A Low Complexity Automated Multi-channel EEG Artifact Detection using EEGNet

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***Abstract*— A complexity reduced Convolution Neural Network (CNN) model for artifact detection of the electroencephalogram (EEG) is developed for a variety of purposes such as brain-computer interfaces (BCI), disease diagnosis, and determining cognitive states. We compare the performance of our previously designed CNN model with that of EEGNet [2] which shows an increase in average accuracy from 74% to 79% for binary classification and 60.06% to 96.15% for multi-class classification across all artifacts with $50\times$ reduction in number of parameters.**

I. INTRODUCTION

EEG has a variety of applications including detecting fatigue, stress, and BCI. However, one major disadvantage of EEG is that it is prone to physiological and non-physiological artifacts such as muscle activity and power noise [2]. Physiological artifacts may occur from ocular movements, jaw movements, and head movements. CNNs, which have been primarily used for image classification, are now a popular choice for detecting artifacts in EEG signals. In this paper we perform a comparison of two architectures and compare their artifact detection accuracy. Both architectures used are able to detect artifact from multi-channel EEG data.

II. PROPOSED METHOD

A. Architecture

Both models receive multi-channel EEG signals and detect artifacts using several convolutional layers. The input to the models are raw time-domain EEG signals to which relevant features are extracted for detecting artifacts.

In EEGNet, a depthwise convolutional layer is used which has the advantage of reducing the number of parameters required to fit [1]. Following this layer is a seperable convolution layer which is a combination of depthwise convolution and pointwise convolution. A dense layer is avoided in both architectures to prevent an increase in number of parameters of the network.

The input to both networks is an EEG epoch of size 64×512. The EEGNet architecture consists of a 2D convolution layer with filter size of 1×64. This is followed by a DepthwiseConv2D layer which has a depth multiplier of 2 which ensure number of filters to be learned for each feature map. AveragePooling2D layer is used with pool size of 1×4 to reduce the feature size. Relu activation function is applied after every convolution layer. A Dropout layer is applied with a drop out rate of 0.25 to incorporate regularization. The SeperableConv2D layer is used with filter size of 1×16. Both networks are trained using an RMSprop optimizer with a learning rate of 0.001 and categorical cross entropy loss.

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B. Results

Table I shows the average detection accuracy for a leave one subject out cross-validation technique among 9 subjects for a given artifact for both the CNN model used in [2] and EEGNet [1]. On average 3790 samples where used for training and 490 samples where used for testing.

Table II shows the average accuracy for artifact identification, which is a 10 class classification problem. Here all 9 artifacts are given as an input to the model along with the plain signal (no artifact).

TABLE I

COMPARISON OF [1] AND EEGNET ACCURACY (STD. DEV.).

Artifact Code	Accuracy (%)	
	CNN[1]	EEGNet[2]
Clenching jaw	74.1(9.2)	86.39(2.7)
Move Jaw	64.3(11.8)	81.2(1.3)
Blink eyes	76.1(10.9)	78.1(2.12)
Move eyes leftwards	77.5(9.6)	76.5(2.3)
Move eyes Rightwards	72.6(9.1)	79.2(2.5)
Raise eyebrows	84.8(7.9)	85.9(6.1)
Rotate head	73.3(11.8)	74.08(2.1)

TABLE II

ACCURACY FOR ARTIFACT IDENTIFICATION. THIS CONSISTS OF 9 ARTIFACTS AND 1 PLAIN SIGNAL

	Accuracy (%)	
All Artifacts	CNN[1]	EEGNet[2]
Average across all patients	60.06	96.15

III. CONCLUSION

In this paper we provide a comparison of our CNN model and EEGNet and show that EEGNet outperformed the CNN model for detecting artifacts with an average accuracy of 79% for leave one subject out cross-validation and 96.15% for intra-patient data. The number of parameters required for EEGNet is much less (1298 i.e. 20 Kbit) as compared to other model (65280 i.e. 1020 Kbit).

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