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× 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 separable 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.

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 were used for training and 490 samples were 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).

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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REFERENCES