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A Noble Machine Learning Technique for Detection of Driver Drowsiness

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ABSTRACT

Accidents are incident, occurs under unpredicted circumstances. The primary cause of inattentiveness and drowsiness when driving is driver weariness. The major goal of this study is to reduce the number of road accidents that are caused by driver inattentiveness. This research introduces a highly accurate sleepiness detection system that warns the driver when they are becoming sleepy while driving. With the development of computer vision technology, smart/intelligent cameras are created to detect driver drowsiness and alert drivers, hence reducing accidents. Machine learning has advanced video processing, allowing for more accurate visual analysis. To identify the face and separate the attention region from the face images, the Viola-Jones face detection method is used. In order to extract features from the recognised features in the camera, a stacked deep convolution neural network is created, and its output is sent to the softmax layer. To categorise the motive force as sleep or non-sleep, a SoftMax layer of the CNN classifier is used. When a motorist exhibits signs of sleepiness, this technique alerts them with an alarm.

Keywords: Viola-jones , Stacked Deep Convolution Neural Network, SoftMax layer, CNN.

1. Introduction

One of the key reasons that endangers road safety and contributes to serious injuries, fatalities, and financial losses is drowsiness. Driving performance is affected by the increasing tiredness and lack of alertness, which causes multiple major road accidents. Therefore, technology for driver sleepiness detection systems is needed to lower traffic accidents. For both industry and researchers, the development of this technology presents significant challenges. The capacity to keep one's eyes open, frequent yawning, shifting the head forward, and other symptoms of driver fatigue can be seen when operating a vehicle. There are several methods used to gauge the extent of driver sleepiness. The measurements in question include physiological, behavioural, and vehicle-based. The greatest approaches to identify driver tiredness are among these behavioural measures. This study uses CNN to create a model to detect tiredness. It is frequently trained for classification between images and comprises of layers for feature extraction from those images with completely connected layers at the end, so that this technique can be utilised for extracting distinguishing features between labelled photos. In a variety of situations, this method has produced findings that are more accurate.

2. Literature Survey

In paper [1] Saini, V., & Saini, R. mainly focused on the majority of drowsiness detection algorithms are used in this work. The three alternative approaches for sleepiness are illustrated in this study. They are: measurements based on vehicles, behavioural, and physiological factors.

The most often used drowsiness detection methods include the electrocardiogram (ECG) and electroencephalogram (EEG), local binary pattern (LBP), steering wheel movement (SWM), optical detection, eye blinking-based technique, and yawning-based method.

This product has a very small market and is ineffective. The market and technologies of today are still developing. Every day, new technologies are developed utilising various methods.

In paper [2] Burke, J. R. Tapamo, and M. Ngxande This article looked at the various metrics and factors used for categorization and gave a brief summary of approaches for detecting driver drowsiness using machine learning techniques.Although there are a variety of ways to gauge tiredness (vehicle-based, physiological, and behavioural methods), this study has concentrated on behavioural methods because they may be utilised in a variety of lighting conditions and don't always need for adjustments to the vehicle. This study examines a number of machine learning and behavioural methods-based algorithms, including SVM, CNN, and HMM. A meta-analysis was carried out using one of these methods. The effectiveness of CNNs was underlined by this analysis. For more accurate sleepiness comparisons, future work will concentrate on building a relevant dataset that includes a variety of various races.

In paper [3] ReddyUyyala, S., Chirra, V. R. R., and Kolli, V. K. K. The identification of driver drowsiness using a new behavioural measure based on eye state is proposed in this research. When the eye is in a drowsy state, an alarm is set off and the eye state is determined. In the Face Detection phase, the Viola-Jones detection technique has been utilised to extract the face and eye areas from the input photos. To extract features, stacked deep convolution neural networks are created. The CNN classifier uses a SoftMax layer to categorise the driver as either asleep or awake. This suggested approach efficiently determines the driver's condition. Future system performance enhancements will make use of transfer learning.

In paper [4] Park, S., Lee, S., Yu, J., and Jeon, M. This research proposes a condition-adaptive representation learning paradigm for 3D-deep convolutional neural network-based driver drowsiness detection. The framework that has been suggested consists of four models: learning spatiotemporal representations, interpreting scene conditions, fusing features, and sleepiness detection. The suggested framework's constraint is that in order to obtain decent detection performance, a high performance GPU computer unit must be installed on a vehicle. Being an offline method, the suggested framework cannot ensure that it will be able to identify tiredness in drivers of completely different types who are not represented in training sets. Future research will build an online updating strategy that uses continuous updating to increase the model's accuracy in detecting sleepiness while also lowering costs and improving computational efficiency. These methods will be applied in embedded board or micro computing systems.

In paper [5] Y. Karalurt, A. G. Yavuz, M. A. Guvensan, S. Kaplan, and In order to promote the fundamental goal of vehicular ad hoc networks (VANET), safe driving, this study developed a paradigm for the active integration of such systems into car-to-car communication. This strategy involves sharing information on driving behaviour through C2C communication. Common alerting mechanisms include sound, vibration, message displays, and automatic car stop systems. This strategy requires more funding.

3. Data Collection

The data is collected from the references and official website of the . The data taken here is the data of people who attended Kumbh mela and hajj.

4. Machine learning

The scientific discipline of machine learning enables computers to learn without explicit programming. One of the most intriguing technologies that has ever been developed is machine learning. The ability to learn is what, as the name suggests, gives the computer a more human-like quality. Today, machine learning is being actively used, possibly in a lot more places than one might think.

Any prospective data analyst or data scientist who wants to turn a vast amount of unstructured data into trends and predictions must have a solid understanding of machine learning. Learn this ability right now with the help of the Machine Learning Foundation - Self Paced Course, which was created and curated by specialists in the field with years of experience. Here we use Cross Validations.

For evaluating the effectiveness of machine learning models, cross validation is a highly helpful technique. Understanding how the machine learning model would generalise to a different collection of data is useful. Using this strategy, you want to gauge how accurate your model's predictions will be in real-world situations.

Two types of data sets—known data (training data set) and unknown data—will be provided to you when you are assigned a machine learning challenge (test data set). Using cross validation, you would be "testing" your machine learning model during the "training" phase to look for overfitting and to get a sense of how it would generalise to independent data, which is the test data set provided in the challenge.

You will have to separate your initial training data set into two portions for one cross validation round:

Set for cross-validation training

Validation set or cross validation testing set

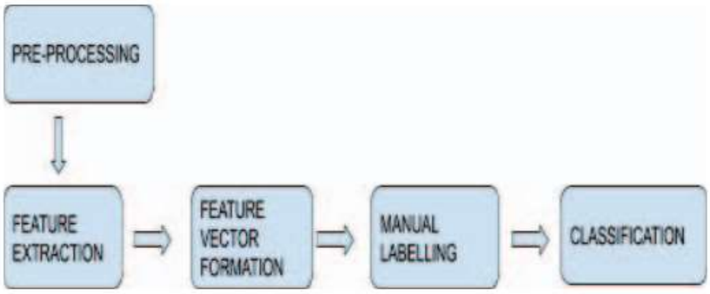
You will use the cross-validation training set to train your machine learning model and the validation set to test its predictions. When you compare the model's predictions on the validation set and the actual labels of the data points in the validation set, you can determine how accurate your machine learning model's predictions are.

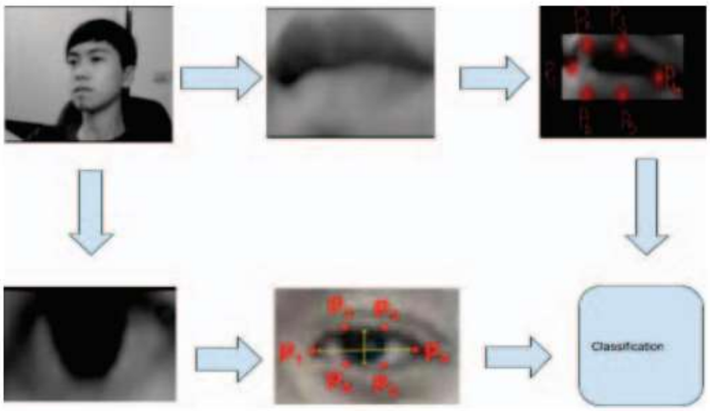
Multiple cross validation rounds are carried out utilising various cross validation training sets and cross validation testing sets in order to reduce the variation. To determine the machine's accuracy, the results from all the rounds are averaged.

6. Methodology

Method 1: Proposed Work

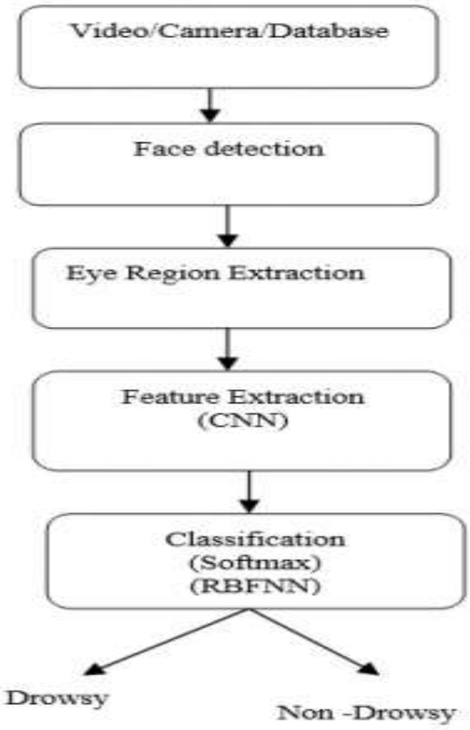
In this study, a system that watches the driver's face from the moment the engine fires up has been developed. This primarily enables us to continuously monitor and record the driver's eye blinking. They classified drowsy drivers based on their facial features, eyes, and mouth movements in addition to using a speed control device to monitor the vehicle's speed. The input video was obtained by putting a camera on the car's dashboard for the real-time application of the model, and it can accommodate the driver's face, hands, upper body, and occlusions like non-tinted glasses. The pre-trained 68 facial landmark detector from the library is utilised for the real-time application of the model. The input video may be obtained by putting a camera on the dashboard of the automobile and can accommodate the driver's face. Implemented was a face detector based on the Histogram of Oriented Gradients (HOG). The suggested approach used the Mouth Aspect Ratio (MAR) and Eye Aspect Ratio (EAR) to track the driver's blinking behaviour and detect yawning in the frames of the continuous video stream, respectively. The model currently performs very well under excellent to perfect lighting conditions, such as those shown in the dataset films, however the real-time testing was carried out under a variety of lighting conditions, leading to lower results for real-time detection. Real-time testing can also be carried out under a range of lighting setups. It focuses primarily on a system that can conduct a variety of functions, including analysing the driver's awareness, detecting lane changes, detecting alcohol, estimating the distance between objects in the road, and analysing the driver's emotions. An alarm is played when the motorist needs to be made aware of the situation. The suggested remedy is to use EAR to forecast the driver's drowsiness (Eye Aspect Ratio). Eye Blinking in Real Time Using Facial Landmarks For facial detection, a pretrained Histogram of Oriented Gradients + Linear Support Vector Machine Object Detector is used. The prototype successfully identified numerous vehicles, a person, and a stop sign. If the alcohol sensor determines that the alcohol level is higher than what is allowed, the system stops the engine from starting. The prototype successfully identified several types of cars, a person, and a stop sign.





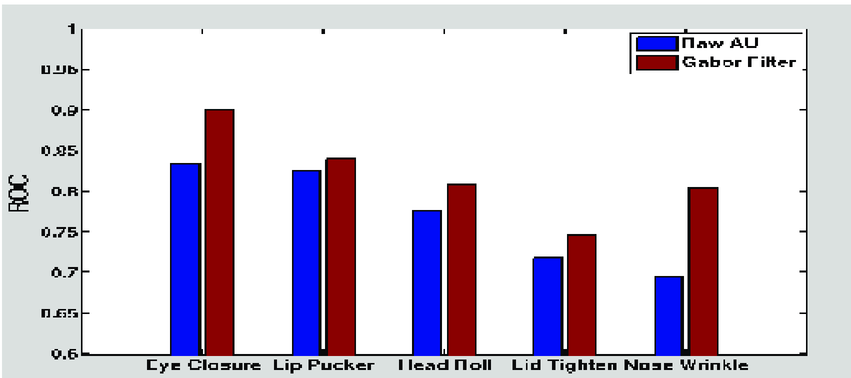
Method 2 : Proposed System Architecture

To identify faces in photographs, the Viola-Jones face identification method is utilised. The results are then fed into the Viola-Jones eye detection algorithm. In order to extract the eye region from the facial images and provide it as input to CNN, the Viola-Jones eye identification technique is employed once the face has been identified. Deep features are extracted using a CNN with four convolutional layers, which are then fed to a fully connected layer. CNN's Soft Max layer divides the images into sleepy and non-sleepy categories. The CNN model that was created for this work. A new Deep CNN model based on Eye State is created for the purpose of detecting driver drowsiness using deep learning. Viola-Jones is better able to detect frontal faces than faces gazing sideways, above, or downwards because it was created for frontal faces. The image is changed to grayscale before a face is detected since it is simpler to deal with and requires less processing power. The Viola-Jones algorithm locates the position on the coloured image after first identifying the face on the grayscale image.



7. Results and Discussion

In 2001, Paul Viola and Michael Jones proposed the Viola-Jones object detection framework, a machine learning object detection framework. Although it can be modified to detect other object types, the challenge of face detection was the main inspiration for it. The average detection rate is 97.41%. The Viola Jones method was a quick and precise way for processing images.



8. Conclusion

This study provides an overview of the detection of driver fatigue. On the basis of eye condition, a new technique is suggested for detecting driver fatigue. This determines if the eye is drowsy or not, alert, and sounds an alarm when the eye is drowsy. Using the Predict and Detection method, the face and eye region are located. To extract features, stacked deep convolution neural networks are created. This is used to categorise the driver as either sleeping or not. The proposed system's accuracy was (95%>). The suggested technology efficiently detects the driver's alertness by sounding an alarm. when the model consistently predicts a sleepy output state. By doing this, the number of accidents will be decreased and driver and vehicle safety will be improved. The presentation of a system for vehicle and driver safety. Drowsiness detecting systems can be used to improve driver safety.

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