IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Driver Drowsiness Detection Using Deep Learning Techniques

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Abstract- The majority of human injuries and fatalities are caused by traffic accidents and other kinds of accidents. According to World Health Organization data from 2015, traffic accidents killed approximately 1.25 million people worldwide, or one person is killed every 25 seconds. While the cost of road accidents in Europe is projected to be around 160 billion euros, according to the US National Highway Traffic Safety Administration, drowsy driving is responsible for approximately 100,000 accidents in the United States alone (NHTSA). A non-invasive approach to detecting driver drowsiness is discussed in this paper. To identify the driver's drowsiness, the face features are retrieved, and then the extracted facial features are put to a deep learning model. The Real-life Drowsiness Dataset (UTA-RLDD) from the University of Texas at Arlington is used in this work. The suggested method successfully determines the driver's level of awareness.

Keywords- Driver Drowsiness Detection, Deep Learning, University of Texas at Arlington Real-life Drowsiness Dataset (UTA-RLDD).

I. INTRODUCTION:

Drowsiness is a condition in which a person's level of awareness decreases as a result of a lack of sleep or fatigue. It may cause the driver to sleep soundly. As a result, the driver may lose control of the vehicle, causing it to leave the road or collide with another vehicle. Driver fatigue is one of the main factors in accidents on the road. According to research [1] by the AAA Foundation for Traffic Safety, sleep was a factor in 16.5% of fatal and 7% of non-fatal crashes, or 23.5% of all car accidents reported in the United States in 2015. In essence, this analysis suggested that sleep-related car accidents claimed the lives of more than 5,000 Americans.

The creation of drowsiness detection technology is a challenge for both industry and academia. In the automotive sector, Volvo has created Driver Alert Control, which uses a camera mounted on the car connected to its Lane Departure Warning System to alert drivers who may be driving while fatigued (LDWS). In a similar vein, Mercedes-Benz has created and launched an attention support system that gathers information on the driver's driving behaviors and continuously verifies whether the data acquired correlates with steering movement and driving conditions at your fingertips. The driver sleepiness detection system supplied by Bosch makes choices based on data from the steering sensor, the vehicle's driving velocity, the use of turn signals, and the lane-assist camera installed in front of the car.

However, drowsy driver detection safety technologies are hard to come by. This study's main goal is to analyses the University of Texas Arlington Real-Life Drowsiness Dataset (UTA-RLDD) and develop a deep learning model that can track the driver's condition and determine whether or not they are drowsy. An image-based non-invasive technique is used from the video to detect the driver's facial features over time, and to classify if the driver is drowsy or not.

II. LITERATURE REVIEW:

With the aim of increasing accuracy and accelerating the detection of drowsiness, various approaches have been proposed. This section seeks to summaries past sleepiness detection methods and approaches. The first method described above is based on driving behaviors and is highly dependent on vehicle attributes, road conditions, and driving abilities. To determine the driving pattern, the deviation from a lateral or lane position, as well as steering wheel movement, must be calculated [2,3]. Micro-adjustments to the steering wheel are required when driving to keep the car in a lane. Krajewski et al. [3] detected sleepiness with 86% accuracy based on correlations between micro adjustments and sleepiness. A deviation in lane position can also be utilized to identify a driving pattern. In this scenario, the car's position with regard to a specific lane is tracked, and deviation [4] is calculated. Driving mode-based strategies, on the other hand, are heavily dependent on vehicle attributes, road circumstances, and driving ability.

Data from physiological sensors, such as electrooculography (EOG), electrocardiogram (ECG), and electroencephalogram (EEG) data, are used in the second class of approaches. Brain activity is revealed via EEG readings. Theta, delta, and alpha signals are the three primary signals used to gauge driver tiredness. When a driver is sleepy, theta and delta signals rise while alpha signals barely change. With an accuracy rate of above 90%, this methodology is the most accurate one, in accordance with Mardi et al. [5]. The biggest drawback of this approach is how intrusive it is. The driver must have numerous sensors attached to their bodies, which can be uncomfortable. In contrast, non-intrusive methods for bio signals are much less accurate.

The most recent method relies on computer vision, which extracts face traits. It uses features including eye closure, yawning for a long time, head movement, and stare. Sleepiness was assessed by Danisman et al. [6] at three different levels along the line between the eyelids. This calculation considered the blink rate, assuming that it rises as the driver loses consciousness. In Hariri et al. [7], sleepiness measures are yawning and yawning behaviors. For face and mouth detection, the modified Viola-Jones [8] object detection algorithm was utilized. Deep learning methodologies, particularly convolutional neural network (CNN) methods, have recently acquired popularity for tough categorization issues.

The majority of them represent breakthroughs in various computer vision tasks such as scene segmentation, emotion identification, object detection, image classification, and so on [8,9]. Dwivedi et al. [10] used customised shallow CNNs to detect drowsy drivers with 78% accuracy. Park et al. [11] created a new architecture based on three networks. The first [12] reveals the image feature using AlexNet, which consists of three Fully-Connected (FC) layers and five CNNs. The 16-layered VGG-FaceNet [13] is utilised in the second network to extract facial traits. FlowImageNet [14] is applied in the third network to extract behaviour features. This approach had a 73% accuracy rate. Dwivedi et al. [10] and Park et al. [11] employ binary classification to increase drowsiness detection accuracy. Convolutional neural network (CNN) approaches have generally delivered astounding results in the field of drowsiness detection and are also a great aid in a variety of classification tasks. Because the size of the model is usually huge and demands a high level of computing complexity, installing these methods in actual applications on embedded devices is still time-consuming.

III. Proposed Solution:

A. Data Description:

The dataset used in this study was obtained from the Real-Life Drowsiness Data set at The University of Texas at Arlington (UTA-RLDD). This dataset, which consists of a collection of videos, is the largest realistic drowsiness data set available to date. It features self-recorded videos from 60 healthy participants. Each subject produced three videos, one for each of the three alertness classes that the participant labelled while recording each video based on their prevalent state. The three groups are alert, low vigilant, and drowsy. The driver is alert if he or she is completely conscious and capable of driving for extended periods of time. Low vigilance means the driver is sleepy, while drowsy means the driver is falling asleep. As a result, the whole package includes 180 videos, each roughly 10 minutes long and running at less than 30 frames per second.

Figure 1: Sample pictures from UTA-RLDD dataset

This data set covers a wide range of topics. Participants ranged in age from 20 to 59 years old, with a mean age of 25 years and a standard deviation of 6 years. There were 51 males and 9 women there, representing a wide range of ethnicities (10 Caucasian, 5 non-white Hispanic, 30 Indo-Aryan and Dravidian, 8 Middle Eastern, and 7 East Asian). Those wearing glasses were seen in 21 of the 180 videos, and people with a lot of facial hair were shown in 72 of the 180 videos. Participants in the top row are on high alert, those in the second row are on low alert, and those in the third row are drowsy.

B. Data Preparation:

This model's first phase is to extract the faces from each image. The Viola-Jones Haar-Feature Based Cascading Classifier was used for this. The next stage is to extract the image's facial characteristics, such as the eyes, nose, mouth, and chin, as well as the eye aspect ratio (EAR) and mouth aspect ratio (MAR), to detect drowsiness. These features clearly indicate whether a person is sleepy or not. To extract the features, a convolutional neural network (CNN) is used. Inception v3, a pre-trained model trained on the Image-Net dataset with 1000 classes, was used. The Inception v3 model produces a 2048-dimensional feature vector, which is fed into the sequential neural models. Finally, the extracted features are combined to form a sequence of extracted features.

C. Training The algorithm:

The training data set's stitched features for the sequential model are made up of 2048 feature vectors and 160 batches with 50 frames each. A 1024 dense dropout layer was employed after a 2048 wide LSTM layer. The dropout stops the model from fitting too tightly. The model was trained using Keras and Tensorflow for 10 epochs with Adam Optimizer with a learning rate of 0.00005 to train and optimize the network weights.

IV. RESULTS:

The model can be evaluated with the help of accuracy of correctly predicting the drowsiness of driver. For the purpose of calculating accuracy for the above algorithm, a confusion matrix is created for the actual and expected result constituted of TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative).
The formula for the accuracy is:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN).$$

The overall accuracy of the above model is 99%. The model successfully predicts with 99% accuracy that the driver is alert whereas the model predicts with 98% accuracy that the driver is drowsy.

V. CONCLUSION:

The paper discusses the method of correctly determining whether or not the driver is alert. The model, which was developed using the University of Texas at Arlington Real-Life Drowsiness Dataset (UTA-RLDD), had a 99% accuracy rate. Currently, the models are trained on a limited number of participants, resulting in a limited range of diversity, and then validated using video of a participant that the model has never seen before. The accuracy can be improved even further if we can create a separate model for each user. For this, we can install a video capturing device in the vehicle, and the driver can manually mark the time when they felt alert or drowsy, and this data can then be used for analysis.

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