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DRIVER DROWSINESS DETECTION SYSTEM

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ABSTRACT

Road crashes and related forms of accidents are a common cause of injury and death among the human population. According to 2015 data from the World Health Organization, road traffic injuries resulted in approximately 1.25 million deaths worldwide, i.e. approximately every 25 seconds an individual will experience a fatal crash. While the cost of traffic accidents in Europe is estimated at around 160 billion Euros, driver drowsiness accounts for approximately 100,000 accidents per year in the United States alone as reported by The American National Highway Traffic Safety Administration (NHTSA). In this paper, a novel approach towards real-time drowsiness detection is proposed. This approach is based on a deep learning method that can be implemented on Android applications with high accuracy. The main contribution of this work is the compression of heavy baseline model to a lightweight model. Moreover, minimal network structure is designed based on facial landmark key point detection to recognize whether the driver is drowsy. The proposed model is able to achieve an accuracy of more than 80%

Keywords: Android, OpenCV, Drowsy Driver Detection, Eye Detection

I. INTRODUCTION

Driver drowsiness is one of the leading causes of motor vehicle crashes. This was confirmed by a study1 conducted by the AAA Foundation for Traffic Safety, which showed that 23.5% of all automobile crashes recorded in the United States in 2015 were sleep-related: 16.5% for fatal crashes and 7% for non-fatal crashes. Essentially, this report implied that over 5,000 Americans lost their lives as a result of sleep-related vehicular crashes. The development of drowsiness detection technologies is both an industrial and academic challenge. In the automotive industry, Volvo developed the Driver Alert Control which warns drivers suspected of drowsy driving by using a vehicle-mounted camera connected to its lane departure warning system (LDWS). Following a similar vein, an Attention Assist System has been developed and introduced by Mercedes-Benz that collects data drawn from a driver's driving patterns incessantly ascertains if the obtained information correlates with the steering movement and the driving circumstance at hand. The driver drowsiness detection system, supplied by Bosch, takes decisions based on data derived from the sensor stationed at the steering, the vehicles' driving velocity, turn signal use, and the lane-assist camera mounted at the front of the car. Notably, the use of these safety systems which detect drowsiness is not widespread and is uncommon among drivers because they are usually available in luxury vehicles. An increased embedding and connecting of smart devices equipped with sensors and mobile operating systems like Android, which has the largest installed operating system in cars, was shown by surveys in 20152. In addition, machine learning has made groundbreaking advances in recent years, especially in the area of deep learning. Thus, the use of these new technologies and methodologies can be an effective way to not only increase the efficiencies of the existing real-time driver drowsiness detection system but also provide a tool that can be widely used by drivers. The remainder of this paper is organized as follows. In section 2, the literature review is presented. In section 3, the proposed system along with the implementation of each system's block will be described. The computational results obtained from experiments are discussed in section 4. Finally, in Section 5, conclusions, as well as directions for future research, are presented.

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II. METHODOLOGY

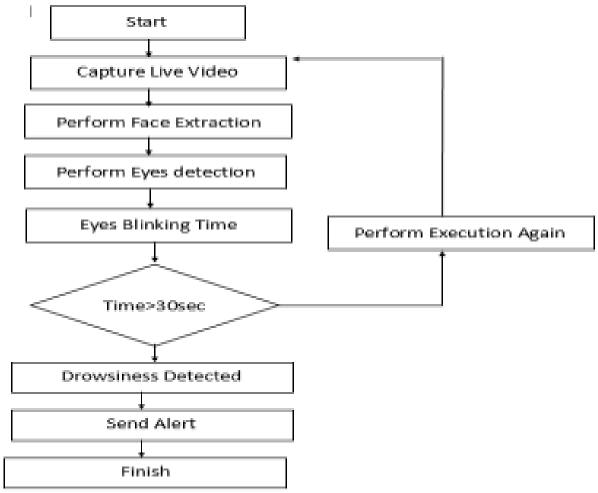

Fig 1. Flow chart drowsy driver detection system

As per the above fig shows the live video is going to capture first then the image is going to be extracted and workout. In this face extraction is going to be workout. The iris detection algorithm will work out. If the eyes will find to be closed then it will give the alert and will send the notification to admin.

III. LITERATURE REVIEW

In a bid to increase accurateness and accelerate drowsiness detection, several approaches have been proposed. This section attempts to summarize previous methods and approaches to drowsiness detection. The first previously-used approach is based on driving patterns, and it is highly dependent on vehicle characteristics, road conditions, and driving skills. To calculate driving pattern, deviation from a lateral or lane position or steering wheel movement should be calculated3,4. While driving, it is necessary to perform micro adjustments to the steering wheel to keep the car in a lane. Krajweskiet al.4 detected drowsiness with 86% accuracy on the basis of correlations between micro adjustments and drowsiness. Also, it is possible to use deviation in a lane position to identify a driving pattern. In this case, the car's position respective to a given lane is monitored, and the deviation is analyzed5. Nevertheless, techniques based on the driving pattern are highly dependent on vehicle characteristics, road conditions, and driving skills. The second class of techniques employs data acquired from physiological sensors, such as Electrooculography (EOG), Electrocardiogram (ECG) and Electroencephalogram (EEG) data. EEG signals provide information about the brain's activity. The three primary signals to measure driver's drowsiness are theta, delta, and alpha signals. Theta and delta signals spike when a driver is drowsy, while alpha signals rise slightly. According to Mardi et al.6, this technique is the most accurate method, with an accuracy rate of over 90%. Nevertheless, the main disadvantage of this method is its intrusiveness. It requires many sensors to be attached to the driver's body, which could be uncomfortable. On the other hand, non-intrusive methods for bio-signals are much less precise. The last technique is Computer Vision, based on facial feature extraction. It uses behaviors such as gaze or facial expression, yawning duration, head movement, and eye closure. Danismanet al.7 measured drowsiness of three levels through the distance between eyelids. This calculation considered the number of blinks per minute, assuming that it increases as the driver becomes drowsier. In Hariri et al.8, the drowsiness measurements are the behaviors of the mouth and yawning. The modified Viola-Jones9 object detection algorithm was employed for face and mouth detection. Recently, the deep learning approaches, especially the Convolutional Neural Networks (CNNs) methods, has gained prominence in resolving challenging classifications problems. Most of them represent a breakthrough for various Computer Vision tasks, including scene segmentation, emotion recognition, object detection, image classification 9,10, etc. With adapted shallow CNNs, Dwivediet al.11 achieved 78% accuracy of detecting drowsy drivers. Park et al.12 developed a new architecture employing three networks. The first one13 uses

AlexNet consisting of three Fully-Connected (FC) layers and five CNNs to reveal the image feature. Furthermore, 16-layered VGG-FaceNet14 is used to extract facial features in the second network. FlowImageNet15 is used for extracting behavior features in the third network. This approach achieved 73% accuracy. Dwivediet al.11 and Park et al.12 attempt to improve the accuracy of drowsiness detection accuracy using binary classification.

IV. PROBLEM STATEMENT

The attention level of driver degrade because of less sleep, long continuous driving or any other medical condition like brain disorders etc. Several surveys on road accidents says that around 30 percent of accidents are caused by fatigue of the driver. When driver drives for more than normal period for human then excessive fatigue is caused and also results in tiredness which drives the driver to sleepy condition or loss of consciousness.

V. PROPOSED WORK

Depending on advantages and disadvantages the most suitable method is chosen and proposed. Then the approach for entire system development is explained using a flow chart which includes capturing the image in real time continuously, then dividing it into frames. Then each frames are analyzed to find face first. If a face is detected then then next task is to locate the eyes. After the positive result of detecting eye the amount of closure of eye is determined and compared with the reference values for the drowsy state eye. If drowsy condition is found out then driver is alarmed else repeatedly the loop of finding face and detecting drowsy condition is carried out.

VI. CONCLUSION

Implementation of drowsiness detection with Android was done which includes the following steps: Successful runtime capturing of video with camera. Captured video was divided into frames and each frames were analyzed. Successful detection of face followed by detection of eye. If closure of eye for successive frames were detected then it is classified as drowsy condition else it is regarded as normal blink and the loop of capturing image and analyzing the state of driver is carried out again and again. In this implementation during the drowsy state the eye is not surrounded by circle or it is not detected and corresponding message is shown. If the driver is not drowsy then eye is identified by a circle and it prints 1 for every successful detection of open eye.

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