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Driver Behavioral Detection & Alert System

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Abstract

Driving involves a collection of actions that demand intense focus. Sometimes other actions like eating, drinking, talking, making phone calls, adjusting the radio, or being sleepy take precedence over these behaviors. Additionally, these are the primary reasons for today's traffic accidents. Therefore, creating application that alerts the driver beforehand is crucial. In this study, a lightweight convolutional neural network architecture along with Haar-cascading and Facial landmark is introduced to identify driver behaviors, assisting the warning system in correct information delivery and traffic collision minimization. Combining feature extraction and classifier modules creates this network. The feature extraction module extracts the feature maps by utilising the benefits of average pooling layers, depthwise separable convolution layers, standard convolution layers, and proposed adaptive connections.

The feature extraction module, which directs the network in learning the salient features, makes use of the benefit of the convolution block attention module. To determine the probability of each class, the classifier module uses a global average pooling and softmax layer. The whole architecture keeps classification accuracy while optimising the network parameters. The Module is trained using YOLO, to train a YOLO model, you first need to prepare a dataset of labeled images. The dataset should include images of the objects you want the YOLO model to detect, along with the corresponding bounding box annotations and class labels. once the YOLO model is trained, it can be used to quickly and accurately detect objects

Introduction

The number and complexity of today's road traffic networks have greatly increased. As a result, accidents also gradually rose in number. According to World Health Organisation figures, 50 million traffic accidents and around 1.35 billion fatalities occur each year [1]. Driver behavior is one of the major factors contributing to a rise in accidents. In addition, it was said in the previous sentence that driving with intense concentration might cut the accident rate in half. The National Highway Transportation and Safety Administration (NHTSA) in the United States (US) reported that roughly 2,895 fatal road accidents involving distracted driving occurred in 2019 [2], making up 8.7% of all fatal traffic accident deaths that year. According to these reports, distracted driving still resulted in between 8% and 10% of all fatalities and accidents, and 14% to 16% of all accidents, between 2010 and 2019. Figures 1 and 2 show the precise number of distracted driving fatalities and collisions in the previous ten years.

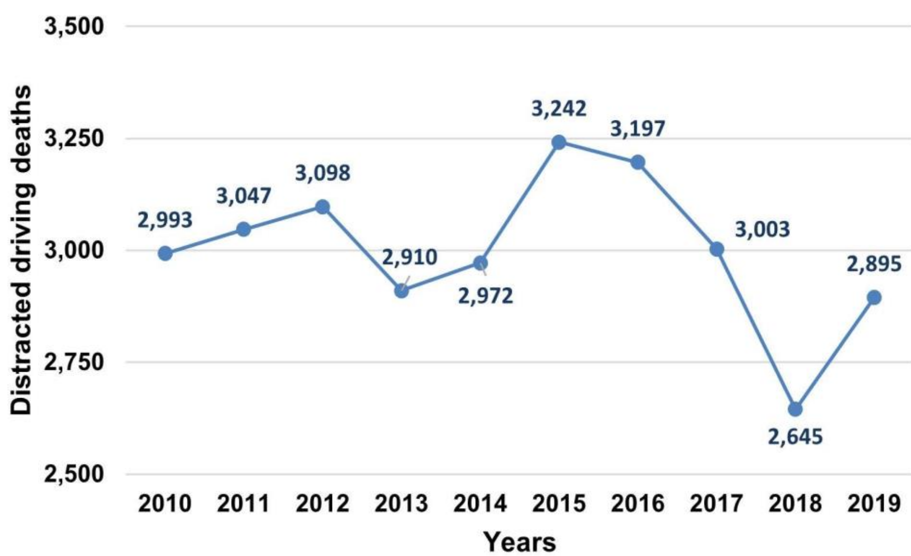

FIGURE 1. Statistics on fatalities from distracted driving in the US during the next ten years.

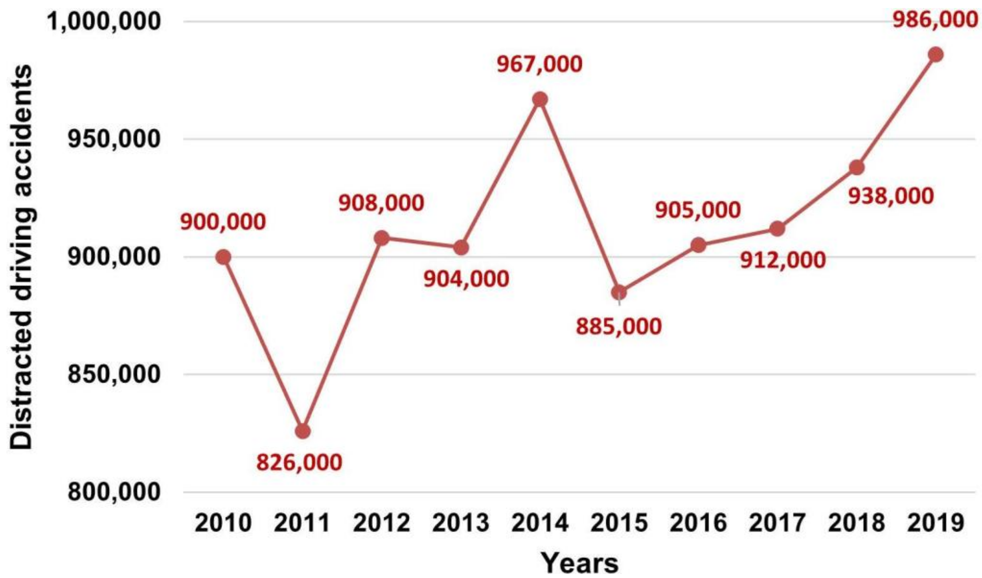

FIGURE 2. **Statistics on distracted driving collisions in the US during a ten-year period.**

The researchers concentrated on defining distracted driving and looking into the causes and remedies of traffic accidents. The authors of [2] define distracted driving as actions by drivers such as using telephones (talking, texting), eating, drinking, and altering the entertainment system (radio, stereo) that divert their attention away from the road. According to a different definition in [3], distracted driving is any activity that prevents the driver from paying attention to the road. The three types of distracted driving in this study are visual, manual, and cognitive. Analysing head posture and eye condition are the main topics of visual distraction. The primary tools for evaluating visual distraction are various sensors and cameras that are mounted on cars or that are physically attached to the driver to collect signals, process, and then record them.

However, the majority are currently undergoing testing. On the other hand, the majority of these gadgets are expensive and challenging to install in ancient cars. Additionally, wearable technology suffers from safe driving practises, and some natural human body structures may interfere with the signals acquired.

This paper presents a method to recognise driving behaviours using a straightforward convolutional neural network (CNN) architecture which is used to detect objects which are the main cause for the driver being distracted coupled with Haar-Cascading and Facial landmark which are used to detect the attention levels of the driver, with the goals of simplifying the devices, making them non-invasive for drivers, and lowering expenses. In order to extract the feature maps and then learn the standout features via the attention mechanism, the proposed network makes use of the standard convolution layers, depthwise separable convolution layers, average pooling layers, and adaptive connections with the convolution block attention module (CBAM). The classifier module then uses the softmax function and the global average pooling (GAP) layer to determine the probability of 10 corresponding driver behaviours in the datasets. The following are the main contributions of this study:

1) To assist the driver warning system, a lightweight convolutional neural network for driving behaviour identification was proposed. Modules for feature extraction and classifiers make up this network. The approach uses fundamental CNN building blocks, proposed adaptive connections, and a convolution block attention module to learn crucial feature map information. Additionally, it replaces all fully connected layers in typical classification networks using global average pooling. As a result, it maintains high speed and accuracy while optimising the network settings. This architecture can be used without incurring any additional installation or modification costs on low-cost and low-computing equipment, including deployment on older vehicles. On the other hand, it doesn't interfere with the driver's psyche because of how the camera's picture signals are used and processed.

2) This paper provides for a solution in which we can integrate object detection, drowsiness and yawning as a single entity which helps to alert the driver and the respective authorities.

II. RELATED WORK

The many strategies used to identify driver behavior, together with their benefits and drawbacks, will be presented in this section.
Both conventional machine learning and CNN-based approach are taken into consideration while evaluating these methods.

A. Machine Learning Methodology

The initial study concentrated on identifying mobile phone use while driving. With an accuracy of 93.9%, Ref. [7] use the Supervised Descent technique, a Histogram of Oriented Gradients (HOG), and an Adaboost classifier to recognise mobile usage. The mobile phone area extraction from face landmark approach, lighting, and occlusion circumstances are limitations of this work. Other research employ Hidden CRF [8] and Support

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Vector Machines (SVM) [9] to categorise cellphone use by measuring the distances between four components, such as the face, mouth, hands, and cellphone. These methods can attain accuracy of 91.2% and 91.57%, respectively, although they still heavily rely on the skin's illumination.

The study in [10] employs the SVM approach to accurately identify mobile use in photos captured by cameras positioned on traffic signals and highways with an accuracy of around 86.19%. Since the study only used a tiny sample of 1,500 photos, its accuracy is extremely poor. The authors of [11] suggested a method for classifying pictures generated from the RGB-D sensors of Kinect devices that imitate mobile use using Hidden Markov models and an Adaboost classifier. 90% of the time, distracted driving can be detected, however the system is made up of numerous intricate components.

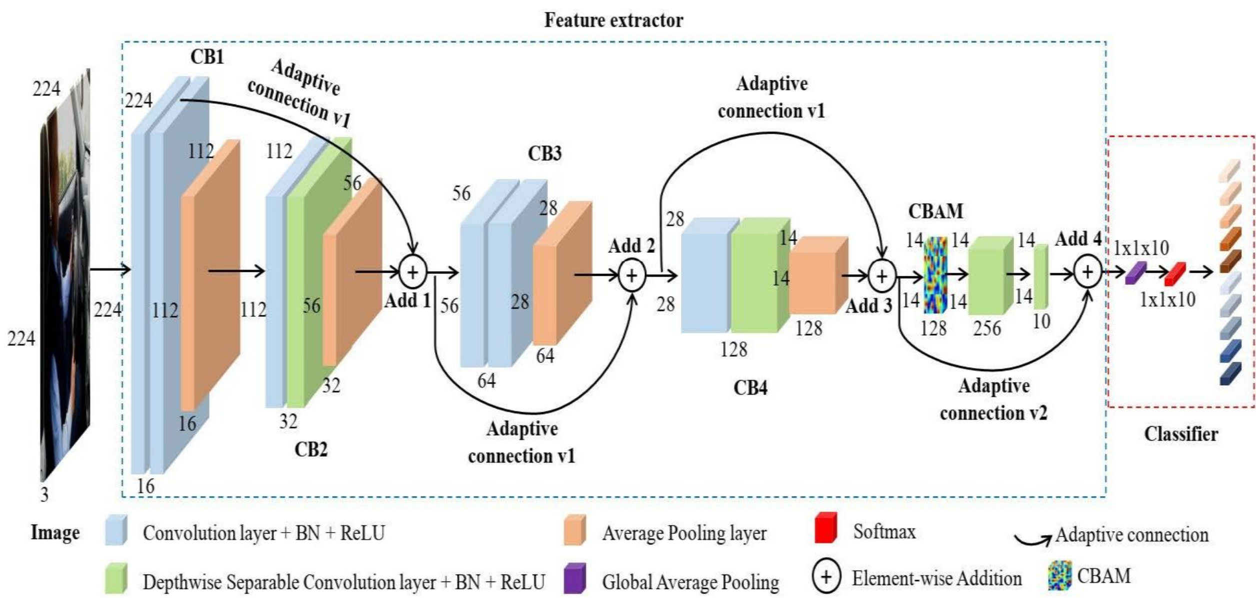


FIGURE 3. The suggested network for classifying driving behavioural.

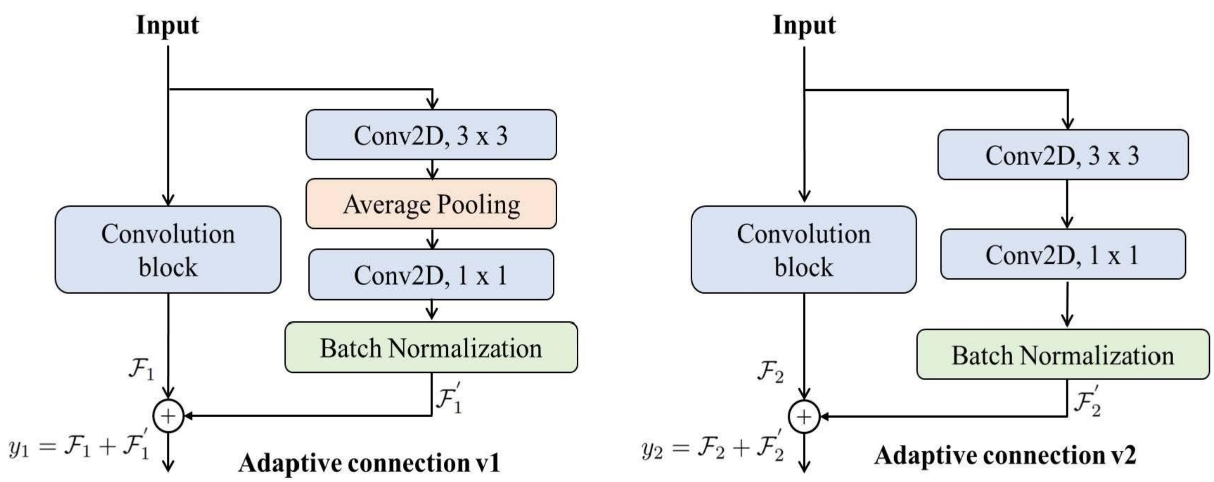


FIGURE 4. The design of the flexible connectors.

B. CNN Based Methodology

Convolutional neural networks have been extensively used in computer vision domains recently. Convolutional neural networks have also been used in studies on human behavior in general and driving behavior in particular to create apps for monitoring and warning. Applications include picture segmentation, image classification, and image detection. A Faster R-CNN network is used in the work in [14] as a detector to infer the hand movements on the steering wheel. According to the findings, this approach accurately detects cases of mobile phone use and hands on the steering wheel with accuracy rates of 92.4% and 91%, respectively. The steering wheel, gear lever, and dashboard are localised in Ref. [15] using the picture segmentation technique.

On previously segmented regions, they suggest a network architecture to identify the driver's hand position with a 74.3% accuracy rate. While this combination approach can address the lighting changes issue, it is computationally challenging. [16] originally presented the Southeast dataset, which has four classes: eating or smoking, chatting on the phone, driving safely, and shifting gears, for the picture classification job. This dataset is utilised in conventional machine learning approaches, and [17] employed a number of convolutional neural network algorithms with an overall accuracy of 99.78% to classify these four groups.

Extended datasets for driving distraction are proposed in [18]–[20] and have eleven classifications (the dataset subsection has further information on each class). Numerous research have employed various CNN network topologies for training and assessment based on these datasets. Additionally, the authors in [19] and [20] suggest an ensemble training strategy using five separate CNN networks, which yields accuracy of 94.29% and 93.65%, respectively. Other common classification neural networks, including VGG [21], [22], DenseNet [23], and GoogleNet [24], have also been used to classify driver behaviours, with accuracy ranging from 95% to over 99%. [25, [26] suggested convolutional neural network designs with depthwise separable convolution operation and a residual network to identify 10 driving behaviours in order to reduce network parameters and deploy low-computation devices.

The aforementioned research, while very accurate, only concentrated on classifying driver behaviour using a small number of classes (four classes) or only assessed individual datasets using a higher number of classes (ten classes). On the other hand, several of the recommended solutions are cumbersome and challenging to implement in real-time systems. This paper suggests a lightweight driver behaviour categorization convolutional neural network as an investigation of the efficacy of standard convolutional and depthwise separable convolution layers, as well as Inception and Residual networks. When compared to many other approaches, the network offers good accuracy while having just 0.43M parameters.

III. IMPLEMENTATION

We achieved this work by dividing the project into three modules.

1. Device Initialization Module

2. Distraction Detection Module

3. Alert Module

1. DEVICE INITIATIZATION MODULE

In this module, the software application takes live input from the camera that is connected to the device on which the application is hosted. This means that the application can capture real-time video or images from the camera, and use them as input for various tasks such as object detection, face recognition, or video streaming. The camera may be built-in to the device, such as a laptop or smartphone camera, or it may be an external camera that is connected to the device via USB or another interface. By taking live input from the camera, the application can provide a seamless and interactive user experience, allowing users to see and interact with the world around them in real-time.

2. DISTRACTION DETECTION MODULE

This module has 3 internal modules:

I. Face detection is implemented using Haar cascading
II. Eye detection is implemented by using Facial Landmark
III. Object detection is implemented by CNN(Convolutional Neural Network)

I. Face detection using Haar cascading

Face detection using Haar cascading can be used in driver alert systems to monitor the driver's attention and alert them if they appear drowsy or distracted. Haar cascading is a popular algorithm for face detection in images and videos, and it works by applying a set of classifiers to different sub-regions of an image.

In a driver alert system, a camera is typically installed in the car to capture the driver's face and monitor their facial expressions and lip movements. The camera feed is then fed into the Haar cascading algorithm, which scans the video frames for faces and extracts features such as the position, size, and orientation of the detected faces.

Once a face is detected, the system can use additional algorithms to analyze the driver's facial expressions and eye movements to determine if they are drowsy, distracted, or not paying attention to the road. If the system detects that the driver is exhibiting signs of fatigue or distraction, it can issue an alert, such as a visual or audible warning, to get the driver's attention and prompt them to refocus on the road.

Overall, face detection using Haar cascading can be a powerful tool in driver alert systems, as it can help prevent accidents caused by driver fatigue or distraction, and improve overall road safety.

II. Eye detection using Facial Landmark

Eye detection using facial landmarks can also be used in driver alert systems to monitor the driver's attention and alert them if they appear drowsy or distracted. Facial landmarks are specific points on the face, such as the corners of the eyes and mouth, that can be used to track the movement and orientation of the face in real-time.

In the context of a driver alert system, facial landmark detection can be used to detect the position and movement of the driver's eyes. This can be achieved by first detecting the face in the camera feed using a face detection algorithm, and then using facial landmark detection to locate the eyes within the face region.

Once the eyes are located, additional algorithms can be used to monitor the driver's eye movements and determine if they are showing signs of drowsiness or distraction. For example, the system can track the position of the driver's pupils and determine if they are consistently looking in the same direction, which could indicate that the driver is not paying attention to the road.

If the system detects that the driver is exhibiting signs of fatigue or distraction, it can issue an alert, such as a visual or audible warning, to get the driver's attention and prompt them to refocus on the road.

Overall, eye detection using facial landmarks can be a useful tool in driver alert systems, as it can provide an additional layer of monitoring to detect signs of driver fatigue or distraction, and improve overall road safety.

III.Object detection module

Object detection using Convolutional Neural Networks (CNN) can be used in driver behavior detection to monitor the driver's actions and provide feedback to improve their driving habits. CNNs are a type of deep learning algorithm that can learn to recognize patterns in images and videos, making them well-suited for object detection tasks.

In the context of driver behavior detection, object detection using CNNs can be used to detect and track various objects in the car and on the road. For example, the system can detect the position and movement of the driver's hands on the steering wheel, or the position and movement of other vehicles or obstacles on the road.

The CNN-based object detection algorithm would be trained on a large dataset of images and videos of different driving scenarios, and would learn to recognize various objects and patterns in the visual input. Once the algorithm is trained, it can be deployed on a system that captures real-time video feed from the car's camera and uses the CNN to detect and track objects in the video frames.

The detected objects can then be used to monitor the driver's behavior and provide feedback or warnings if they are exhibiting unsafe driving habits, such as not keeping their hands on the steering wheel or following other vehicles too closely.

The CNN detects the objects that we have trained for, the list of objects that we have trained for are some of the primary distractions for the driver.

Overall, object detection using CNNs can be a powerful tool in driver behavior detection, as it can provide real-time monitoring of the driver's actions and help improve overall road safety.

3. ALERT MODULE

This application, has been designed to monitor the driver's behavior and the surrounding environment. It uses camera to detect certain movements and objects.

Firstly, the application monitors the driver's eyes lids and lip movements. It has predefined threshold values that it considers normal or safe behavior. If the driver's eyes lids or lip movements cross those threshold values, the application considers it abnormal behavior and triggers an alert to the driver. This is done to help prevent accidents caused by driver fatigue or distraction.

Secondly, the application also monitors the surrounding environment of the driver using a camera. It looks for objects around the driver. If the application detects an object, it also triggers an alert to the driver. This is done to help prevent accidents caused by collisions with objects or obstacles on the road.

This module is divided into two sub modules:

I. Driver alert system

The alert that the application triggers is a beep sound, which is designed to catch the driver's attention and prompt them to take action. The beep sound in this application has decibel values that are catered to get the attention of the driver. By combining these two monitoring systems, the application aims to provide a safer driving experience for the driver and reduce the risk of accidents on the road.

II. Email alert system for the respective authorities

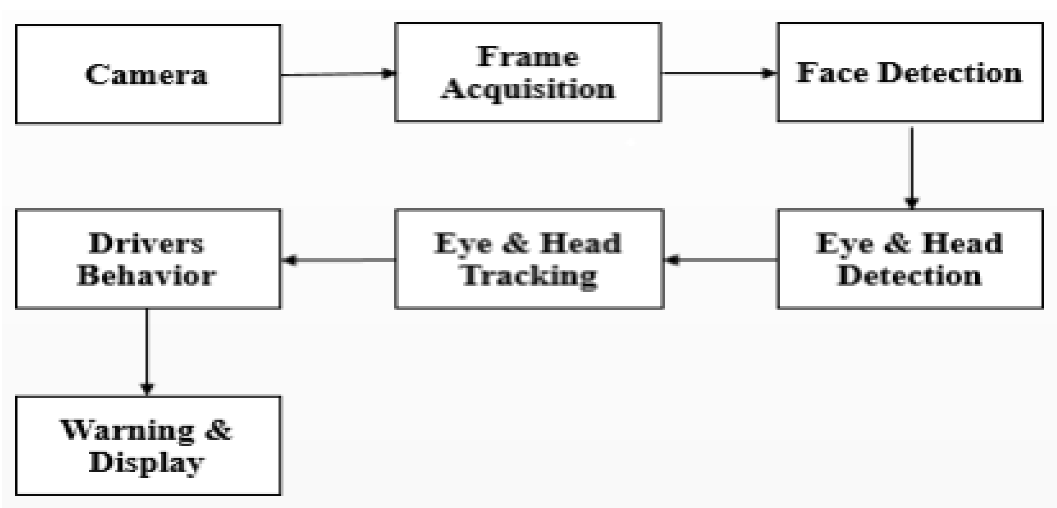
The frequency of distractions while driving. It has a counter that keeps track of the number of times the driver gets distracted during the journey.

The application has predefined threshold values for the number of times a driver can get distracted before it triggers an alert to the authorities. Once the threshold value is reached, the application triggers an email alert system to send an email to the authorities. The email contains details such as the driver's name, license plate number, and the time of the alert.

The email alert system is a communication channel between the application and the authorities responsible for enforcing safe commute of the goods being delivered as well as the safety of driver and his environment. This system ensures that the authorities are made aware of the driver's behavior, and they can take appropriate actions to prevent accidents caused by driver distraction.

The email alert system is an efficient way of notifying the authorities, as it can be sent in real-time, and the authorities can act on it promptly. By using this system, the application aims to promote safe driving practices and reduce the number of accidents caused by distracted driving. The Email alert system uses the SMTP (Simple Mail Transfer Protocol) package in python to send an email to the respective authorities.

FIGURE 5. DFD (Data Flow Diagram):



CONCLUSION

The driver behavior and alert system is a comprehensive and innovative solution to promote safe driving practices and prevent accidents caused by driver fatigue and distractions. By using camera and algorithms, the system can detect if the driver is yawning or drowsy, and if there are objects around the driver that may cause distractions.

The system alerts the driver by triggering a beep alert to grab their attention and prompt them to take action. At the same time, the system sends an email alert to the authorities to inform them of the driver's behavior, ensuring that they can take appropriate actions to ensure road safety.

With its ability to detect and alert the driver and authorities about potential dangers, the driver behavior and alert system can significantly reduce the risk of accidents caused by driver fatigue and distractions. The system's efficiency, accuracy, and reliability make it a valuable addition to any vehicle, providing drivers with the peace of mind they need to focus on the road and stay safe.

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