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 misadventures 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. In recent years, advances in computer vision and deep learning techniques have enabled the development of effective driver drowsiness monitoring systems. This paper presents a novel approach for driver drowsiness detection using convolutional neural networks (CNNs). The proposed system leverages CNNs to analyze facial features and eye movements extracted from real-time video streams captured by an in-vehicle camera. The methodology involves data collection of diverse drowsiness levels, preprocessing of collected data to enhance model performance, and training a CNN-based classification model. Experimental results demonstrate the effectiveness of the proposed approach in accurately detecting driver drowsiness in various environmental conditions and lighting conditions. The system achieves high accuracy, sensitivity, and specificity in drowsiness detection, thereby enhancing driver safety and reducing the risk of accidents caused by drowsy

driving. Furthermore, the system's real-time capabilities enable timely intervention and proactive measures to mitigate the effects of driver fatigue on road safety.

Keywords: Convolutional Neural Networks (CNNs), Driver Drowsiness Detection, Facial Recognition, Image Processing, Real-time Monitoring, Eye Tracking, Feature Extraction, Deep Learning, Computer Vision, Machine Learning, Biometric Data, Alert Systems, Sleep Detection, Driver Safety, Dataset Collection.

I.INTRODUCTION

Many safeties connected driving supporter schemes decreased the danger of four-wheeler accidents, and investigations depicted weariness to be a major reason of four- wheeler accidents. A car organization 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 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, behavioral, and vehicle-based measurements. But these approaches pose some disadvantages in certain real-time scenarios. Advances in artificial intelligence, particularly in the fields of computer vision and deep learning, have paved the way for innovative approaches to driver drowsiness monitoring. Among these, convolutional neural networks (CNNs) have garnered considerable attention for their ability to extract meaningful features from visual data, making them well-suited for tasks such as facial recognition and expression analysis. This paper aims to present a comprehensive overview of the methodology and techniques employed in the development of a driver drowsiness monitoring system using CNNs. By leveraging the power of CNNs, we seek to accurately detect signs of drowsiness in real-time video streams captured from in-vehicle cameras, thereby enabling proactive interventions to prevent accidents caused by driver fatigue. The proliferation of in-vehicle cameras and the growing availability of computing resources make CNN-based drowsiness monitoring systems increasingly viable for deployment in various vehicles, ranging from personal cars to commercial trucks. Such systems have the potential to significantly reduce the incidence of accidents caused by drowsy driving, thereby enhancing road safety and saving lives. By leveraging the capabilities of CNNs and deep learning techniques, we aim to contribute to the development of robust and reliable solutions for mitigating the risks associated with drowsy driving, ultimately saving lives and improving road safety for all.

II.EXISTING SYSTEM

Driving supporter schemes decreased the danger of four-wheeler accidents, and investigations depicted weariness to be a major reason of four-wheeler accidents. A car organization 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 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.

DRAWBACKS

- It is not suitable for real-time processing.
- The existing system uses the orientation of facial characteristics for drowsy detection.
- Based on three factors such as physiological, behavioral, and vehicle-based measurements.
- But these approaches pose some disadvantages in certain real time scenarios.

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.

ADVANTAGES

- If the eyes are both closed, we increase the score and when eyes are open, we decrease the score. We are drafting the outcome to display the actual time condition of the driver.
- Approach enables us to identify driver's face characteristics like eye closure percentage,
- eye-mouth aspect ratios, blink rate, yawning, head movement.

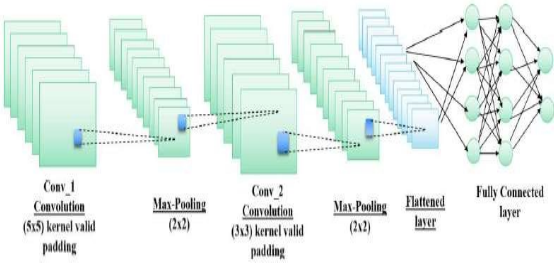

Fig: System Architecture

IV.MODULES

- **User:** The User can register the first. While registering he required a valid user email and mobile for further communications. Once the user register then admin can activate the user. Once admin activated the user then user can login into our system. User can upload the dataset based on our dataset column matched. For algorithm execution data must be in float format. Here we took Driver Drowsiness dataset for testing purpose. User can also add the new data for existing dataset based on our Django application. User can click the Classification in the web page so that the data calculated Precision, Recall, Accuracy, Support and F1-Score based on the algorithms. User can click Prediction in the web page so that user can write the review after predicting the review. That will display results depends upon review like positive, negative or neutral.

- **Admin:** Admin can login with his login details. Admin can activate the registered users. Once he activates, then only the user can login into our system. Admin can view the overall data in the browser. Admin can click the Results in the web page so calculated Precision, Recall, Support Accuracy and F1-Score based on the algorithms is displayed. All algorithms execution complete then admin can see the overall accuracy in web page.

- **Data Preprocessing:** A dataset can be viewed as a collection of data objects, which are often also called as a records, points, vectors, patterns, events, cases, samples, observations, or entities. Data objects are described by a number of features that capture the basic characteristics of an object, such as the mass of a physical object or the time at which an event occurred, etc. Features are often called as variables, characteristics, fields, attributes, or dimensions. The data preprocessing in this forecast uses techniques like removal of noise in the data, the expulsion of missing information, modifying default values if relevant and grouping of attributes for prediction at various levels.

- **Machine Learning:** Based on the split criterion, the cleansed data is split into 60% training and 40% test, then the dataset is subjected to Two machine learning classifiers such as Deep Learning, Convolutional Neural Networks. The accuracy Recall, Support, Precision and F1-Score of the classifiers was calculated and displayed in my results. The classifier which bags up the highest accuracy could be determined as the best classifier.

V.ALGORITHMS

CONVOLUTIONAL NUERAL NETWORKS

Convolutional Neural Networks (CNNs) are a class of deep neural networks designed
specifically for processing structured grid data, such as images and videos. CNNs have revolutionized the field of computer vision by enabling automatic feature extraction and hierarchical learning directly from raw pixel data.At their core, CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolutional operations to input data,

using learnable filters or kernels to extract features such as edges, textures, and patterns. Pooling layers downsample the feature maps produced by convolutional layers, reducing spatial dimensions while preserving important features. Fully connected layers combine the extracted features to make predictions or classifications. The key advantage of CNNs lies in their ability to automatically learn hierarchical representations of data, capturing increasingly abstract and complex features as
information flows through the network. This hierarchical learning enables CNNs to achieve state-of-the-art performance on various computer vision tasks, including image classification, object detection, segmentation, and more.

Working of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) function by leveraging layers of learnable
filters to extract meaningful features from input data, typically images, enabling powerful pattern recognition and classification capabilities. At the outset, the network's input layer receives raw pixel values from the image. Subsequently, convolutional layers apply filters across small regions of the input, detecting features like edges, textures, or shapes through convolution operations. Activation functions, such as Rectified Linear Units (ReLU), introduce non-linearity, enabling the network to capture complex relationships and abstract features effectively. Following convolutional layers, pooling layers downsample the feature maps, reducing spatial dimensions while retaining essential information. This hierarchical feature extraction process allows the network to discern increasingly complex patterns as data progresses through subsequent layers. Fully connected layers further process the extracted features, learning to combine them for accurate predictions or classifications. Throughout training, CNNs optimize their parameters through backpropagation and gradient descent algorithms, minimizing the discrepancy between predicted and actual outputs. Through this iterative process, CNNs develop hierarchical representations of input data, enabling them to excel in tasks such as image classification, object detection, and segmentation.

VI.SCREEN

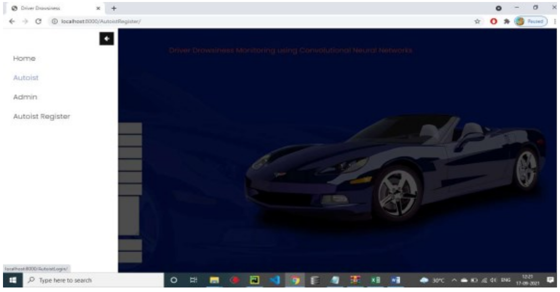

Fig: System Menu

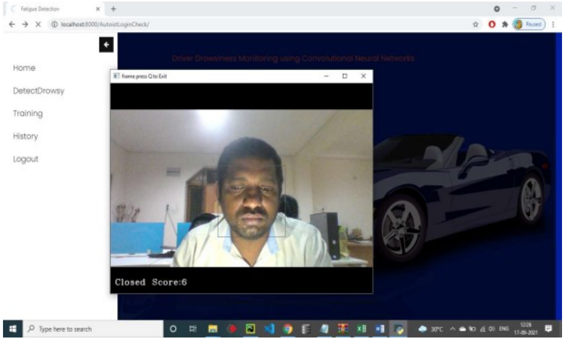

Fig 7.1.12: Alarm Started

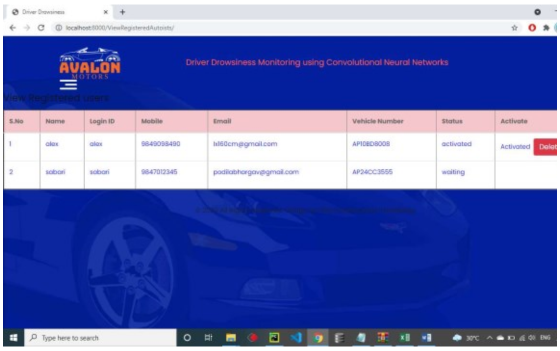

Fig: View Registered Autoist

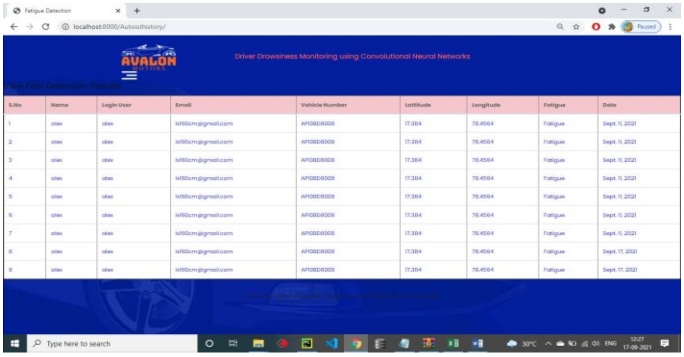

Fig: Fatigue History Results

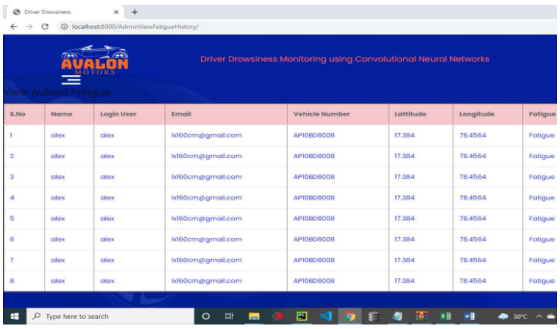

Fig: Drowsiness Detections

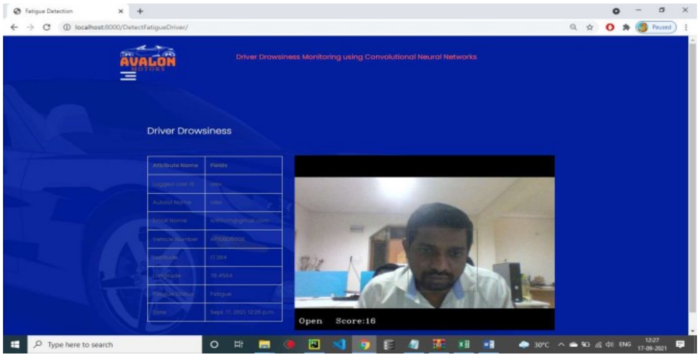

Fig: Fatigue Alarm Results.

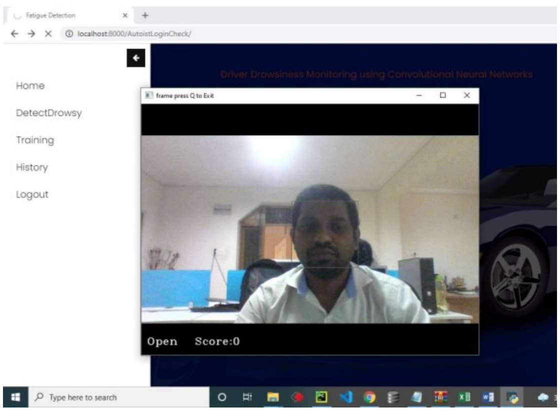

Fig: Detection Process Started

VII.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 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.

VIII.FUTURE ENHANCEMENTS

The proposed CNN gives a training accuracy of 97% and a testing accuracy of 67%. For future works, extra face 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. Future enhancements for driver drowsiness monitoring utilizing Convolutional Neural Networks (CNNs) are poised to revolutionize road safety further. One avenue of advancement lies in multi-modal data fusion, where additional sensor modalities such as steering wheel movements and physiological signals are integrated to provide a comprehensive understanding of the driver's state. This holistic approach can enhance drowsiness detection accuracy by capturing subtle cues indicative of fatigue. Moreover, the development of models capable of long-term contextual understanding is crucial. By leveraging recurrent neural networks (RNNs) or attention mechanisms, these models can analyze temporal patterns in driver behavior, distinguishing between short-term distractions and sustained drowsiness. Personalization and adaptation are also key areas for improvement, as future systems could dynamically adapt to individual driver characteristics and preferences, optimizing alert thresholds and intervention strategies over time.

IX.REFERENCES

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