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# Driver Drowsiness Monitoring Using Convolutional Neural Networks

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***Abstract:*** The advancement in computer vision has assisted drivers in the form of automatic self-driving cars etc. The misadventure are caused by driver's fatigue and drowsiness about 20%. It poses a serious problem for which several approaches were proposed. However, they are not suitable for real-time processing. The major challenges faced by these methods are robustness to handle variation in human face and lightning conditions. We aim to implement an intelligent processing system that can reduce road accidents drastically. This approach enables us to identify driver's face characteristics like eye closure percentage, eye-mouth aspect ratios, blink rate, yawning, head movement, etc. In this system, the driver is continuously monitored by using a webcam. The driver's face and the eye are detected using haar cascade classifiers. Eye images are extracted and fed to Custom designed Convolutional Neural Network for classifying whether both left and right eye are closed. Based on the classification, the eye closure score is calculated. If the driver is found to be drowsy, an alarm will be triggered.

***Keywords:*** Convolutional Neural Network; Data Augmentation; Deep Learning; Drowsiness.

## I. INTRODUCTION

Many safety connected driving supporter schemes decreased the danger of four-wheeler accidents, and investigations depicted weariness to be a major announced an idea that whole deadly accidents (17%) would be attributed to weary drivers. Many revisions showed by Volkswagen AG specify that 5-25% of all accidents are produced by the sleeping of driver. The lack of concentration damage steering actions and decrease response period, and revisions illustrated that sleepiness raises threat of crashes. This figure points the demand for a dependable intelligent driver sleepiness sensing system. The aim is to create an intelligent processing scheme to avoid road accidents. This can be done by period of time monitoring the drowsiness and warning driver of inattention to prevent accidents.

Based on the literature survey, the driver's drowsiness can be detected based on three factors such as physiological, behavioural, and vehicle-based measurements. But these approaches pose some disadvantages in certain real time scenarios. So, we aim to apply Deep Learning algorithms to this problem statement. Our methodology is to use a Convolutional Neural Network (CNN). CNN offers a computerized and effective way to categorize the driver as drowsy or non-drowsy correctly.

With the advancement of computer vision and deep learning, driver drowsiness can be detected in real time using a camera. In this project, the driver’s face is continuously monitored and features such as eye closure and facial expressions are analyzed. If drowsiness is detected, the system generates an alert to warn the driver, helping to prevent road accidents.

## II. RELATED WORK

Many researchers have developed systems to detect driver drowsiness in order to reduce road accidents caused by fatigue. Earlier methods mainly focused on physiological signals such as EEG, heart rate, and eye movement to detect sleepiness. Although these methods provide accurate results, they require special sensors attached to the driver’s body, which makes them uncomfortable and

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impractical for real-time driving environments.

Later, researchers proposed computer vision–based approaches that use cameras to monitor the driver's face. These systems analyze facial features such as eye blinking, eye closure duration, yawning, and head movements to determine the driver's alertness level. Algorithms like Haar Cascade classifiers have been widely used to detect the face and eyes from video frames captured by a webcam.

With the advancement of machine learning and deep learning, Convolutional Neural Networks (CNN) have been widely applied for driver drowsiness detection. CNN models can automatically extract important features from eye images and classify whether the eyes are open or closed. Several studies have shown that CNN-based methods provide higher accuracy and better performance compared to traditional machine learning techniques.

Some recent approaches combine facial landmark detection, eye aspect ratio (EAR), and deep learning models to detect drowsiness more effectively. These systems continuously monitor the driver in real time and trigger an alarm when drowsiness is detected, helping to prevent accidents and improve road safety. However, challenges such as changes in lighting conditions, variations in facial appearance, and head movements still affect detection accuracy. Therefore, more robust deep learning–based systems are required to improve the reliability of driver drowsiness monitoring systems.

## III. PROPOSED SYSTEM

Our proposed system will provide a solution for monitoring driver's drowsiness. The cons of the existing system in extracting only selected hand-crafted features is overcome by using custom- designed CNN by giving an input driver image. Now the driver will be continuously monitored by a webcam. The video captured is converted into a sequence of frames. For each frame, the face and eye are detected using predefined classifiers available in opencv called haar cascade classifiers. Eye images are extracted and sent to a series of 2D CNN layers (5x5, 3x3 kernel valid padding), max- pooling layers(2x2) and finally, the fully connected dense layer classifies whether eyes are closed or not. A score is calculated based on eye closure. If both eyes are closed consecutively in 15 frames then the system predicts as drowsy and an alarm sound is triggered to alert the car operator. The categorization of driver drowsiness is done correctly and the normalization issues in the existing model are eliminated by using custom designed CNN.

## IV. SYSTEM ARCHITECTURE

Figure 1 depicts the flow of the system to be created.

In the initial step, the driver is monitored by using a webcam. The video input is converted into a sequence of frames. In each frame, driver's face and eyes are detected by using haar cascade classifiers. The detected eyes are stored as images to form a data set for CNN. The system also provides provision for the preparation of the eye data set to train CNN model. To train the image and to increase the number of data sets Data augmentation is done. The images of both eyes are then subjected to a series of image preprocessing steps such as grayscale conversion, re-sizing and normalizing, etc. It is then fed to a pre-trained CNN model consisting of convolution layers, max- pooling layers, and dense layers to predict eye closure. Based on the prediction, a score is calculated. If the system finds the driver as drowsy, then an alarm will be triggered to alert the driver.

The implementation consists of the following modules.

### 1. Face and Eye Detection

In this module, the system uses a webcam to capture real-time video frames of the driver. The OpenCV library provides pre-trained models for face and eye detection. These models are loaded using the load method available in OpenCV.

 

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The pre-trained Haar Cascade classifiers are stored in the OpenCV data folder as XML files. The system loads these XML files using the Cascade Classifier method. After loading the classifier, the detectMultiScale() function is used to detect faces and eyes in the captured image frames. This method returns rectangular bounding boxes around the detected eye regions. These detected eye regions are then extracted and passed to the next processing stage.

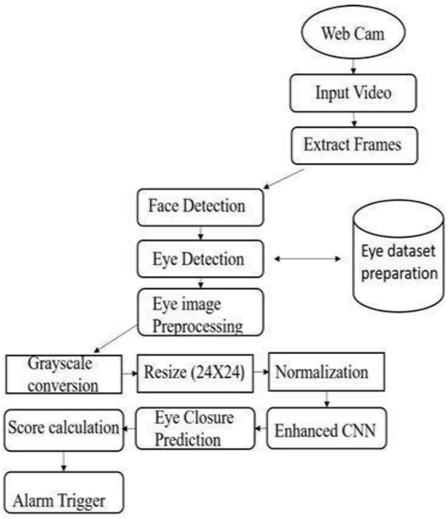

Fig. 1 System Architecture of CNN

**2. Preprocessing and Labeling**

In this module, the extracted eye images are prepared for training the CNN model. The eye images obtained from the webcam are labeled into two categories: Open Eyes

**Closed Eyes**

The preprocessing steps include converting the eye images into grayscale format, resizing them to 24 × 24 pixels, and normalizing the pixel values. This preprocessing helps reduce computational complexity and improves the efficiency of the CNN model.

**3. Data Augmentation**

Data augmentation is used to increase the diversityvof the dataset without collecting new images. Instead of gathering new data, the existing eye images are transformed using various techniques. In this project, data augmentation is implemented using the Keras Image Data Generator. It performs transformations such as: Rotation, Brightness adjustment, Shear transformation, Zooming.

These transformations help the model learn different variations of eye images and improve the overall accuracy and robustness of the CNN model.

**4. Enhanced CNN Model**

The Convolutional Neural Network (CNN) is used to classify the eye state as open or closed. The CNN model consists of several layers that extract features from the input images.

The convolutional layers use the ReLU activation function with a kernel size of 3 × 3 to extract important visual features from the eye

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images. These layers are followed by pooling layers to reduce the size of the feature maps and retain important information.

The final layers of the network are fully connected layers, where the Softmax activation function is used to classify the output into two categories: open eyes or closed eyes. The CNN model is trained using the Adam optimizer, which helps improve the learning efficiency and reduces the loss during training.

**5. Triggering Alarm**

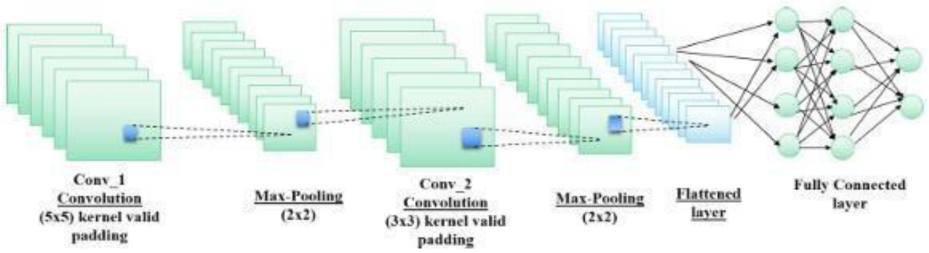
This module is responsible for alerting the driver when drowsiness is detected. During real-time monitoring, the system continuously checks the eye state predicted by the CNN model.

If the system detects that the driver's eyes remain closed for several consecutive frames, it identifies the driver as drowsy. At this point, an alarm sound is triggered to alert the driver. This warning helps the driver regain attention and prevents possible accidents.

**CNN Model**

The Convolutional Neural Network (CNN) is the main part of the driver drowsiness detection system. It extracts features from eye images and classifies whether the eyes are open or closed. The convolution layer identifies important features like edges and patterns. The ReLU activation function introduces non-linearity to help the model learn complex patterns. The max pooling layer reduces the size of feature maps while keeping important information. These features are then passed to the fully connected layer for classification. Finally, the softmax layer gives the probability of the eye state as open or closed. The CNN model is trained using labeled eye image datasets to detect drowsiness accurately.

**Representation of convolution layer process**




**Data Augmentation**

Data augmentation is used to increase the size and diversity of the eye image dataset without collecting new data. The existing images of open and closed eyes are modified using transformations such as rotation, zooming, brightness adjustment, and shifting. These transformations help the CNN model learn different variations of eye images under different lighting and angles. Data augmentation is implemented using Keras ImageDataGenerator, which improves the model's accuracy and helps reduce overfitting during training.

## V. RESULTS

In this project, we developed a Driver Drowsiness Detection System using deep learning techniques. The system detects driver fatigue by analyzing facial features such as eye blinking and facial expressions through a webcam. The model is trained using TensorFlow and Convolutional Neural Networks (CNN) to identify drowsiness conditions in real time.

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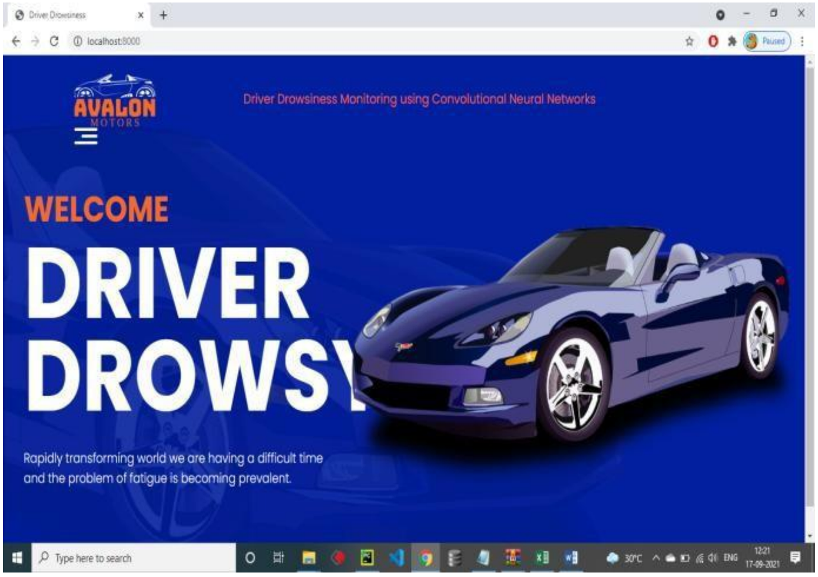
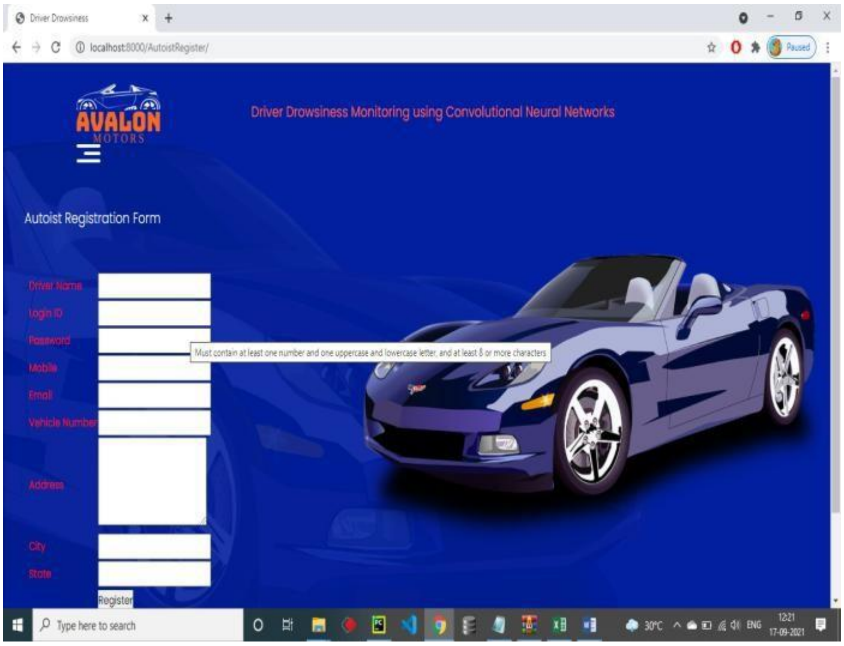
In below, Home Page is the initial interface of the system. It provides options for users to navigate through the system such as Admin Login and Autoist Registration/Login. This page acts as the entry point for accessing different functionalities of the system.




The Admin Login module allows the administrator to log into the system using valid credentials. After successful authentication, the admin can manage user information and monitor the system operations.




In above screen Autoist Register, new drivers (Autoists) can register into the system by providing their details such as name, username, password, and other required information. After successful registration, the driver can log in to the system and access the drowsiness detection features.

In below Screen When the driver starts the detection process, the system activates the webcam and begins analyzing the driver's facial

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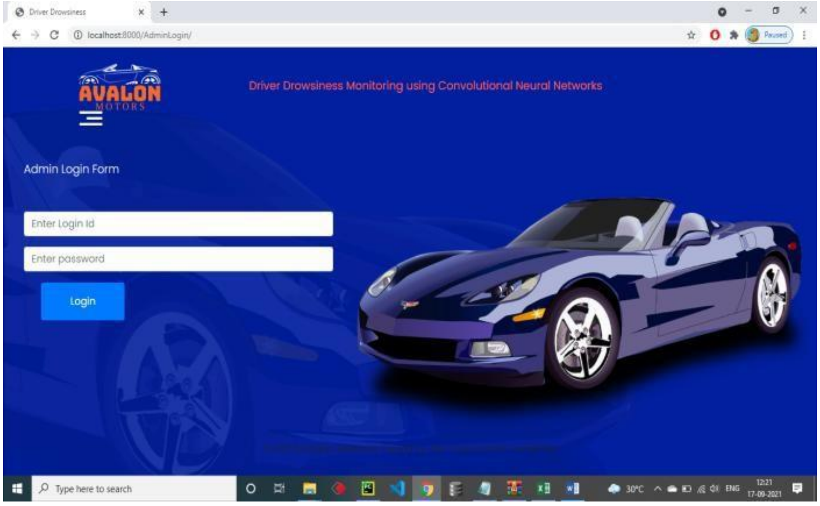
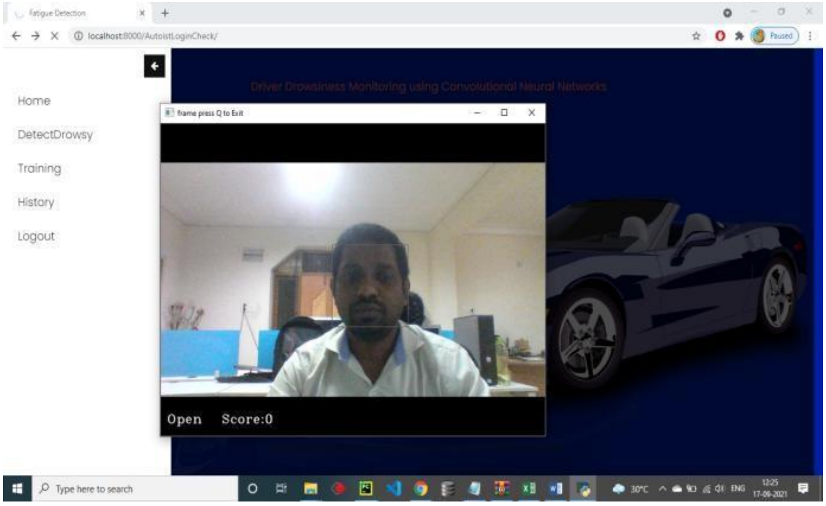
features in real time.




In this stage, the system detects eye blinking patterns using facial landmark detection. Frequent eye closure or longer blink duration indicates possible driver drowsiness.

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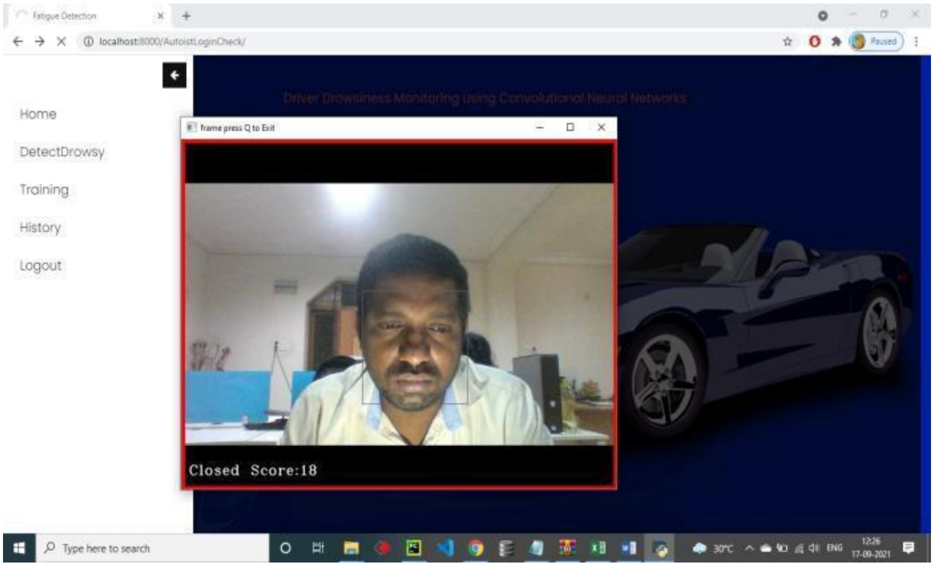
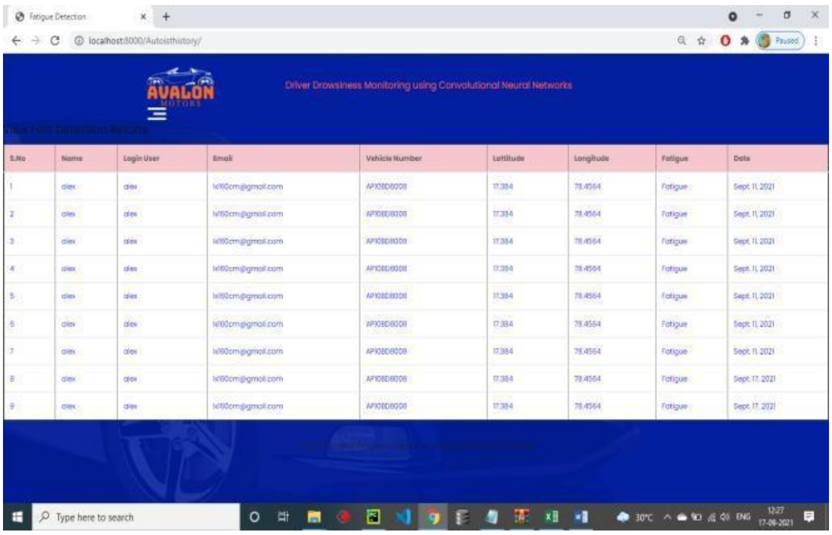



In above screen the system detects signs of fatigue or drowsiness, an alarm is triggered to alert the driver. This warning helps prevent accidents by waking the driver.




In above screen the Fast History Results module stores previous detection records. Drivers or administrators can view past detection results for monitoring driver alertness over time.

## VI. CONCLUSION

A model for drowsiness sensing depends on effective CNN architecture, planned to observe drowsiness based on eye closure. The implementation started preparing image datasets for both open and closed eyes. 75% of the data set is used for the custom- designed CNN training and the balance 25% of the dataset is utilized for test purposes. First, the information video is transformed into frames and in each frame, the face and eyes are detected. The enhanced CNN supplied an automated and effective learned characteristics that aid us to categorize the opening or closing of eyes. If the closing of eyes occur in 15 successive frames, an alarm is triggered to alert the driver. The proposed CNN gives a training accuracy of 97% and a testing accuracy of 67%. For future works, extra face

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characteristics can be added to give more accuracy in detection. We can also combine vehicle driving pattern information obtained using On- Board Diagnostics sensors with the facial features extracted.

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