DETECTION OF DISTRACTED DRIVERS ON THE ROAD USING DEEP LEARNING APPROACH

B.Vanipriya,
M.E. Assistant Professor, Department of CCE,, Panimalar engineering college

Muthu Shruthi S,
Department of CCE, Panimalar engineering college

Archana Priya S,
Department of CCE, Panimalar engineering college

Abstract—Although there are many factors that contribute to traffic accidents, such as breaking traffic laws, driving too fast, etc., one of them is drowsy driving. According to the Central Road Research Institute, sleepy/drowsy driving causes 40% of collisions (CRRI). Every year, incidents caused by drivers falling asleep at the wheel result in the deaths of roughly 1.5 lakh individuals. Convolutional Neural Network (CNN) algorithms can be used to identify the sleepy drivers and warn them whenever they appear to be falling asleep to resolve this problem. With the help of the CNN algorithm, which is built on the TensorFlow and Keras frameworks, we take pictures of the person riding the wheels and categories them as open or closed. The current algorithm functions properly when compared to the CNN algorithm.

Keywords— ,CNN, Lethargic, CRRI, OpenCV

I. INTRODUCTION

Driving a car is a difficult undertaking that requires complete concentration. Any hobby that diverts a driver's attention from the road is considered distracted riding. A number of studies have identified the three most significant types of distractions: visible distractions (driver's eyes off the road), manual distractions (driver's hands off the wheel), and cognitive distractions (driver's thoughts off the task of operating the vehicle). According to the National Highway Traffic Safety Administration (NHTSA), 36,750 people died in car accidents in 2018, with distracted driving accounting for 12% of those deaths. The most dangerous distraction by far is texting. You must take your eyes off the road for five seconds in order to send or analyze text. The equivalent of riding a soccer field's length with your eyes closed at 55 mph is to ride in a single motion. The use of mobile devices while driving is now prohibited by law in several places, including texting, talking on the phone, and other distractions. We concur that computer vision can boost government efforts to prevent accidents caused by inattentive driving. Regularly identifying and alerting drivers who are distracted by their hobbies is part of our set of guidelines. In order to prevent injuries from inattentive driving, we see this kind of technology being integrated into motors.

II. RELATED WORK

According to [1], the purpose of the equipment is to inform the driver in drowsy conditions as well as the traffic department in order to control and prevent any potential accidents. This technology seeks to warn the Driver when they are drowsy as well as the Traffic department to avoid any potential accidents. This system is not obtrusive. Three separate subsystems make up it. Drowsiness detection unit is the name given to the first system that recognizes sleepiness. As soon as drowsiness is identified, it transmits a message through Controller Area Network (CAN) to the Dashboard unit, the second subsystem. The motorist receives warnings and alerts from this system. A sophisticated drowsiness warning system has been created. The after-effect is never used; the sleepiness detection is typically the only detection. This system makes an effort to get around this restriction. Moreover, a sleepiness detection alarm system has been designed to wake up the driver. According to the authors of [2], it comprises of detecting algorithms, sensing systems, and their accompanying accuracy and limitations. Problems and potential solutions, such as combining the phone conduct class device with the concepts of context-aware, mobile crowdsensing, and active guiding control, are analysed. Data acquired from the phone provide a vast supply of statistics for understanding motive force conduct. Several approaches put out by unique authors to identify unique forms of odd utilising have been examined. Despite the fact that phone answering devices have many advantages over telematics boxes, there are still a number of difficult situations that should be taken into account for a proper driver conduct class.

According to [3], when neuromorphic vision sensors, such the Dynamic and Active-pixel Vision Sensor (DAVIS), which uses silicon as its retina, are triggered by organic vision, they produce streams of asynchronous activity that reflect changes in the brightness of nearby neighbourhoods. They are a great fit for many programmes of movement belief inside the smart automobile due to their properties of high temporal resolution, low bandwidth, light weight processing, and reduced latency. Neuromorphic imagination, on the other hand, is virtually ever associated with the smart car because it is a younger and smaller research area than traditional computer imagination. We provide three brand-new datasets that were captured using DAVIS sensors and an intensity sensor for this purpose, with a focus on driving fatigue detection, driving force gaze-area recognition, and driving force hand-gesture recognition. We simultaneously record the RGB, intensity, and infrared data with an intensity sensor in order to assist the analysis with traditional computer vision. The need for intelligent vehicles to handle challenging circumstances and, more crucially, the smallest manoeuvres that an intelligent vehicle will make. Researching potential strategies for a neuromorphic vision sensor is much more valuable than developing algorithms for conventional cameras since it can not only provide a complementary sensor to handle different situations but also improve the robustness and accuracy of the performance in challenging circumstances. In this work, we build the first-ever database, NeuroIV, and provide some baseline reviews that connect studies on sensible cars and neuromorphic architecture. The NeuroIV revolutionises the use of a vision-based holistic belief system in intelligent vehicles by introducing new ways to feel and interpret the environment. [4]claims that driver tracking systems (DMSs) had been suggested as a way to reduce the risk of accidents caused by people. Conventional DMSs focus on identifying specific, specified weird riding behaviours, such as drowsy or distracted driving, and employ frequent patterns educated with data gathered during strange driving. Unfortunately, it is difficult to gather widespread detection models that apply to all drivers from adequate consultant schooling data. In light of this, this study suggests a new, completely private hierarchical DMS (HDMS). The proposed HDMS's first layer, which is used while riding, may distinguish between normal and unusual riding behaviour based solely on typical, private riding patterns that are represented by sparse representations. When abnormal riding behavior is identified, the second layer of the HDMS makes a similar determination about whether the behavior is due to drowsiness or distraction. The experimental results for three datasets show that the proposed HDMS outperforms the most recent DMS approaches in identifying normal riding behavior, drowsy riding behaviour, and distracted riding behavior. They suggested an original hierarchical DMS (HDMS) for monitoring drivers' riding behaviour. The proposed method uses part-based, fully temporal face descriptors to effectively depict the driver's face changes as they arrive during the course of the ride. Additionally, the proposed HDMS's unusual detection performance has been improved by simultaneously filtering out normal riding behaviour inside the first layer of the HDMS shape by comparing the facial descriptors that were received during the check with preset normal private riding fashions (PDMs). Interestingly, by assembling the common PDMs with the help of a sparse depiction, the computational complexity of the assessment method is reduced. Drowsy PDMs and distracted PDMs are used to identify the riding behaviour as both sleepy riding conduct and distracted riding conduct, or any other (unspecified) type of weird riding conduct, in the event that an odd behaviour is discovered using the primary layer of the HDMS.

[5] is grateful that this work suggests a novel drowsy driving detection system with those characteristics. A lively sport machine (AGS), which corresponds to the second and 0.33 features, and a sleepiness detection technique (DDS), which relates to the primary feature, are both included in the suggested system, known as a wakefulness-retaining help machine (WKSS). The AGS is a simple sport that motivates participants to engage in distinctively vibrant behaviour. While using the AGS for gambling, drivers can maintain their alertness, while it is possible that false sleepiness alarms will also occasionally occur. They put forth a wakefulness-retaining assistance system (WKSS) that consists of a drowsiness detection system (DDS) and an active sport system (AGS). The AGS requires a driving force to engage in active behaviour, such as a head gesture when using the AGS-Body or speaking when using the AGS Voice. When compared to a conventional alarm clock and beep noises alone, the riding simulator trials demonstrated that active behaviour was more effective in maintaining a driver's alertness. In terms of maintaining awake, the AGS-Body outperformed the AGS-Voice. Even though they were aware that the DDS had provided a phoney alarm, the members were no longer agitated thanks to the use of both AGS.

According to [6], it is a technique that employs mobile software for driver monitoring, analysis, and recommendations based entirely on recognised unsafe using behaviour for accident avoidance when using a personal phone. The phone's cameras and built-in sensors (accelerometer, gyroscope, GPS, and microphone) are utilised to monitor the behaviour of the motive force. A sophisticated approach includes reference modelling, dangerous nation detection, and risky country classification. The following driver risky states are supported by the method: drowsiness, distraction, and an offline risky condition linked to an elevated heart rate. Ten individuals participated in the experiment in which we tested the Android smartphone gadget. a technique for identifying unsafe driving behaviour by using a front-facing digital camera and the phone's sensors. The dangerous driving behaviours that cause injuries on public roadways that are documented in this paper include distraction and sleepiness. High pulse rate is the offline risky nation; this is determined by phone. The following risky states, such as intoxicated use, competitive use, and pressure condition, may be detected based on the facts of excessive pulse charge and in accordance with the suggested phone usage strategy for risky states identification. In the future, the authors hope to predict those dangerous conditions. We developed the application for Android OS mobile devices and uploaded it to the Google Play Market. Our device may be used by five drivers to enhance their driving safety and lower the likelihood of a twist of fate. According to [7], this observation was made by analysing an electroencephalogram (EEG) dataset that was recorded during a simulated endurance riding test. An important brain-computer interface (BCI) paradigm from a software perspective is the use of EEG data in driving safety research. We modify the terms used in the riding examination to fit the reinforcement learning framework in order to construct the difficulty of drowsiness estimation as an optimization of a Q-learning task. Based on that, a deep Q-community (DQN) is tailored by taking into account the most cutting-edge DQN technology. The intended community is entitled to the EEG information's characteristics and may make decisions that indirectly gauge sleepiness. The results show that the trained version can nicely infer the versions of thinking states in opposition to the testing EEG data, confirming the viability and applicability of this new computation paradigm. Deep reinforcement research, in particular, deep Q-learning for tiredness estimation to focus on driving safety. They created different deep Q-community iterations and utilised those to run the test to evaluate our approach. Excessive correlation coefficients between the measured RT and expected RT in both the single-concern instance and the cross-concern situation were one way in which the effects made their practicality evident. Our work necessitates capability future studies to systematically ignore reinforcement learning in BCI for certain applications due to reinforcement learning's low dependence on the quality of the label data and its high information usage performance.

III. PROPOSED WORK

The suggested technique involves categorising eye photos taken with an OpenCV (computer vision) camera based on the labels Open or Closed. Next, deep learning CNN models using TensorFlow and the Keras Framework for classification. The accuracy of distracted drivers for binary classification based on classification CNNs is higher than other algorithms, according to a comparison between the existing and current methods Pre-processing of the photos was required since we employed full images for the classification, which required collecting samples from a larger number of images that represented various classes, such as eyes open and closed. this Varying numbers of photos are gathered for each class that was submitted into the classification system. To prevent drivers from falling asleep at the wheel, we put forth a Deep Learning (DL)-based solution for distracted driver prediction. The Convolutional Neural Network is the DL technique employed in the study (CNN). If the CNN method is backed by the addition of other feature extraction techniques and can correctly categorise distracted drivers, it is projected that the success of the results will grow.

Import images from dataset

Our data set must be imported using the keraspreprocessing picture data generator tool, which also allows us to build size, rescale, range, zoom range, and horizontal flip. Finally, using the data generator tool, we import our image dataset from the folder. We've got train, test, and validation here. With the help of this feature, we can also specify the targetsize, batch size, and class-mode. Next, we may train with the help of our own network by employing CNN layers that are added on top of one another.

To train the dataset by using AlexNet.

With the use of a classifier, a fit generating function, and training steps based on epochs, we may train our dataset by using validation data, validation steps, and an overall number of validation epochs. They have 4 layers in their network, with 1,024 input units, 256 units in the first hidden layer, 8 units in the second hidden layer, and output units.

To train the model using LeNet:

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning technique that can take in an input image, give various elements and objects in the image weights and biases that can be learned, and distinguish between them. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input image, assign importance (learnable weights and biases) to various characteristics and objects in the image, and distinguish between them. It is the input layer, convo layer, pooling layer, completely extracted layer, and logistic layer.

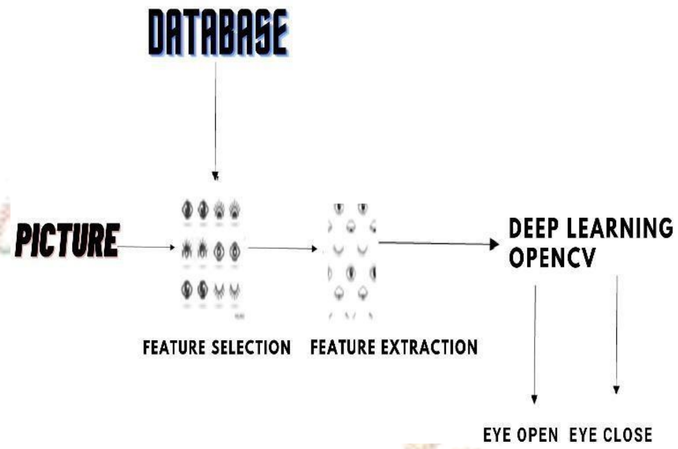


FIGURE 3. ARCHITECTURE DIAGRAM

Implementation of drowsiness by haar cascade classifierby using the deep learning model

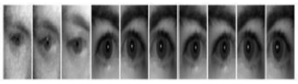
Using the haar cascade classifier algorithm, this component determines if the eye is open or closed. Every level of the classifier assigns one of two labels—advantageous or poor—to the specific location defined by means of the current region of the window. Advantageous signifies that the desired object was observed, while poor suggests that it was no longer visible in the image.

4. ALGORITHM

One of the most well-known subtypes of deep neural networksis the convolutional neural network, sometimes known as CNN or ConvNet. A CNN uses 2D convolutional layers to improve its ability to interpret 2D data, including images, by learning features from input data. CNNs do not require human feature extraction, which eliminates the step of identifying features utilised to categorise images. Direct feature extraction from live images is how CNN operates. Although the network is being trained on a set of photos, the relevant features are not being retrained on these learned images. Deep learning models are created via automated feature extraction for computer vision applications like object categorization and image identification.CNNs learn to detect different features of animage using tens or hundreds or thousands of hidden layers. Every hidden layer increases the complexity of the learned and trained image features. For example, the first hidden layer could learn how to detect edges using image recognition, and the last learns how to detect more complex shapes specifically categorized to the shape of the object we are trying to detect.

5. RESULTS

Using deep learning, this system is built to be able to identify sleepydrivers on the road. This technique uses a camera to take pictures of the driver, detecting face traits from which the eye region may be separated, and then detecting tiredness using values from the Haar cascade. The system's results are displayed in the photos below.



OPENED EYE

CLOSED EYE

Training data for apple_healthy type:
====Images in: Eye_dataset/train/close_lookImage count:3338
Min_width:53 Max_width:231Min_height:53
Max_height:231

Training data for close_look type:
====Images in: Eye_dataset/train/close_lookImage count:3828
Min_width:61 Max_width:168Min_height:61
Max_height:168

6. DISCUSSION

Because of its superior accuracy than current techniques, this system employs deep learning. Although it appears to have some potential for advancements in the future, such as the deployment of real-time processes by displaying the prediction results in online applications or desktop applications, and the optimization of work for implementation in an artificial Intelligence setting.

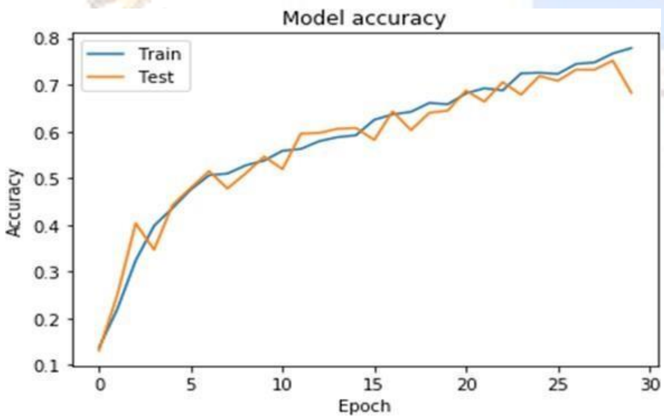


FIGURE : ACCURACY

7. CONCLUSION

A deep learning approach called convolutional neural network was used to train the dataset of closed-eye and opened-eye photos. Three different versions of manual CNN, AlexNet, and LeNet were used to compare the accuracy of the two, with AlexNet outperforming both. OpenCv uses the h5 file hierarchical data format, which is derived from the Alexnet model, to quickly identify sleepiness.

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