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Intelligent Alarm System for Driver Drowsiness Detection

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Abstract: With increase in the population, accident rates are also increasing rapidly, the main reason is drowsiness of the driver. Such lethal incidents can be prevented if the driver is warned in time. To implement this technology, we proposes a smart alarm system to detect the drowsiness of driver using facial expressions and eye movements. Here open computer vision is used to detect driver's eye movements for a long time.

We propose an approach based on Convolutional Neural Networks (CNN) that describes the object detection problem as sleepy detection. Based on the drivers' real-time video feed, it can detect and identify whether the eyes are open or closed. The technology used in this object detection challenge is the cellular CNN architecture with a single-shot multi-box detector. A different algorithm is used based on the output produced by the SSD_MobileNet_v1 architecture. A dataset of approximately 4,500 photographs of yawning, non-yawning, eyes-open, and eyes-closed subject faces was labelled to train the SSD_MobileNet_v1 network. The trained model is tested on about 600 randomly selected photos. The suggested strategy will guarantee improved computing efficiency and accuracy.

Keywords: single shot multi-box detector, Deep learning, Smart alarm, eye tracking, drowsiness detection.

I. INTRODUCTION

The World Health Organisation and the National Highway automobile Safety Administration estimate that at least 1.35 million individuals each year pass away in automobile accidents. Poor driving is the primary cause of accidents. When a driver is sleepy or exhausted, a number of things can happen. There is a higher chance of mishaps and accidents when driving while fatigued. In order to create a smart or intelligent automotive, advanced technologies must be used. A driver alarm system is being developed as part of the scope of this attempt. Automobile manufacturers like Samsung have investigated the degree of driver attention by studying face characteristics and patterns. The majority of these technologies, however, are special and only offered in pricey vehicles.

These processes for recognising fatigue can be further divided into other categories, including physiological, behavioural, and vehicle-related. There are many methods that have been developed in the past to detect drowsiness. For instance, sleepiness identification techniques are used to track lane changes, speed, and pedal compressions.

These techniques entail tracking the driver's physiological signals, assessing performance using vehicle data, and recording behaviour. Because it only considers the driver's state of mind, the biomarker measurement method, unlike other methods, has shown the best ability to detect driver drowsiness. A camera is needed to monitor the drivers' behaviours, such as specific eye closure, yawning, head position, and tiredness detection. An further stage in physiological drowsiness recognition approaches is to monitor exhaustion in connection to physiological signals like the ECG and electrooculogram. The need for the driver to wear electrodes on their body limits this technology.

The purpose of this study is to recommend a low-cost solution for identifying driver fatigue while operating a vehicle. To create this application for detecting sleepiness, we employed a CNN architecture. Using the main contribution as a guide, this work can be divided into two phases: (a) using Convolutional Neural Networks (CNN) to detect sleepy detection process for object detection, and (b) using sleepiness data sets to help researchers develop a way to detect sleepiness.

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II. LITERATURE REVIEW

This section assesses the research projects carried out by various researchers that are relevant to the proposed work. Eye movement is usually a more reliable measure of sleep. Many developed systems are thought to rely on eyelid closure to determine the driver's fatigue, although other behaviors such as faster blinking, sneezing, slow blinking, repetitive blinking, fixed eyes, and slouching posture also predict the driver. fatigue Several literatures have recommended the use of conventional cameras, infrared (IR) cameras, and stereo cameras to predict sleepiness. Dwivedi et al. developed a model for drowsiness detection using CNN. That approach used CNN-based representative feature learning with an accuracy rate of 78. To reduce accidents caused by tired drivers, Alshaqaqi et al. recommended a dedicated driver assistance system. An algorithm was proposed to locate, map and score faces and eyes to test PERCLOS and detect drowsy driving. Said et al. suggested driver drowsiness based on eye tracking. The method detects awareness by generating an alarm, the technique warns drivers when a driver is feeling sleepy while performing this duty. Using Viola Jones' model, the face and eye regions were identified in this paper. In tests conducted indoors, it offered an accuracy of 82 percent, and outside, it offered an accuracy of 72.8 percent.

Mehta et al. created smart apps that can calculate eye aspect ratio (EAR) and eye closure ratio (ECR), detect facial cues and predict driver drowsiness with 84 percent accuracy. Enter Ellcie-Healthy's smart glasses, which offer a sleep monitoring system that detects blinks, records eyes and manages vital signs. The driver is advised to take a break with smart glasses that monitor these inputs and interrupt drowsiness with a beep. Combination strategies combine multiple sensors, such as infrared, cameras, and heart rate monitors, in a single device to achieve significant efficiency. These devices are very expensive and require the use of unique solutions. Mandal et al. presented a vision-based method to detect driver fatigue for monitoring bus drivers. In this study, AHOG and SVM are used for head and shoulder detection and driver detection, respectively. They used OpenCV face detector and OpenCV eye detector for face and eye detection. Eye anatomy was discovered through spectral regression embedding, and new techniques for determining eye opening were also created. Fusion was used to combine the features obtained from two eye detectors, I2R-ED and CV-ED. Perclos was chosen as an indicator of sleepiness. Xie et al. Jabbar et al. introduced a deep learning-based concept for driver fatigue detection for Android applications. Here, a model was created that focuses on finding landmarks in faces. Dlib software was used to extract the coordinates of the landmarks after the original images were made from the video frames. These oriented coordinate points are fed into a multilayer perceptual classifier. Their point classifier used the Mobile Net-SSD architecture for a training dataset of 350 images. The model achieved an average accuracy of 0.84. Since the algorithm could be applied to an Android device and the camera stream could be classified in real time, the method was effective and successful. Jie Lyu et al. long-term multi-grain depth structure is recommended to detect driver drowsiness with 90.05% accuracy. However, the technology could not be implemented on mobile devices due to its complexity.

III. METHODOLOGY

This section defines the general research methodology.

A. Algorithm

It believes that detecting sleepiness is a task related to object detection. Images from incoming video streams are used. With the help of a single shot multi box detector (SSD) system built on top of the mobile net architecture, we conduct experiments using Mobile Nets, a lightweight convolutional neural network architecture.

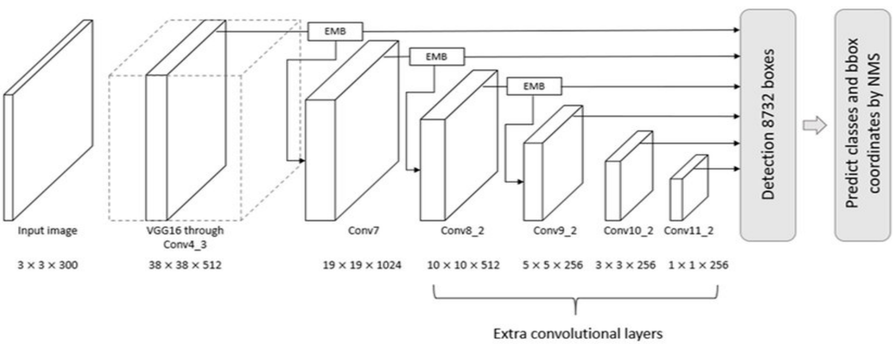

Fig. 1 SSD Architecture

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Convolutional neural network (CNN) technology is used to identify driver sleepiness. When compared to other classification methods, CNN's pre-processing is significantly more extensive. The three types of pooling, convolution, and fully connected layers that often make up CNN. The first two pooling layers use convolution to perform feature extraction, and the third layer, which is fully linked, maps the extracted characteristics, such classification, onto the output. For our challenge, we combine an SSD (Single Shot Multi Box Detector) system built on a cellular network architecture and cellular networks, a light convolutional neural network architecture. There are two classes of algorithms for traditional object detection. RCNN and faster RCNN algorithms use a two-step process to detect individual objects only in certain regions and define zones where objects can be found. Algorithms like SSD and YOLO, on the other hand, use convolution entirely, allowing the network to identify the location of each object in the photo using Conv Net instantly. One-shot algorithms are more efficient and have satisfactory accuracy, while area recommendation methods usually have slightly higher accuracy but are slower to run. The SSD architecture is described in the f1g.1.

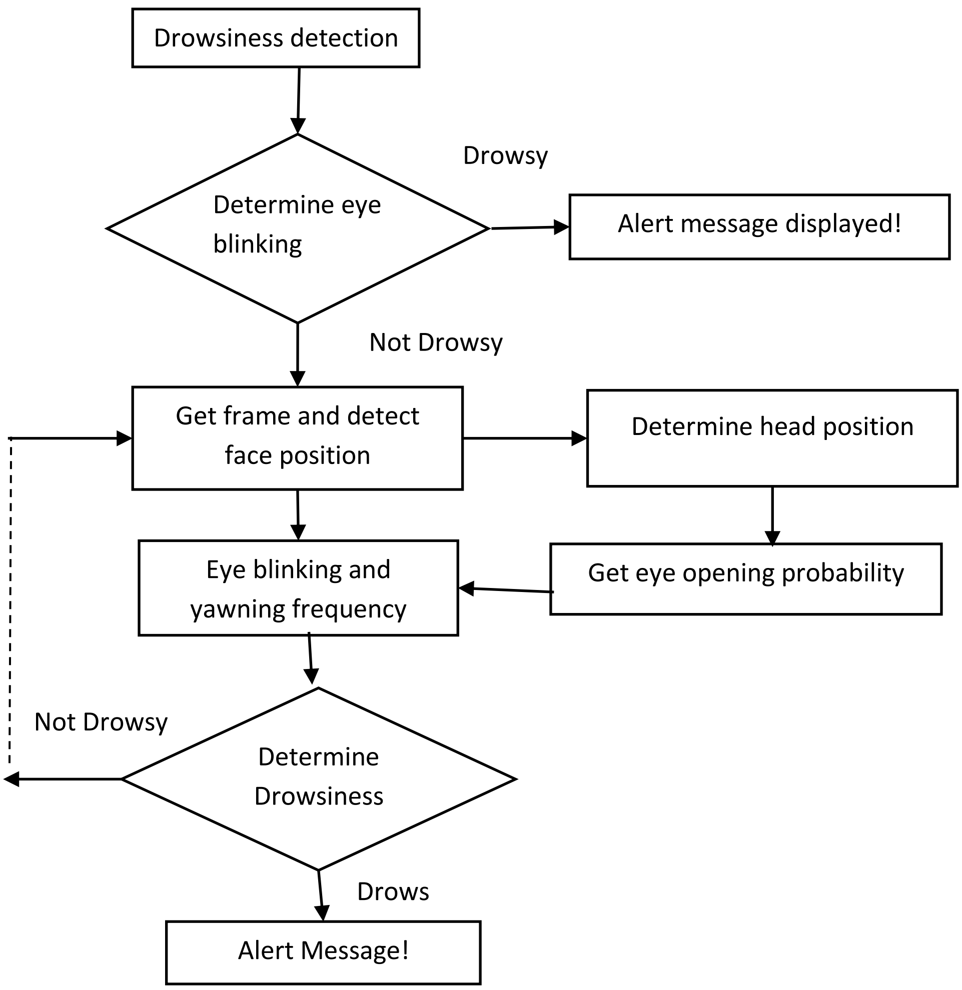

Fig. 2 Drowsiness detection system methodology

An SSD consists of two parts: a backbone model and an SSD head. The backbone model is often a pre-trained image classification network operating as a feature extractor. There are few essential factors in SSD. The SSD uses a grid to split the image rather than a sliding window, and each cell of the grid needs to contain a list of the objects that are present in the picture region. All that is needed for object identification is to predict the kind and location of an object within a sector. We respect it as the context class if there isn't an object and the location isn't taken into account. Each grid cell receives the position and shape of the thing that it contains. Mobile Nets' architecture enables depth-wise separable convolutions and the construction of compact deep neural networks for mobile applications. The mobile net is a separable convolution, with the first layer being an exception. The first layer is a full convolutional layer. Each layer is complemented by batch normalisation and ReLU non-linearity.

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IV. DATASET

Open and closed eye databases are taken from an open source database. This dataset contains both open and closed human eyes. There are JPG versions of all the images. With no comments, there are 1234 photos totaling about 10 MB. This dataset's images are all annotated.

A. Custom Used Images

The images used can be reused and are openly accessible. The primary goal of using these images is to enhance our categorization algorithm. This dataset is flexible with a range of positions and lighting conditions.

Fig. 3 Dataset images

B. Dataset Training

The Tensor Flow API can be used to train our model. The TFOD API can only read files in the TF Record file format, so we need to convert our dataset to this format. We need an RGB image dataset in jpeg or png format before we can define bounding boxes for the image and the classes of those boxes. Computer-based training is also available through services such as AWS, Google Cloud, PaperSpace, etc. The model was refined until it was sufficiently accurate. The learned model was exported to a single TensorFlow graph file after training was finished. It's called a frozen inference graph.

C. Yawn and Noyawn while Driving

The data on yawning and not yawning while driving comes from the University of Ottawa in Canada. Two distinct types of films from two different inside-the-vehicle camera perspectives make up the dataset. The device is attached to the dashboard of the car for the first set of data and then to the windshield for the second set. They have both male and female managers. In these films, some of the drivers are seen without glasses. A handful of drivers also laugh, look around, yawn or don't yawn.

V. RESULT AND DISCUSSION

The experiment's findings and related outcomes have been thoroughly detailed in this section. The experiment is performed on Google Cloud using the Tensor Flow object detection API. When training for 800 000 steps at an average step speed of 0.5 seconds, our SSD model needs 6 days. Our network generates a frozen inference graph after training, which we then turn into an inference model. Our final model delivered 8 frames per second (FPS) for the SSD architecture during the first round of laptop testing.

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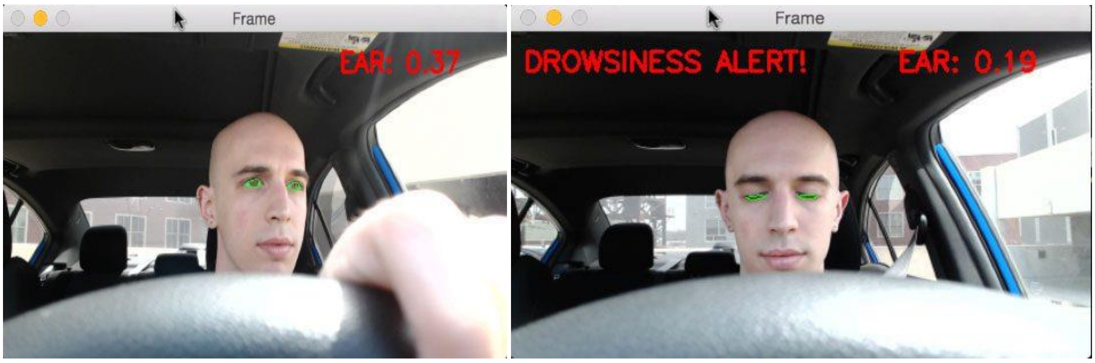

Fig. 4 Drowsiness detection

Machine learning algorithms were once used to manually extract features, but deep learning architecture today eliminates this step. There is automatic learning. Currently, deep learning architecture automatically extracts its features. As a result, it saves considerable time compared to spending time on feature definition needed to improve classification results.

VI. CONCLUSION

The issues and restrictions with several earlier proposed similar systems have been resolved by the proposed vehicle drowsiness detection system. by creating comparable systems. Basic road security safety against sleepy or exhausted drivers can be established with the development of this system at a low cost, effectively, and efficiently. Driver drowsiness detection and an alert driver warning system (which sounds an alarm) are included in the proposed system. The number of accidents caused by drowsy or sleepy driving can be indirectly decreased by putting the proposed system into practice.

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