A COMPARATIVE STUDY OF DROWSINESS DETECTION FROM EEG SIGNALS USING PRETRAINED CNN MODELS

Budhi Veera Bharath Chandra
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
bvbharathchandra8985@gmail.com

Chigurupati Naveen
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
naveenchigurupati09@gmail.com

Mahapatra Medha Sampath Kumar
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
jagadishnrt@gmail.com

Madhavarapu Srinivasa Sai Bhargav
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
bhargavmadhavarapu@gmail.com

Poorna S S
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
poorna.surendran@gmail.com

Anuraj K
Department of Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Amritapuri, India.
anuraj19@gmial.com

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Abstract— **Drowsiness has become one of the major causes of road accidents now-a-days. In order to alleviate this issue, a system has been developed, which uses electroencephalogram (EEG) signals to detect drowsiness with sufficient reliability. This experiment was conducted on a small population and the EEG signals were acquired using a 14-channel wireless headset, while they were in a virtual driving environment. To extract the eye closures, the EEG signal was segmented, and pre-processed. Further the scalograms which describes the time-frequency characteristics of these segments were taken. Pretrained Convolutional Neural Network based architectures viz. ResNet-152, ResNet101, VGG16, VGG19, AlexNet were used to distinguish three states of the driver namely "Sleepy or Drowsy", "Asleep" and "Awake".**

Keywords— Drowsiness, EEG, Scalogram, Transfer Learning, CNN, ResNetT152, ResNet101, VGG16, VGG19, AlexNet, Accuracy, Loss, Recall, Precision.

I. INTRODUCTION

Based on the statistics given by the foundation established on traffic safety, American Automobile Association (AAA) in Washington DC, Drowsiness plays an important role in road accidents. On an average of 382000 drowsy crashes occur annually, which results in 6,400 deaths and 109,000 were injured, these statistics was only based on the reported cases. Further according to National highway traffic safety administration in the US, drowsy crashes result in injury or death cost 109 billion US dollars annually, which affects the economy as well. Some of the causes of drowsiness are driving at night by taking heavy meals, medication side effects, long working hours causing stress, consumption of alcohol etc. There are numerous methods put forth by research to detect drowsiness. Onset of drowsiness could be detected from face [8], eye blinks, heart rate [6], head movements, respiration rate, EEG, yawning rate, movement of vehicle etc. Our study uses EEG signals to identify the status of the driver.

II. RELATED Works

Some of the related research works are discussed below. In [1], a survey of state-of-the-art techniques used for driver drowsiness detection is elaborated. The paper by Chuanqi Tan et al. [2], gave the traditional drawbacks of EEG signal classification using multimodal information and equips us with a new perspective to resolve this. They have characterized EEG data pertaining to the cognitive events by utilizing EEG optical flow. This enables us to reduce the complication in the EEG categorization to a level of video classification, which could be further sorted out by using advanced computer vision technology. A comparative study was carried out using transfer learning framework, with the help of public datasets and CNN architectures trained on both EEG optical flow as well as ImageNet. Among the traditional training models, VGG19 gives a better result contrasting VGG16, AlexNet and ResNet.

A driver fatigue classification system from EEG using semi supervised and supervised deep learning techniques is discussed in [3]. For comparison of the performance measures, the classification techniques such as ANN, Bayesian Neural Networks (BNN), Deep Belief Networks (DBN) and Sparse-DBN were used. The data was taken from 45 subjects in two states viz. alert and fatigue. Autoregressive (AR) based feature extraction with Sparse-DBN classifier yields better results.

This paper is an extension of the work done by the same author. In [4], where the eye blinks were used as a factor of drowsiness detection employing EEG signals. The Emotive Epoch headset was used for EEG data acquisition with sampling frequency 128Hz from 18 subjects. In general, human eye blinks at least once in 2 to10secs, so the analysis was done by segmenting the EEG waveform for a period of 10 Sec duration with 2 Sec overlap. The blink related features were obtained from time as well as spectral domain features, after suitable preprocessing followed by Principal

Component Analysis. A comparative study was carried out using classical machine learning techniques such as K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN). The results state that ANN gives better performance than KNN.

In the succeeding analysis carried out by the same author in [5], the same preprocessed data was used for extracting the time-frequency features using Continuous Wavelet Transform (CWT). Deep learning based pretrained CNN model viz. ResNet-50 with the scalograms as the input was employed to detect the drowsy state of the driver.

III. Methodology

The methodology follows the block diagram given in fig 1. It involves extraction eye blinks from EEG signals acquired in [4], followed by segmentation and feature extraction. As followed in [5] the scalograms corresponding to the three states of the driver namely "Sleepy or Drowsy", "Asleep" and "Awake" are used here for comparative study. The scalograms inputs are fed to pretrained CNN architectures [9], trained using ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [7] dataset.

Transfer learning involves of reusing pre-trained model knowledge for other tasks. It can be used for classification, regression, and clustering problems. It surpasses the limitations of deep learning, which requires massive amount of information to coach these algorithms, which is practically not possible. In contrast to deep learning, transfer learning provides a remedy by utilizing the data available in abundance to train a network and utilize this pretrained model to perform classification of identical data scarce problems.

Different Convolutional Neural Network based architectures were introduced by various researchers for improving the classification accuracy of ImageNet dataset. It is a bench-marked dataset which includes 1.2 million high clarity images for object classification. This dataset contains combination of variable-resolution images of 1000 different classes. These pretrained CNN models are fine-tuned so that it could be reused for classifying the state of the driver.

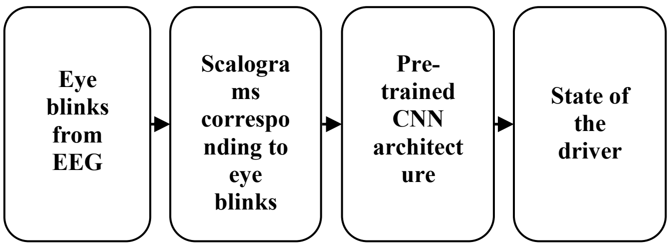


Fig. 1. Block diagram

IV. Experiments Carried Out

The scalograms corresponding to the three states of the driver viz. "Sleepy or Drowsy", "Asleep" and "Awake", used in [5] was utilized for this comparative study. The database consisted of 346 scalogram images of 224x224 dimension, and further they were resized to 256×256 resolution. The CNN based pretrained models such as AlexNet, VGG16, VGG19, ResNet 101 and ResNet 152 were used for this analysis. AlexNet includes 8 layers out of which the convolutional layers are 5 the rest are fully connected layers. VGG16 architecture includes 16 layers out of which the convolutional layers are 12 the rest are fully connected. VGG19 architecture with 19 layers out of which the convolutional layers are 16 the remaining fully connected. Similarly, ResNet152 and ResNet101 has 152 and 101 residual layers, respectively.

The pretraining was given using ImageNet dataset. The output layers of these pretrained models were chopped off and reinserted with a fully connected layer consisting of three neurons, since there are three output classes. This is followed by a Softmax layer. Optimizers used for analysis were Adaptive Moment Estimation (Adam) or Stochastic Gradient Descent (SGD) and categorical cross entropy loss function was used. The CNN models were trained with a batch size of 32 with 50 epochs. Here 80% and 20% of the data were used for fine tuning and testing respectively.

V. Results

This work employed five different types of pre-trained models trained using ImageNet dataset to distinguish driver's status in three states such as 'Awake', 'Drowsy' and 'Asleep'. AlexNet, VGG16, VGG19, ResNet152 and ResNet101 are the CNN models used. The performance measures accuracy, precision, recall and F1 score of the CNN models using SGD and Adam optimizers are given in table 1 and 2, respectively. The comparative bar diagrams for the respective tables are shown in fig.2(a) & (b) respectively.

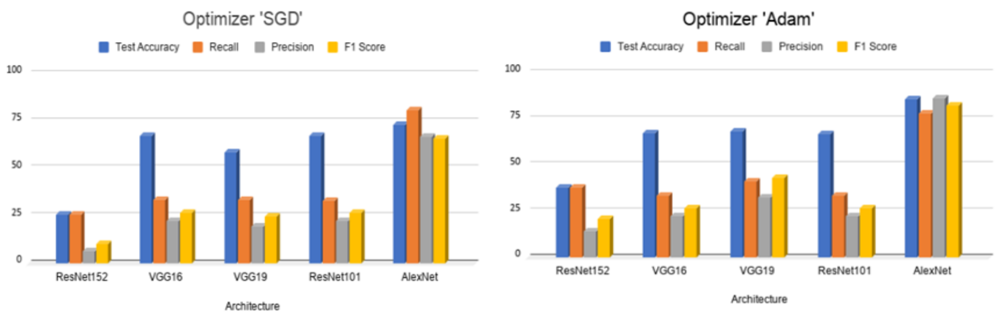
TABLE I. Results Of Pretrained Models Using SGD Optimizer(all figures in %)

Architecture	Accuracy	Recall	Precision	F1 Score
ResNet 152	25.7	25.7	6.6	10.5
VGG16	67.1	33.3	22.4	26.8
VGG19	58.5	33.3	19.5	24.6
ResNet 101	67.1	33	22.4	26.8
AlexNet	72.9	80.8	66.6	65.8

TABLE II. Results Of Pretrained Models Using ADAM Optimizer(all figures in %)

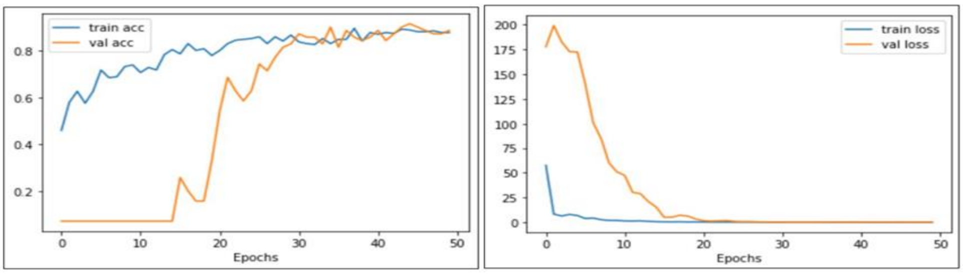
Architecture	Accuracy	Recall	Precision	F1 Score
ResNet 152	38	38	14	20.9
VGG16	67.1	33.3	22.4	26.8
VGG19	68.5	41.1	32.4	43
ResNet 101	67	33.3	22.4	26.8
AlexNet	85.7	`77.8	85.9	82.2

The accuracy, precision and F1 score showed an improvement while Adam optimizer was used in the pretrained models. Of these pretrained models analyzed, AlexNet with Adam optimizer gave highest accuracy of 85.7%, precision of 85.9%, and F1 score of 82.2%. The recall rate was highest for AlexNet with SGD optimizer. The accuracy, precision and F1 score showed an improvement while Adam optimizer was used in all the pretrained models. The validation accuracy using AlexNet was 73% and 68% respectively for Adam and SGD optimizers. The accuracy vs epochs as well as the loss vs epochs plots for AlexNet based drowsiness detection is shown in fig. 3 (a) & (b) respectively.



(a) (b)

Fig. 2. CNN models with SGD optimizer (a) and Adam optimizer (b)



(a) (b)

Fig.3. Accuracy Vs Epochs (a) and Loss Vs Epochs (b) for AlexNet

VI. Conclusion

A comparative study of transfer learning-based drowsiness detection system was done in this work. The study was carried out using five different CNN architectures and utilizing Adam and SGD as optimizers. The models were pretrained using ImageNet and fine-tuned with scalogram data obtained from the driver's EEG signals acquired during three different states namely "Sleepy or Drowsy", "Asleep" and "Awake". The performance measures were high when AlexNet architectures was employed. Further Adam optimizer gave slightly higher performance compared to SGD. Future work aims at incorporating multimodal data from videos for the same analysis.

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