Chapter 3
Deep Learning Architecture for a Real-Time Driver Safety Drowsiness Detection System

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ABSTRACT

According to the reports from the World Health Organization (WHO), one of the primary causes that led to death in the world was road accidents. Every year, numerous road accidents are caused by drivers due to their drowsiness. It can be minimized by alerting the driver, and it has been done by identifying and recognizing the initial stages of drowsiness. Several models have been proposed to detect drivers' drowsiness and alert them before a road accident occurs. However, the most prominent one is VGG16 with a transfer learning mechanism that is utilized to view the status of the respective regions of interest. By utilizing these models, the drivers are monitored, and alarms are generated to alert the drivers as well as the passengers. This experimental analysis was carried out on the Kaggle Yawn-Eye-Dataset (KYED), and the results showed the low computational intricacy and high precision of the eye closure estimation and the ability of the proposed system for drowsiness detection.

INTRODUCTION

Drowsiness is considered to be a prime factor in causing road accidents. It is a central point behind injuries and fatalities happening in high-risk workplaces and road traffic. It is expressed by a diminished degree of concentration and vigilance that can produce health consequences, impaired performance, cognition, workplace accidents, and motor conveyance crashes (Gangadharan, S.et al., 2022). Consistently, drowsy driving records for around 71,000 injuries, 1,550 fatalities, and 100,000 crashes, as indicated by the National Safety Council (NSC). The principal impacts of drowsy driving are nodding off, inability to focus, inability to judge distance and speeds, poor judgment, and delayed reaction times.

The main objective of the drowsiness detection system is to prevent accidents involving commercial vehicles. Three networks are considered to be potential networks for eye status classification, one of

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which is a Convolutional Neural Network (CNN). By utilizing this network based on the VGG16 model, it can be used to detect the drowsy state depending on the eye aspect ratio. This system will detect the early symptoms of drowsiness before the drivers have completely lost all attention and it will caution the drivers that they are presently not equipped to operate the vehicle securely.

RELATED WORK

A system was implemented by using the Convolution Neural Network (CNN) and the Bidirectional Long-Term Dependencies (BiLSTM) approach (Rajamohana, S. P et al., 2021) to detect the driver's drowsiness. This system works in three phases. In the first phase, a web camera was used to observe the driver's face image. In the second phase, the eye image features were extracted using the Euclidean algorithm. In the final phase, the eye blinks were continually monitored. When drowsiness was detected, the system warns the driver with an alarm message. A new deep learning algorithm (Guarda, L.et al., 2022) known as a capsule neural network for detecting drowsiness was developed by Guarda *et al.,* This algorithm was used to maintain the data's hierarchical relationships, which was an essential role in working with biomedical signals. It has been used concatenated spectrogram images of Electroencephalogram (EEG) signal channels for detection purposes. By using this CapsNet model, the average accuracy has been obtained by 86.44% and 87.57% of sensitivity.

A wireless consumer-grade electroencephalogram to detect symptoms of driver drowsiness based on EEG signal was proposed (Gangadharan, S.et al., 2022). Data accumulation was done by utilizing a muse headband with concurrent heart rate measurement and performed feature selection to find optimal features for detection. EEG data was used to segregate the drowsy states and alerts, and it has been done with a precision of 78%.

A deep-rhythm-based method has been proposed (Turkoglu, M.et al., 2021) to detect drowsiness efficiently. The Short-time Fourier transform (STFT) has been used to convert EEG signals into EEG images and also, based on frequency intervals, by partitioning EEG images, the rhythm images were then extracted from them. There are five kinds of rhythm, Delta, Theta, Alpha, Beta, and Gamma. Based on pre-trained CNN with ResNet (Residual Network), the deep features were extracted for each rhythm image. The obtained features were fed into the long short-term memory (LSTM) layer to recognize the class labels of input signals. The average accuracy has been achieved at 97.92%.

The Genetic Algorithm-based Support Vector Machine (GA-SVM) for detecting drowsiness was implemented (Wang, H.et al., 2021). In this experiment, by dividing the initial signals into several epochs, a disintegration process has been carried out on the signals of every epoch by utilizing the Haar wavelet transform and db10. For detection purposes, two methods have been widely used for selecting a definite rhythm and evaluating its performance. They are GA-SVM and LOSO-CV (Leave-One-Subject-Out Cross-Validation), respectively, with an accuracy rate of 89.52%.

Based on the Convolutional Neural Network, the drowsiness state has been identified by using deep learning algorithms (Allam, J. P.et al., 2022). From the raw EEG signal, different features have been extracted automatically by using this algorithm, and the most important one is that the signal should be a single channel. By using the deep learning classifier, the detection of the drowsiness state was done with an accuracy of 98.20%. To discover shared EEG features across different subjects for driver drowsiness detection was done (Cui, J.et al., 2022) using CNN. Incorporating a Global Average Pooling (GAP) layer into this model structure, the input signal regions were localized using the CAM (Class