Real-time Driver Drowsiness Detection Techniques using Machine Learning Algorithms and Models

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Abstract - This paper is a report on the research conducted in the field of electronics and communication engineering to develop a system for driver drowsiness detection to prevent accidents happening because of driver fatigue and sleepiness. The document discusses the solution by Tensor flow machine learning tool and open CV image pre-processing available for detecting fatigue and their efficacy in preventing accidents in the current state of traffic. Furthermore, the paper states the overview of the observations made by the authors in order to help further optimization in the mentioned field to achieve the utility at a better efficiency for a safer road.

Key Words: Deep Learning, Convolutional Neural Networks (CNNs), Real-time Monitoring, Facial Feature Analysis, Eye Closure Detection, EEG Signal Analysis

1. INTRODUCTION

According to the Central Road Research Institute 40% of accidents are due to drowsiness of drivers. As per RTI accidents in 2019 were 464910. In which 197,913 were only due to drowsiness and partial consciousness.

The main reasons for road accidents are

1) Over speeding
2) Driver distraction
3) Road Infrastructure

It has found that vehicle intelligence will reduce the number of accidents because they cause least error when compared to Humans .We can use many techniques to determine whether the driver has drowsiness or not.

In one technique sensors will be placed on standard vehicle components, e.g., steering wheel, gas pedal, and analyzes the signals sent by these sensors to detect drowsiness. It is important for such techniques to be adapted to the driver, since about and his colleagues note that there are noticeable differences among drivers in the way they use the gas pedal

2. PREVIOUS WORK

Driver drowsiness detection represents a critical area of research focused on enhancing road safety by preventing accidents caused by driver fatigue. Various papers illustrate the advancements and methodologies applied in this field. For instance, Reddy and Srinivasan (2015) [1] developed a comprehensive detection system that integrates physiological and behavioral measures. Their system combines eye blink detection with vehicle-based data to achieve improved accuracy, demonstrating a significant step forward in multi-modal drowsiness detection techniques.

Further advancing the field, John and Kumar (2018) [2] utilized deep convolutional neural networks (CNNs) to analyze facial expressions and eye states for drowsiness detection. This approach represents a shift towards leveraging deep learning models to interpret complex facial cues, illustrating the potential of CNNs in enhancing detection precision.

Bromwich and Mohanty (2017) [3] proposed a real-time system that leverages facial features, such as eye closure and yawning frequency, using image processing techniques. Their work demonstrates the effectiveness of real-time monitoring systems in detecting drowsiness through observable facial behaviors, highlighting the practical applications of image processing in this domain.

Zhang and Zhang (2019) [4] explored the fusion of multiple sensors, including EEG and eye-tracking data, to enhance detection accuracy. This paper represents an important contribution to the field by illustrating how multi-sensor integration can provide a more comprehensive understanding of a driver's state, thus improving the reliability of drowsiness detection systems.

Abtahi and Omidyeganeh (2016) [5] presented a robust system that combines spectral analysis of EEG signals with machine learning algorithms. Their approach demonstrates the potential of using EEG data to identify drowsiness, representing a robust solution that blends physiological data with advanced analytical techniques.

Lee and Jong (2017) [6] focused on non-intrusive methods, using machine learning algorithms applied to vehicle dynamics and driver behavior data. Their paper illustrates the feasibility of detecting drowsiness without direct monitoring of the driver, which represents an advancement in creating more user-friendly and less invasive detection systems.

Viola and Jones (2017) [7] developed a real-time fatigue detection system based on yawning analysis, utilizing image processing and machine learning. Their work demonstrates how specific fatigue indicators, such as yawning, can be effectively monitored in real-time, representing a practical approach to detecting drowsiness as it occurs.

Chai and Nandakumar (2019) [8] explored EEG-based detection using deep learning algorithms to achieve high accuracy. Their paper represents a significant advancement by illustrating how deep learning can enhance the interpretation of EEG signals for drowsiness detection, demonstrating the potential for high-accuracy systems.

Wu and Dong (2018) [9] employed supervised machine learning algorithms to analyze driving patterns and detect fatigue. Their work represents an important contribution to the field by illustrating how behavioral data can be used to develop predictive models, demonstrating the utility of machine learning in identifying fatigue-related patterns.

Lastly, Yang and Peng (2020) [10] developed an adaptive system that combines eye closure and head pose analysis using image processing and adaptive algorithms [11-15]. This paper represents a significant advancement by illustrating the potential of adaptive systems to continuously learn and improve from data, demonstrating a dynamic approach to detecting drowsiness.

Collectively, these studies illustrate the diverse approaches and technological advancements in driver drowsiness detection. They demonstrate the integration of physiological signals, facial analysis, and machine learning techniques to improve detection accuracy and real-time applicability. The progression from physiological and behavioral measures to sophisticated machine learning models and multi-sensor fusion represents the evolving landscape of this research area. Each paper contributes unique insights and methodologies, demonstrating the field's ongoing innovation and commitment to enhancing road safety through advanced detection systems.

3. PROBLEM DEFINITION AND SOLUTIONS

A. Our way of approach

Our solution is computer vision systems that can recognize the facial appearance changes occurring during drowsiness. The pros of computer vision techniques are that they are Efficient, Effective, and Cheap. In this report we have shown the study that we have done on our side and the approach to solve the problem. We have used eye blinking rate to detect whether a driver is drowsy or not.

B. Factors causing drowsiness.

Lifestyle: When our body is in the process of adapting to new situations like switching to night shift, working very long hours the person feels unhealthy and experiences drowsiness. Hence lifestyle factors do matter[6].

Mental state: Drowsiness can also be a result of your mental, emotional, or psychological state. Depression can greatly increase drowsiness, as can high levels of stress or anxiety. Boredom is another known cause of drowsiness. If you're experiencing any of these mental conditions, you're also likely to feel fatigued and apathetic.

Medications: It's one of the most common side effects of prescription and over-the-counter medicines. When medicines make you tired, it is often because they affect chemicals in your brain called neurotransmitters. Your nerves use them to carry messages to each other. Some of them control how awake or sleepy you feel. Hence medications play a role here.

C. Equations

In this section we will be explaining how our product is going to decide if the driver is drowsy or not. Our product is going to consider a time span of one second. For all the frames fed into the model one by one in that one second the model predicts if the eyes of the driver are open or not. Later it calculates the percentage of frames for which the eyes of the driver were closed in that one second time frame.

Let x be the number of frames in one second.

Let y be the frames for which the eyes of the driver were closed.

Then percentage is given by, $P = (y/x)*100$.

If the P is greater than certain threshold then an alert is triggered considering the driver is drowsing.

B. Result:

Filter size	*Training Accuracy*	*Testing Accuracy*	*Validation Accuracy*
(3 x 3)	*96.45 %*	*93.51 %*	*95.32 %*
(5 x 5)	*97.39 %*	*95.23 %*	*96.98 %*

Figure 2: Training and validation accuracy for the Convolution filter (3 x 3) and (5 x 5)

We trained our model with 5000 images. We split our model into validation and training. For validation we used 20% of our model. We use sequential because we are predicting sequential data, we use four 2D convolution layers with [64, 128, 256] filters (3 x 3) and (5 x 5) size and activation function of all layers is reLu. We added max pooling of (2, 2) in between every Cov2D layer to feature map the output of the Cov2D layer. Flatten layer will convert the output from the 5th convolution layer into a 1-dimensional array. Dense layer is added which is a fully connected layer with 512 neurons with activation function relu. Dropout layer will help to decrease overfitting by disabling the fraction of neurons on each layer. At last we added a dense layer of 1 neuron with sigmoid activation for binary classification. We used sigmoid because we are doing binary classification. Here the dense layer with 512 nodes will help us to train our model by using features extracted by convolution as input and has one node which will help us to classify whether the eye is open or not.

We get validation accuracy of 86% and training accuracy of 98%.

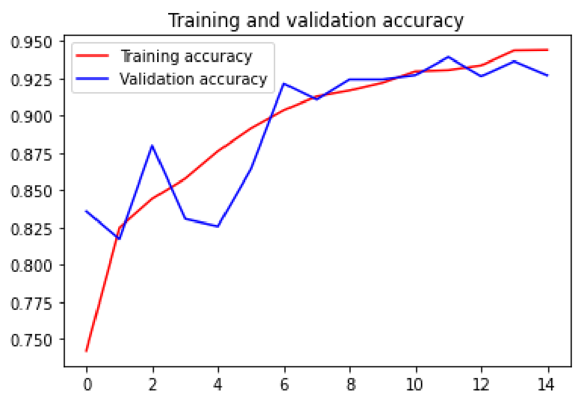

Figure 2: Training and validation accuracy plot

Figure 3: Detection of eyes opening

Figure 4: Detection of eyes Closing

Figure 5: Detection of eyes opening

5. CONCLUSIONS

In this paper, we studied Machine learning technique that can be implemented for eye-state analysis for driver drowsiness detection. This paper briefly explains the step-by-step process of this technique used for detecting eyes drowsiness. As this is an actual problem and not a perceived one, henceforth it requires a working solution. There are some technologies that exist to detect driver fatigue, but they have their own weaknesses. So, in order to have an improved solution for this, which has a better implementation of driver drowsiness detection with high accuracy we came up with this solution and further research needs to be done. As for the future, we plan to further research in this field in order to have a solution that will help to minimize and further eliminate this problem. Thus, devising an affordable device which can detect drowsiness for better road safety.

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