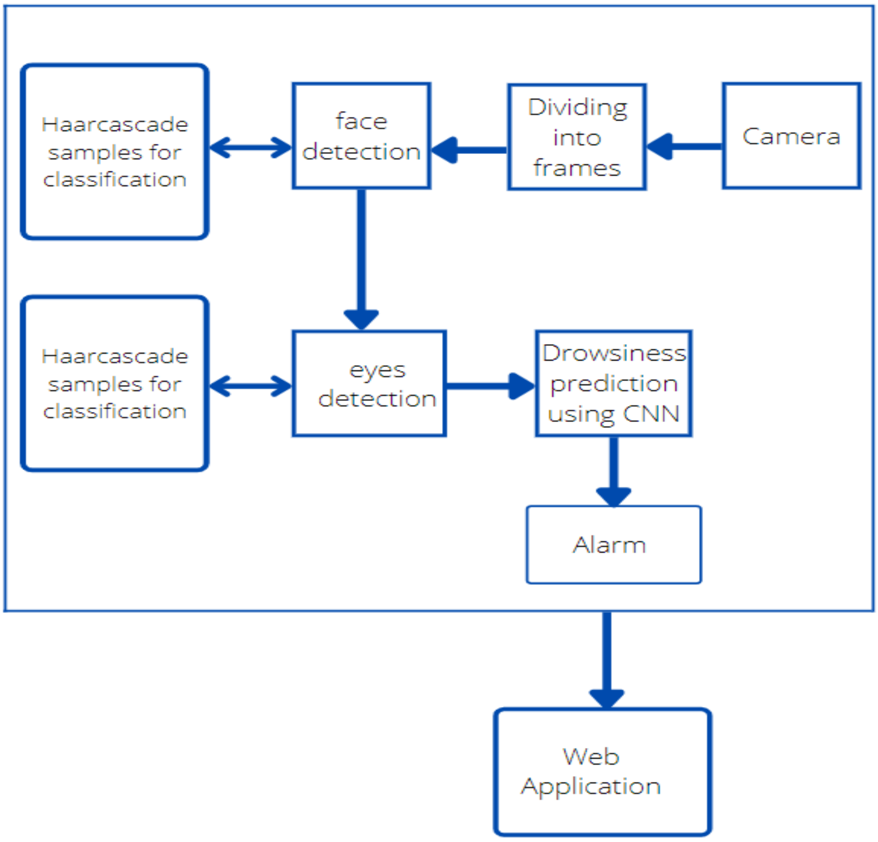

Fig 1. Block diagram of the system

B. Face detection and eye region extraction

The whole face region may not be required in order to detect the drowsiness but only the eyes region is enough for detecting drowsiness. At the first step by using the Haar face detection algorithm, the face is detected from the images. Once the face is detected, Haar cascade eye detection algorithm is used to extract the eye region from the facial image and implemented using OPENCV with python. The Haar cascade classifier uses Haar features for detecting the face from images.

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C. Feature extraction and classification

Feature extraction is a form of resizing in which useful parts of an image are referred to as feature vectors. In this work, features are extracted from eye region images using the Convolution Neural Network (CNN). CNN is used in the proposed system to detect the drowsiness of the driver. Since each drowsy image requires a feature vector, it should be compared with the features available in the database to determine if it is drowsy. CNNs usually require fixed size images as input, so preprocessing is required. Preprocessing is the process of capturing important frames from video based on temporary changes and saving them in the database. From these stored images, feature vectors are generated by CNN's convolution layer which are used to identify driver drowsiness. CNN contains 4 layers such as convolutional layers, pooling layers, ReLU layers and fully-connected layers. The convolution layer consists of kernels and each kernel has a width, depth and height. This layer generates feature maps by computing the scalar output between the kernel and the local image region. The feature uses pooling layers to reduce the size of the feature map to speed up the calculations. In this layer, the input image is divided into different areas and tasks are performed on each region. In max pooling, the highest value for each position is selected and placed at the corresponding position of the output. The ReLU layer uses the max function for all values in the input data and converts all negative values to zero. The following equation shows the ReLU activation function.

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

Fully connected layers are used to generate class scores from the activations used for classification.

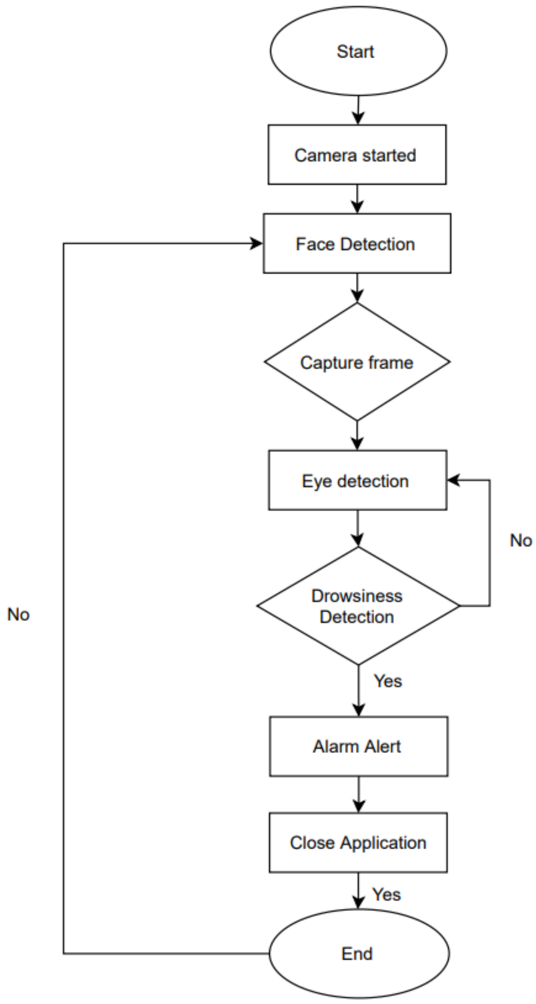

Fig 2. Flow diagram of the system

D. Features which makes the proposed system different from the existing ones

1. The model has been trained with the additional images that have been taken in different lighting conditions, which improved the accuracy by 2%.
2. A web application is created with the user interface for the driver to enter his details.

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3. When the drowsiness is detected, the details of the driver along with the time is stored in a CSV file which the vehicle owner can check.

IV. EXPERIMENTAL RESULTS

The tests were performed under various conditions including:
1. Different lighting conditions.
2. Different position of the driver's face.
3. With the driver's head tilted.

A. Test case 1 : Lighting conditions

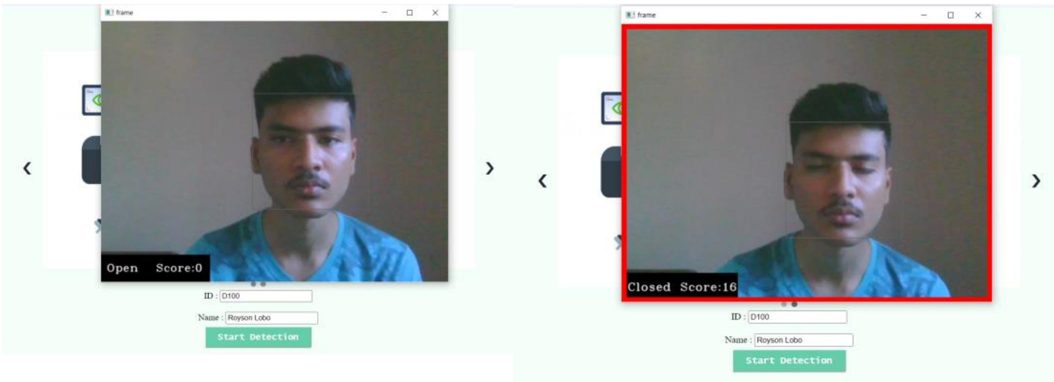

Fig 3. Result when there is mild darkness

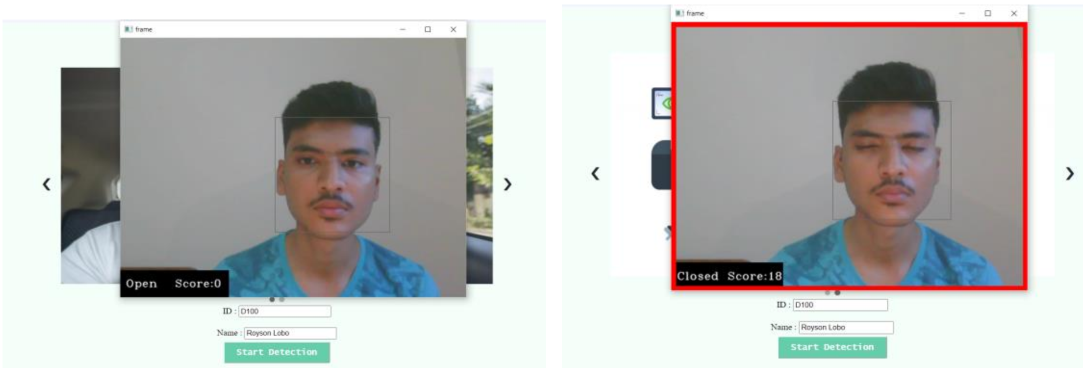

Fig 4. Result when there is more light

Result: From Fig 3 and Fig 4 above, it is clear that when there is plenty of light or when there is mild darkness, the face of the driver is successfully detected producing the alarm audio when the drowsiness is detected.

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B. Test case 2 : Position of driver face

1. Face is at center:

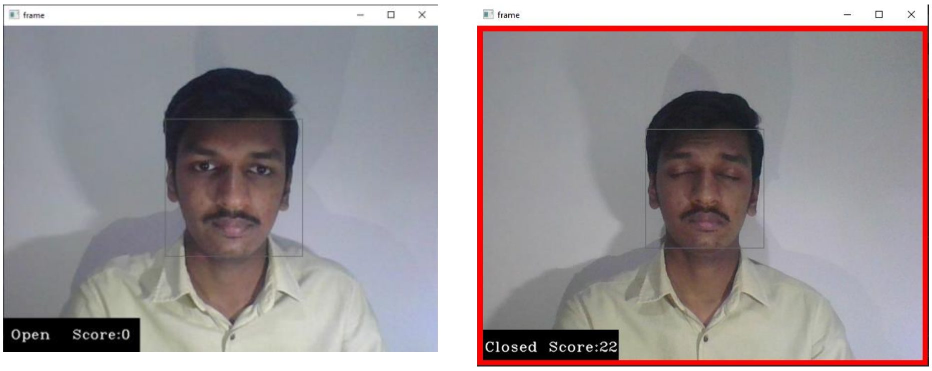

Fig 5. Face at center position in frame

Result: From Fig 5 above, it is noted that the face is successfully detected when it is at the center of the camera producing the audio alarm when the drowsiness is detected.

2. Face is at left:

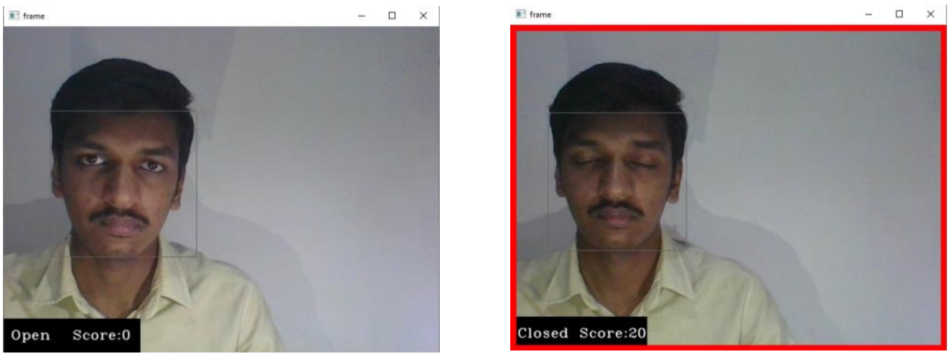

Fig 6. Face at left position in frame

Result: From Fig 6 above, it is noted that the face is successfully detected when it is kept at the left side of the camera producing the audio alarm when the drowsiness is detected.

3. Face is at right:

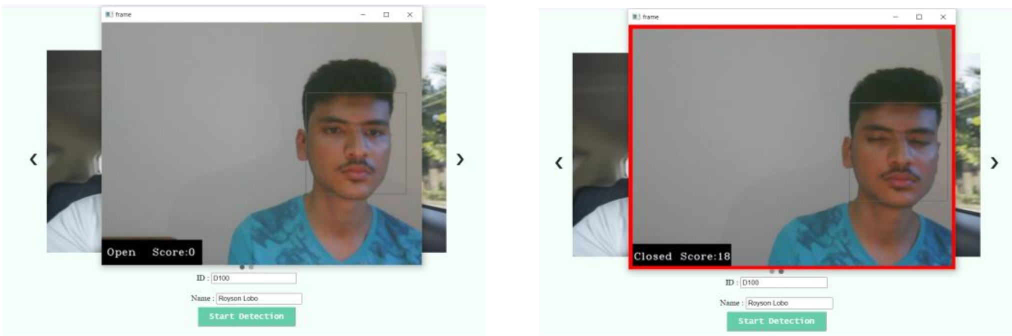

Fig 7. Face at right position in frame

Result: From Fig 7 above, it is noted that the face is successfully detected when it is kept at the left side of the camera producing the audio alarm when the drowsiness is detected.

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C. Test case 3 : Driver's head tilted

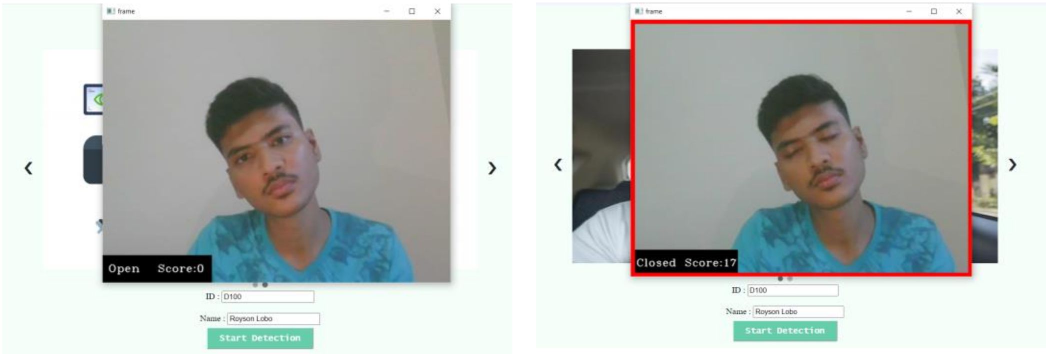

Fig 8. Tilted head position in frame

Result: From Fig 8 above, it is noted that when the driver's head is tilted to any angle while capturing the video input, the face is detected clearly thereby producing the beep alarm sound when the drowsiness is detected.

D. Training and Validation results:

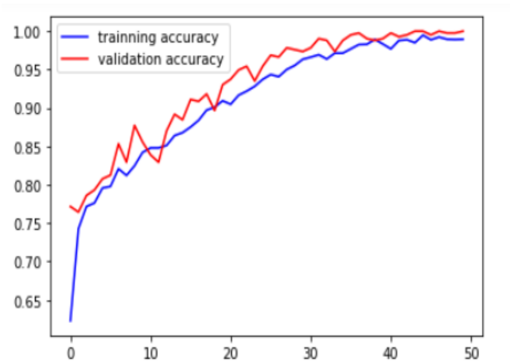

Fig 9. Training vs Validation accuracy

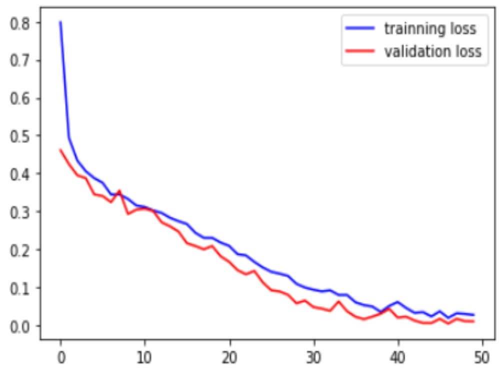

Fig 10. Training vs Validation loss

RESULT:

After training the model for 50 epochs the accuracy was observed to be 98.5%.
The dataset of the drowsiness observation model was largely tested with several light conditions, under a broad range of conditions. The model was tested on different ages and colors of people and a good result was observed. The success rate in real-world situations was considered flawless. It was also found that the system's efficiency is not very good in some cases. In low-light conditions or when the flashlight is pointed to the camera lens in the background, at that time, the performance of the trained model was not fully satisfied.

CONCLUSION

This research tells how to build drowsiness detection using deep learning techniques with the help of OpenCV and other Python libraries. In this research work we have proposed a method for finding the driver to be drowsy based on the status of the eyes. This system determines the state of the eye that is drowsy or non- drowsy and alerts with an alarm when the state of the eye is drowsy. Face and eye regions are detected using the Haar cascade algorithm. Convolutional neural networks are developed to extract features and used for the learning phase. A SoftMax layer in CNN classifier is used to classify the driver as sleep or non-sleep. Proposed system achieved 98.5% accuracy. It effectively identifies the driver's status and alerts with an alarm when the model predicts drowsy output state continuously. The results are discussed and found satisfactory. Once the whole system is developed, the model is incorporated and the working system appears to the users. Once these progressions are consolidated, the upkeep period of the system life cycle begins. This includes keeping up with the latest innovations in the field of deep learning algorithms, scaling it by including more features and making the prediction more effective in accuracy. The system can be deployed as a service on cloud platforms which the general public can utilize.

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