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Driver Drowsiness Detection System using Convolutional Neural Network

Nirma B[1] , Shilpa Abhang[2]

[1]Student, Department of Computer Science(PG), Jyoti Nivas College Autonomous, Bangalore, India
[2] Associate Professor, Department of Computer Science(PG), Jyoti Nivas College Autonomous, Bangalore,

Abstract

Driver drowsiness detection is crucial for preventing fatigue-related accidents, particularly in transportation. Traditional detection methods relying on physiological sensors are intrusive and impractical. This study proposes a deep learning-based behavioural approach to detect drowsiness using Convolutional Neural Networks (CNNs) and computer vision techniques.

A custom dataset of drowsy and non-drowsy driver images is used for training. The preprocessing pipeline includes grayscale conversion, data augmentation, and transformations to enhance feature extraction. The Google MediaPipe Face Mesh model is utilized for real-time facial landmark detection, enabling precise localization of the eye region. The extracted eye features are then fed into a CNN model, which leverages transfer learning to improve classification performance.

By providing real-time alerts, this system enhances road safety, reducing the risk of fatigue-related accidents. The study highlights the effectiveness of deep learning and computer vision in developing non-intrusive, practical drowsiness detection solutions.

Keywords: Driver Drowsiness, Machine Learning, Deep Learning, CNN.

1. Introduction

Driver drowsiness is a major contributing factor to road accidents worldwide, leading to severe injuries and fatalities. Fatigue impairs cognitive functions such as reaction time, attention, and decision-making, making drowsy driving as dangerous as driving under the influence of alcohol. Traditional methods for detecting driver fatigue often rely on physiological sensors, such as electroencephalography (EEG) and heart rate monitors. However, these approaches are intrusive, uncomfortable for drivers, and require precise sensor placement for accurate results, making them impractical for real-world deployment.

To overcome these challenges, computer vision-based behavioural analysis has emerged as a non-intrusive and effective alternative for drowsiness detection. This approach monitors facial features such as eye closure, yawning frequency, and head movements to determine a driver's alertness level. Advances in deep learning and Convolutional Neural Networks (CNNs) have significantly improved the accuracy and reliability of such systems, enabling real-time detection of drowsiness with minimal hardware requirements.

This study presents a deep learning-based drowsiness detection system that utilizes Google MediaPipe Face Mesh for real-time facial landmark detection and a CNN model for classifying eye states. The system processes live video input, extracts key facial features, and detects signs of fatigue, triggering timely alerts to prevent accidents. A custom dataset is used for training, incorporating various lighting conditions and facial orientations to improve generalizability.

The proposed method offers a non-intrusive, real-time solution for detecting driver fatigue, enhancing road safety by preventing accidents before they occur. This paper explores the implementation, performance evaluation, and potential improvements of the system in real-world conditions.

2. Literature Review

The main idea of this project [1] is to create a non-disruptive system that can detect driver fatigue and issue a timely warning because a lot of road accidents happen due to the driver's drowsiness. This program will therefore help prevent many accidents, and as a result save money and reduce human suffering. This system will monitor the driver's eyes using a camera and by developing algorithms we can detect signs of driver fatigue in advance to avoid accidents. The project will therefore help to detect driver fatigue in advance and will provide sound warning and seat vibration in the seat frequency range of between 100 and 300 Hz. In addition the warning will be disabled by hand rather than automatically. For this purpose, a stop button will be used to disable the warning. Also if the driver feels drowsy, there is a sudden acceleration or deceleration then we can judge this by plotting a graph on the time domain and where all three input variables indicate that it is possible to get tired at one particular second or moment then a warning signal in the form of a text or red circle will be given. Here, a stop button is used for deactivating the warning signal which increases the hardware requirements and can also distract the driver further from the road.

This work [2] detects the characteristic of EEG signal in drowsy driving. A method based on power spectrum analysis and FastICA algorithm for determining fatigue levels was suggested. In the driving simulation system, the EEG signals of the driver were taken with the NT-9200 tool in two states, one was awake and sober and the other was drowsy. Channel signals are analysed with FastICA algorithm for ocular electric, myoelectric and power frequency interface removal. Power spectral densities were calculated after FFT, and the F fatigue index was finally obtained. The test results show that the method presented in this paper can be used to determine the drowsiness of the EEG signal effectively. But, the cost of manufacturing is high and it cannot be deployed in every vehicle.

In this paper [3], an algorithm for driver drowsiness is introduced based on visual sigs that can be extracted from high frame rate video analysis. A study of visuals that differ from the statistical database is proposed to assess their suitability for drowsiness by data mining. Subsequently, an algorithm is developed that combines the most closely related blinking features (duration, eye closure percentage, blinking frequency and amplitude-velocity ratio) using fuzzy logic. This algorithm was tested on a large database representing 60 hours of driving from 20 different drivers. The main advantage of this algorithm is that it is independent of the driver and does not require any modifications. In addition, it provides good results with more than 80% positive outcomes. Since CNN helps to perform prediction, recognition and classification tasks instead of pattern recognition, we will be implementing our project using CNN.

In this paper [4], a light weight, real time driver's drowsiness detection system is developed and implemented in the Android app. The system records videos and detects the driver's face in all frames using image processing techniques. The system is able to detect facial contours and then calculates the Eye Aspect Ratio (EAR) and the Eye Closed Ratio (ECR) to detect driver drowsiness depending on the adaptive threshold. Mechanical learning algorithms were used to test the effectiveness of the proposed method. The technical results show that the proposed model is able to achieve 84% accuracy using random forest classification. However, 3 different classification models are used here which are Naïve bayes, SVM and random forest classifier.

We have researched that CNN is a better classification model and it can be used instead of above 3 classification models.

3. Methodology

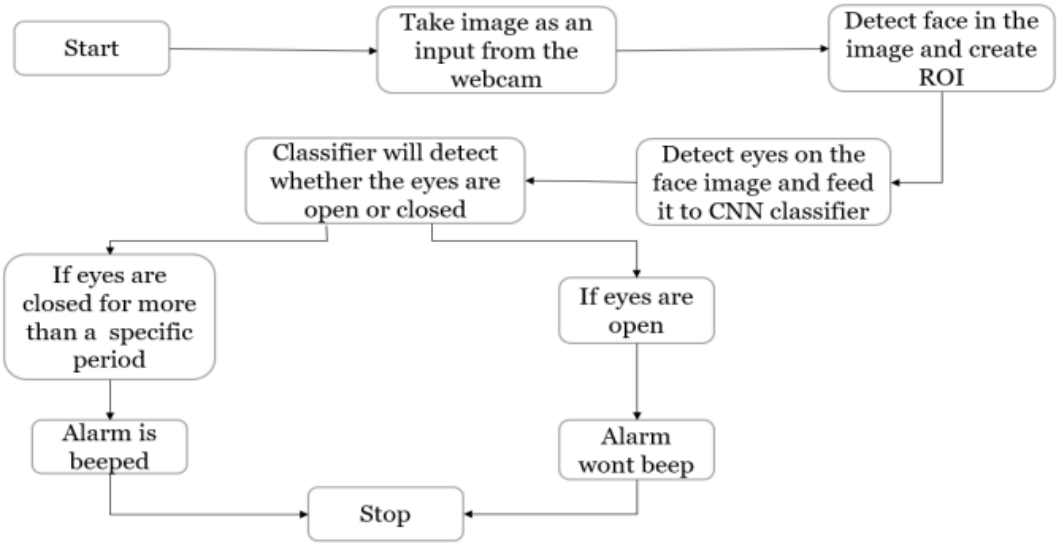


Fig.1 Proposed Methodology

Algorithm:

Start – The system initializes and prepares to capture real-time images from a webcam.

Take Image from Webcam – The system continuously captures frames from the webcam to analyse the driver's face.

Detect Face in the Image & Create ROI (Region of Interest) –

- The system applies face detection algorithms (e.g., using OpenCV, MediaPipe) to locate the driver's face.
- A Region of Interest (ROI) is created around the face to focus on key features.

Detect Eyes on the Face Image & Feed to CNN Classifier –

- The system extracts the eye region from the detected face.
- The CNN classifier processes the extracted eye images to determine whether the eyes are open or closed.

Classifier Decision (Eyes Open or Closed)

- If eyes are open, the system concludes that the driver is alert, and no alarm is triggered.
- If eyes are closed, the system continues monitoring for a specific period to confirm drowsiness.

Drowsiness Detection (If Eyes Closed for a Specific Time)

- If the eyes remain closed beyond a predefined threshold (e.g., 2-3 seconds), the system identifies the driver as drowsy.
- An alarm is triggered to alert the driver.

Stop – The system continues monitoring until manually stopped or until it detects alertness again.

Convolutional Neural Network (CNN)

It is the most influential innovations in the field of computer vision and image processing for Image Classification and recognition. Successful in identifying faces, objects and traffic signs. They're basically just neural networks that use Convolutional layers which are based on the mathematical operation of convolution. It consists of a set of filters, which you can think of as just 2D matrices of numbers.

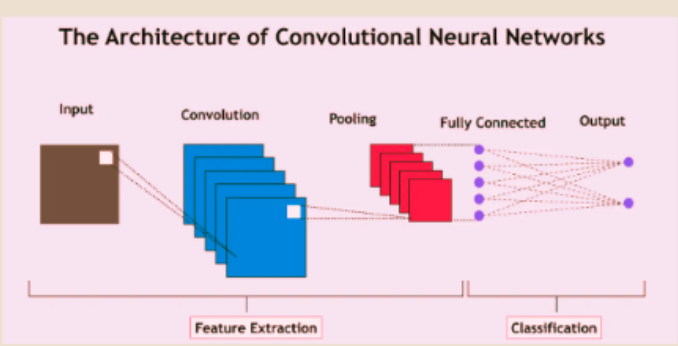


Fig.2 CNN model

Working:

We can use an input image and a filter to produce an output image by convolving the filter with the input image. This consists of Overlaying the filter on top of the image at some location. Performing element-wise multiplication between the values in the filter and their corresponding values in the image. Summing up all the element-wise products. This sum is the output value for the destination pixel in the output image. Repeating for all locations.

CNN layers:

Input layer: The input layer in CNN must contain image data. Image data is represented by a three-dimensional matrix. We need to reshape it into one column.

Convolutional layer (with ReLU activation): Primary purpose of Convolution is to extract features from input image and ReLU is rectified linear unit and it is an activation function.

Pooling layer: It reduce the number of parameters when input is too large. Pooling layers solve this problem. All they do is reduce the size of the input it's given by pooling values together in the input. The pooling is usually done by a simple operation like max, min, or average. It is also called down sampling which reduces dimensionality of each map but retains important information.

Fully connected Layer with Softmax Layer: Softmax turns arbitrary real values into probabilities. What softmax really does is help us quantify how sure we are of our prediction, which is useful when training and evaluating our CNN.

Output Layer: The output layer contains a label in the form of one-hot encoded.

4. CONCLUSION

Driver drowsiness is a major cause of road accidents, making real-time fatigue detection an essential safety measure. This study presents a deep learning-based behavioural approach using Convolutional Neural Networks (CNNs) and computer vision techniques to detect drowsiness

in drivers. By leveraging Google MediaPipe Face Mesh for real-time facial landmark detection, the system efficiently extracts the eye region and classifies open or closed eye states.

The proposed system provides a non-intrusive, real-time solution that eliminates the need for wearable physiological sensors. Through image preprocessing techniques such as grayscale conversion, noise reduction, and normalization, the model achieves improved feature extraction and classification performance. The implementation of a CNN classifier enables accurate detection of drowsiness by analysing the driver's eye behaviour.

This research highlights the effectiveness of deep learning in developing real-time fatigue detection systems. The system is capable of operating in varied environmental conditions, making it a practical solution for enhancing road safety. By issuing timely audio alerts, it can help prevent fatigue-induced accidents and promote safer driving habits.

Although the system demonstrates strong performance, further improvements can be made by: Enhancing dataset diversity to improve robustness across different demographics, Integrating head posture analysis for more reliable drowsiness detection, Optimizing computational efficiency for deployment on low-power embedded systems (e.g., Raspberry Pi), and Extending the system to multi-modal detection, incorporating both facial and behavioural cues for higher accuracy.

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