A Pre-Tranind Model for Driver Drowsiness Detection

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Abstract: Drowsiness is among the important factors that cause traffic accidents; therefore, a monitoring system is necessary to detect the state of a driver's drowsiness. Driver monitoring systems usually detect three types of information: biometric information, vehicle behaviour, and the driver's graphic information. Drowsiness detection methods based on the three types of information are discussed. A prospect for arousal level detection and estimation technology for autonomous driving is also presented. The technology will not be used to detect and estimate wakefulness for accident prevention; rather, it can be used to ensure that the driver has enough sleep to arrive comfortably at the destination. In this paper, we propose a Resnet (50) pre-trained model for driver drowsiness detection that achieves robust results and reaches 98% accuracy.
Keywords: Drowsiness Detection, deep learning, ResNet (50)

1. Introduction

Drowsy Driving is a deadly combination of driving and sleepiness. The number of road accidents due to Drowsy Driving is increasing at an alarming rate worldwide. Not having a proper sleep is the main reason behind drowsiness while driving. However, other reasons like sleep disorders, medication, alcohol consumption, or driving during night shifts can also cause drowsiness while driving. The National Highway Traffic Safety Administration (NHTSA) estimated that drowsy driving accounted for 91,000 traffic accidents, which caused approximately 50,000 injuries and 800 deaths, as reported by the police in 2017. However, individuals in the fields of traffic safety, sleep science, and public health have unanimously agreed that these figures underestimate the impact of drowsy driving [1]. The National Sleep Foundation reports that 54% of adult drivers feel drowsy while driving, and 28% have attested that they fall asleep while driving. In addition, more than 40% admit falling asleep at the wheel at least once while driving [2][3][4]. Drowsiness is considered a transition from arousal to sleep [3]. The first sign of drowsiness is the inability to keep one's eyes open. Frequent closing of one's eyes makes it impossible to perform their task effectively. Next, one's head tends to be shaken back and forth when they are drowsy. Yawning is also a sign of drowsiness [5][6][7]. Driving when one is sleep-deprived is like drunk driving. As one feels sleepier, the response time increases, the ability to foresee danger decreases, and the durability of attention decrease. Driving with no sleep for more than 20 h is equivalent to driving with a blood-alcohol level of 0.08%, which is the legal limit in the United States[8][9][10].

2. Related Works

Magán et al. [1] suggest a recurrent and convolutional neural network, which is subsequently put into practise in a system built on fuzzy logic. Both systems achieve similar levels of accuracy: about 65% accuracy over training data and 60% accuracy over test data. The fuzzy logic-based system, however, stands out since it doesn't issue erroneous alerts and achieves a specificity of 93% (the percentage of videos in which the driver is not drowsy that are correctly identified). AlKishri et al.[2] the fuzzy control system provides different alert sounds based on the tracked information from the face, eyes, and mouth in separate cases, such as race, wearing glasses or not, gender, and various illumination backgrounds. The experiments' results show that the proposed approach achieved high accuracy of 94.5% in detecting driver status compared with other studies. Chang et al.[3] selected the appropriate RGB channel under different light sources to obtain LF/HF ratio from HRV of PPGI. The main drowsiness judgment basis of the proposed drowsiness detection system is the use of algorithm to obtain sympathetic/parasympathetic nervous balance index and percentage of eyelid closure. In the experiment, there are 10 awake samples and 30 sleepy samples. The sensitivity is 88.9%. Fauzi et al.[4] Proposes a drowsiness detection technique using artificial intelligence. In this paper, a webcam is used to record a video that focuses on the face of the driver. The Viola-Jones algorithm is applied for the face detection process to locate the eyes of the driver in the face region. After doing some training analysis, the system will decide whether the eye of the driver is in a normal or drowsy condition. Pawale et al. [5] propose a system automatically monitors and calculates the eye blink durations and yawning changes and prevents road accidents by alerting the driver by detecting drowsiness. These types of crashes are about 50% more likely to result in death or serious injury as they tend to be high speed impacts because a driver who has fallen asleep cannot break or swerve to avoid or reduce the impact. Magar et al. [6] proposed an algorithm to locate, track, and analyze both the drivers face andeyes to measure percentage of eye dosure, a scientifically supportedmeasure ofdrowsiness associated with slow eye closure. Bebin et al.[7] propose a system, capturing face gestures, eye movements and eye aspect ratio (EAR) shows that driver is in proper driving condition or not. Driver fatigue can increase the chances of car accidents. The reason for this type of car accidents is since driver fails to take necessary actions prior to the accident [11][12][13].

3. Proposed work

The aim of this work is to develop a system that can estimate the fatigue of a driver by using sequences of images that are recorded in such a way that the face of the subject is visible. The drowsiness detection system developed in this work is part of a driver based ADAS system, with two important restrictions: early detection and minimization of the number of false positives. The idea is that the system will warn the driver only in real cases of fatigue, to avoid false positives, which would cause boredom in the driver, causing them to turn off the ADAS, without executing the rest of the functionalities [14][15][16]. This section shows the detection algorithm used to detect the driver's drowsiness level by investigating and analysing the different visual cues of the driver. The main two parameters are eye blink duration and mouth state information. This article presents a solution for driver drowsiness detection using a Convolutional Neural Network. The implementation of the project uses a custom CNN architecture with less than 250K trainable parameters for easy deployment on edge or computationally less efficient devices. As a result, the driver can be alerted at the right time if the system detects that the driver has fallen asleep before anything dangerous happens [17][18].

3.1.Building the CNN Model

The implementation uses a custom-designed Convolutional Neural Network that has the characteristics — Three Convolution Blocks having 2, 3, and 3 convolutional layers, respectively.

A BatchNormalization Layer follows each Convolution Layer.

A Dropout Layer follows each Convolution Block for avoiding overfitting and a MaxPool Layer.

3 Fully Connected Layers follow convolution Layers for classification.

4.Results and Experimental

4.1. Dataset

the Drowsiness Detection Dataset, which is a large-scale dataset created using MRL, Closed Eyes in Wild (CEW) dataset, and a unique dataset. The dataset contains images of open and closed human eyes, primarily used for eye detection and drowsiness detection. The images in the dataset were captured under various conditions, such as different lighting, distance, resolution, face angle, and eye angle to ensure accurate results and minimize low accuracy outcomes as shown in Figure (1)[8].

4.2. Results and Evaluation

In this paper, we achieve a robust model to drive drowsiness detection using a pre-trained ResNet-50 model. This deep learning model demonstrates exceptional performance in detecting driver drowsiness, achieving a remarkable 98% accuracy rate. The use of the ResNet-50 architecture ensures robust results, contributing to improved safety and effectiveness in monitoring driver alertness. In Figure (2) and Figure (3) show the testing visualization data results. Figure (4) shows the learning curves.

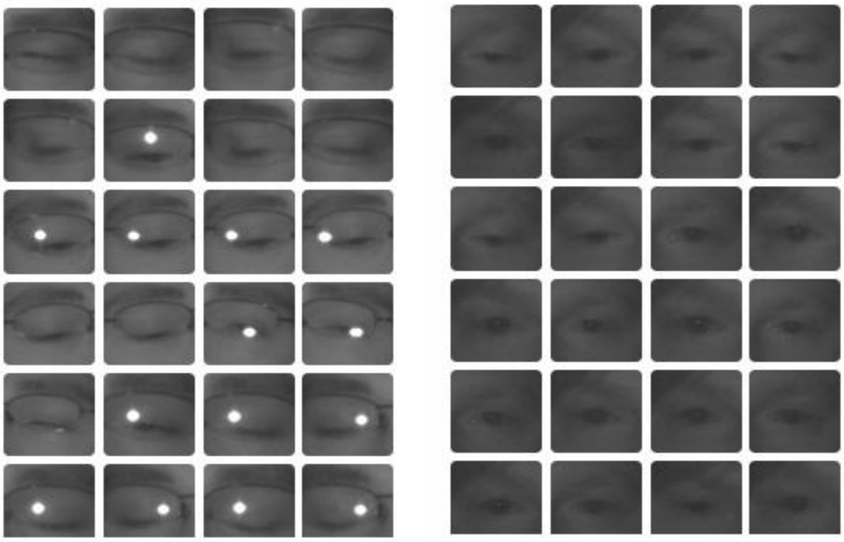

Figure 1: the Dataset Samples

Figure 2: The testing results for closed and open eyes

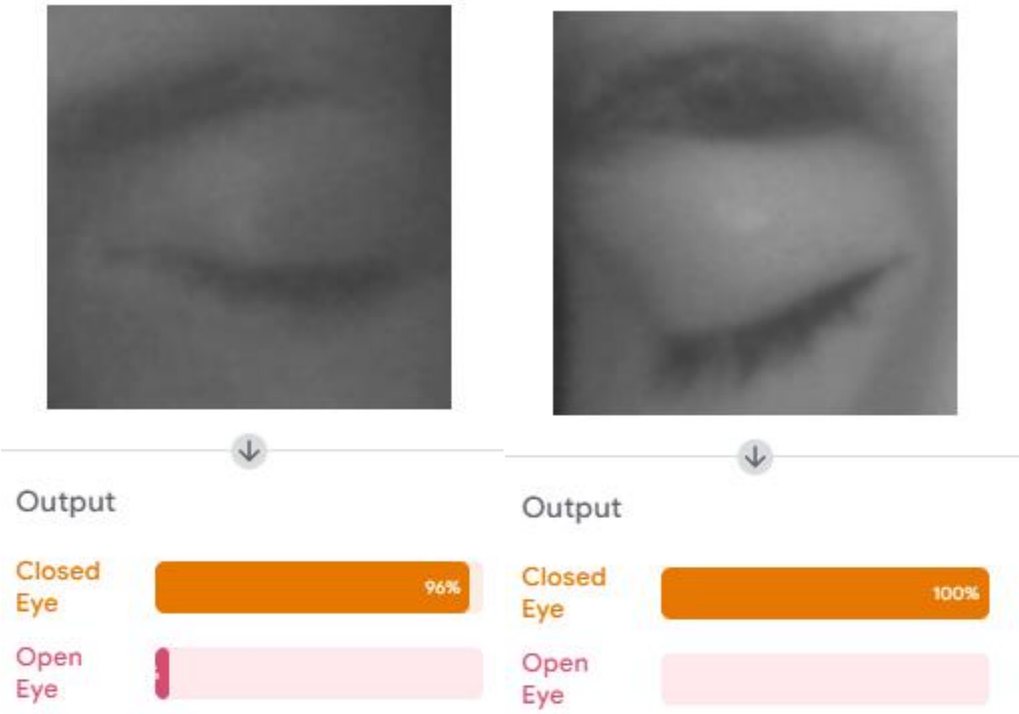

Figure 1: The testing results2 for closed and open eyes

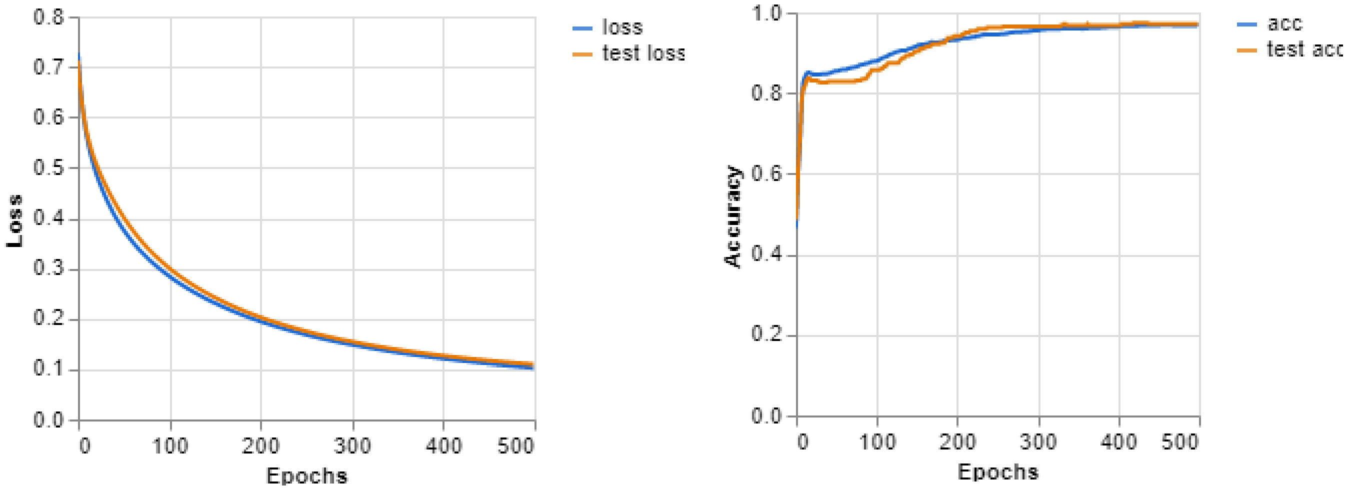

Figure 2:the learning curves

The evaluation of the model's performance is based on a confusion matrix that presents the true positive, true negative, false positive, and false negative rates, providing a comprehensive understanding of the model's effectiveness in classifying drowsiness states as shown in Figure (5). Furthermore, the authors discuss the optimal hyperparameters used in the ResNet-50 model, such as learning rate, batch size, and the number of epochs. These hyperparameters are fine-tuned to ensure the highest possible accuracy and generalization capabilities for the drowsiness detection task. By leveraging the power of the ResNet-50 architecture and optimizing hyperparameters, this paper presents a highly effective solution for monitoring driver alertness and preventing drowsiness-related accidents that illustrated in Table 1.

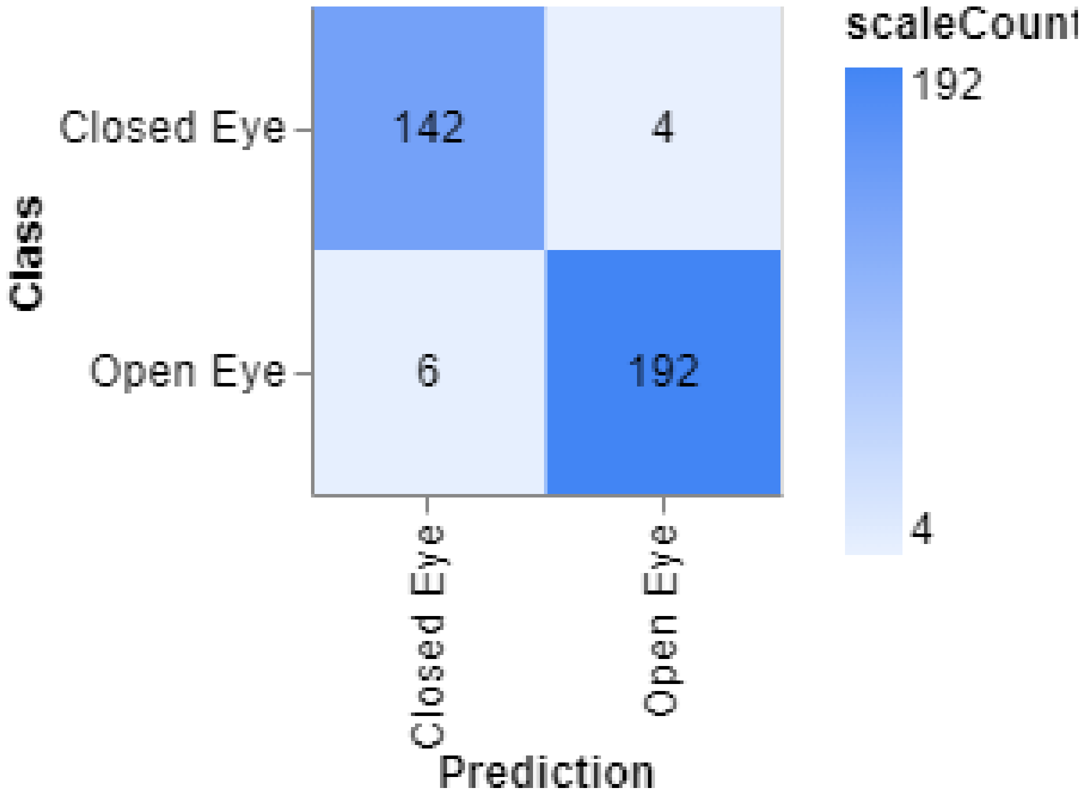

Figure 3: The confusion matrix

Table 1: The hyperparameters

Hyperparameters	Values
No. Epochs	500
Batch Size	16
Learning Rate	0.000001

5.Conclusion

In conclusion, this paper addresses the critical issue of drowsiness in drivers, a significant factor contributing to traffic accidents. To tackle this issue, the authors propose a monitoring system that detects driver drowsiness using three types of information: biometric, vehicle behavior, and driver's graphic information. Various drowsiness detection methods based on these information types are explored and discussed. A pre-trained ResNet-50 model for driver drowsiness detection. This deep learning model demonstrates exceptional performance, achieving a remarkable 98% accuracy rate. By leveraging the power of the ResNet-50 architecture, the authors present a highly effective and reliable solution for enhancing driver safety and preventing drowsiness-related accidents. Future work may focus on further refining the model and exploring its applicability in real-world scenarios, paving the way for safer and more comfortable driving experiences.

Data Availability : https://www.kaggle.com/datasets/prasadvpatil/mrl-dataset

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