Drowsiness Detection Using Machine Learning Algorithms

V.Yasaswini[1] P.Reeshika[2] K.Jahnavi Roy[3] N.Kalpana[4] Rajesh Yamparala[5], Department of Computer Science and Engineering, Vignan's Nirula Institute of Technology and Science for Women, Pedapalakaluru, AP, India, Corresponding Author mail id:yasaswini.velidandla30@gmail.com

Abstract:

The abstract presents a literature review of driver drowsiness detection based on behavioural measures using machine learning techniques. Faces contain information that can be used to interpret levels of drowsiness. There are many facial features that can be extracted from the face to infer the level of drowsiness. However, the development of a drowsiness detection system that yields reliable and accurate results is a challenging task as it requires accurate and robust algorithms. A wide range of techniques has been examined to detect driver drowsiness in the past. As a result, machine learning techniques which include convolution neural networks in the context of drowsiness detection. Here convolution neural networks performed better than any other techniques.

Keywords:-*Drowsiness detection, Machine Learning, Convolution Neural Networks.*

1. Introduction

Real Time Drowsiness behaviors which are related to fatigue are in the form of eye closing, head nodding etc. Hence, we can either measure change in physiological signals, such as brain waves, heart rate and eye blinking to monitor drowsiness or consider physical changes such as sagging posture, leaning of driver's head and open/closed state of eyes. The former technique, while more accurate, is not realistic since highly sensitive electrodes would have to be attached

directly on the driver's body and hence which can be annoying and distracting to the driver. In addition, long time working would result in perspiration on the sensors, diminishing their ability to monitor accurately. The second technique is to measure physical changes (i.e. open/closed eyes to detect fatigue) is well suited for real world conditions since it is nonintrusive by using a video camera to detect changes. In addition, micro sleeps that are short period of sleeps lasting 2 to 3 minutes are good indicators of fatigue. Thus, by continuously monitoring the eyes of the driver one can detect the sleepy state of driver and a timely warning is issued.

Image Capture: Utilizing a web camera introduced inside the automobile we can get the picture of the driver. Despite the fact that the camera creates a video clip, we have to apply the developed algorithm on each edge of the video stream. This paper is only focused on the applying the proposed mechanism only on single frame. The used camera is a low cost web camera with a frame rate of 30 fps in VGA mode

II. Literature Survey

In this section, we have discussed various methodologies that have been proposed by researchers for drowsiness detection and blink detection during the recent years. Ashish Kumar in 2018 has proposed based on visual behavior and machine learning. Here, visual behavior features like eye aspect ratio, mouth opening ratio and nose length ratio are computed from the streaming video, captured by a webcam. An adaptive thresholding technique has been developed to detect driver drowsiness in real time. The developed system works accurately with the generated synthetic data. Subsequently, the feature values are stored and machine learning algorithms have been used for classification. Also, the system will be implemented in hardware to make it portable for car system and pilot study on drivers will be carried out to validate the developed system.

Luigi Celona, Lorenzo Mammana, Simone Bianco, Raimondo Schettini in 2018, has proposed a Multi-Task Driver Monitoring Framework (MT-DMF), which is able to simultaneously estimate the status of the driver's eyes, mouth, head and drowsiness. The framework involves the use of a specifically designed

Multi-task CNN. Experimental results show that the proposed framework outperforms not only other methods in the state-of-the-art, but also human-based visual assessment.

M. Tayab Khan, H. Anwar, F. Ullah, A. Ur Rehman, R. Ullah, A. Iqbal, B.-H. Lee and K. S. Kwak in 2019, A method for image-based drowsiness detection in real time driving surveillance videos is proposed. It is a four step method that first detects the face of the driver in the image from among several detected faces. Secondly, it extracts the eyes from the detected faces. In the third step, the curvature of the eyelids is detected using a modified Sobel operator. Finally, the eyes are classified as closed or open based on the curvature of the eyelids. Te proposed method achieved an average classification accuracy of 95% on a simple image dataset with homogeneous backgrounds, an average classification accuracy of 70% on a complex benchmark image dataset, and greater than 95% classification accuracy on two real-time driving surveillance videos.

However, the proposed method works only in the day time; its adaptation to night time will be explored in future work with more statof-the-art face and eye detection algorithms. Similarly, more challenging face images where subjects might have glasses or phones will be used to evaluate the proposed method.

Rateb Jabbar, Khalifa Al-Khalifa, Mohamed Kharbeche, Wael Alhajyaseen, MohsenJafari , Shan Jianga in 2018, drowsiness detection system based on multilayer’s perception classifiers. It is specifically designed for embedded systems such as Android mobile. The role of the system is to detect facial landmark from images and deliver the obtained data to the trained model to identify the driver's state. The purpose of the method is to reduce the model's size considering that current applications cannot be used in embedded systems due to their limited calculation and storage capacity. According to the experimental results, the size of the used model is small while having the accuracy rate of 81%. Hence, it can be integrated into advanced driver-assistance systems, the Driver drowsiness detection system, and mobile applications. However, there is still space for the performance improvement. The further work will focus on detecting the distraction and yawning of the driver.

III. Related Work

Conventional machine learning techniques rely on designed feature extraction algorithms which attempt to summarize the source data. The summaries are then fed to classifiers to reach conclusions. Convolutional neural networks (CNN) have been proved a robust and precise ability to extract features and reach a conclusion, without the need for user design or intervention. CNNs were first inspired by cat’s visual cortex and are built from multiple layers performing convectional transforms with parameterized filters, followed by decimation through pooling and ending with a full connected convolutional network for final classification. The given network consists of seven layers starting from the input layer. We provide the layer size and the number of colour channels on the figure. The input image is convolved with multiple filter kernels in the convolution layers. Filter weights are learned. The output volumes of the convolutional layers are processed by the next pooling layer for down sampling. The idea is to reduce the size while maintaining important information. Reducing the size reduces the number of trainable parameters. The most common form used is max pooling. Convolutional layers followed by pooling layers form a pair or a block. The depth of the network is achieved by adding (repeating) more of these blocks. The generated feature maps from sequential convolution and pooling layers need a fully connected layer at the end which uses the summarized information produces so far (the automatically produces feature space) to generate an output equal to the number of classes in our classification problem. Deeper CNN perform better when trained on very large data sets. Transfer learning allows researchers to reduce the demand for data by starting the search for the optimum parameters for the problem in hand from initial conditions obtained through searching for other similar problems where the data is available. For example, transfer learning on a data set already trained on faces reduces the need for data to practical levels.

IV. Convolution Neural Networks

1) Convolutional Layer: The convolutional layer is the core of any convolutional network accomplishing the main role of extracting input image features. It is usually the first layer and consists of multiple learn-able filters to produce an activation map. It accepts an input size of (W ×H×D) which correspond to our data image size of (100 × 100 × 1) since we are converting RGB images into grey-scale to focus on facial features rather than skin tone. We use double convolutional layers as this has experimentally produced a balance between accuracy and computations.
2) Max-Pooling Layer: A common non-linear downsampling method to reduce the spatial size of the representation in order to decrease the number of parameters, hence reduce computation time and control over-fitting.
3) Dropout: The dropout layer can be used as an image noise reduction technique when applied after max-pooling layer. When it used with fully connected layers it deactivates part of the neurons in order to improve generalization by allowing the layer to learn the same concept with different neurons and avoid over-fitting.
4) Fully-Connected Layer: Dense hidden layers take an input volume from the output of the last max-pooling layer to produce an N-dimensional vector, where N corresponds to the number of classes. In our case, the model has to choose from two classes (fatigued and control) for classification.
5) Model Parameters: We build our sequential model by adding a stack of linear layers. The system is trained after defining an optimizer and a loss function. We use the Adam optimizer, which is a stochastic optimization technique. For the loss function, the objective function that the training tries to minimize, we use the categorical cross entropy. For performance evaluation, we use the accuracy.

V. Experimental Results

Output can be generated when the eyes are opened and when eyes are closed. The score is also displayed.

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V. Conclusion

The drowsiness detection and correction system developed is capable of detecting drowsiness in a rapid manner. The system can differentiate normal eye blink and drowsiness by which we can prevent the driver from entering the state of sleepiness whiledriving.

VI. References

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