Source Localization of Electroencephalogram (EEG) Waves with Convelutional Neural Network

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***Abstract*—This paper investigates the use of deep learning as a means for source localization of prioritizing electroencephalogram (EEG) waves that are used to detect different eye states of a subjects. The machine was trained to recognize the values of different EEG reading and bases on the results predict whether the subjects' eyes were open or closed. Next the machine was trained on the recognition of "good" EEG nodes vs "bad" EEG nodes highlighting the nodes that gave a clear reading. This was done by using a convolutional neural network to determine the hemisphere of stimulation that was occurring in the brain. The final training was on removal of the "bad" nodes allowing the algorithm to focus solely on the good nodes to ensure a faster and more accurate prediction of eye state. With more data point the algorithm should be able to determine the intensity of certain eye states in order to predict emotion that the subject is experiencing while wearing an EEG head set Training a machine to detect the location of an EEG wave would have many applications in the medical and industrial fields.**

Keywords—Source Localization, electroencephalogram (EEG), Convolutional Neural Network

I. Introduction

The brain is the most vital organs in our body, yet the least is known about it. EEG waves are used to detect the electric potentials that being fired from neuron to neuron and provoking the body to action. EEG waveforms have been utilized as a predictive and diagnostic tool and although they have been effective in these respects EEGs are limited by their very high signal-to-noise ratio (SNR). With out a copious amount of preprocessing and filtering the relevant waves are lost in the residual noise picked up the sensors. This paper explores the possibility that the combination of deep learning and source localization can provide an alternative to traditional approaches preprocessing and filtering of EEGs. Conducted in the three parts the experiments show the power that deep learning and source localization have separately on the computation of time of EEG waves. Increasing the processing time of EEG would serve a sizable advantage to the many fields that use the waveforms by allowing a close to real time insight into the functionality of thought.

II. Eye State Experiment

A. Data Set

The initial data set that was used for the experiment is known as EEG Eye-State data set. The data was collected from one subject in a 117 second time interval. 14 channels were monitored in the time. The eye state was captured through a recorded video and was appended to its associated time after the data collection. An open eye state is represented by a '0' and a closed eye state is represented by a '1' The EEG waves were converted to values and recorded in a CSV file as 1 x 14980 1 dimensional arrays based on time. The data set was originally used to conduct a study on the fastest open source processing that was available to classify the eye states and predict future ones. The researcher of the project used

B. Data Processing

The data was processed using a python script.

III. Convalutional Neural Network

Convolutional Neural Networks are use mainly to classify images and have been very effective at doing so. They are made up of three type of layers known: known as convolution layers, max pooling, and dense layers. The convolution layer partitions each passed image using a grid then the max pooling finds the max value in that gird section. That gird of values then becomes represented by the max value found within that section. This can be performed several times. Before the image is passed through dense layer.

A. Convalutional Layer

For the data set there are two 2D convolution layers. The first layer has a filter of 256, with a kernel size of (3,3), the activation function is listed as "relu" which is short for____. The second layer of convolution has a 255, with a kernel size of (3,3) and a "relu" activation function as well.

In the convolutional layer, the first required Conv2D parameter is the number of filters that the convolutional layer will learn. The layers that are earlier in the network should be lower so that the computer has more to learn from but then layers that are deeper within the network with learn more filters. The kernel size refers to the size of each section that are with the convolution. The activation parameter to the Conv2D class is simply a convenience parameter, allowing you to supply a string specifying the name of the activation function you want to apply *after* performing the convolution. "relu" layer will apply an elementwise activation function, such as the max (0, x)) thresholding at zero. This leaves the size of the volume unchanged.

Not account for in this activation function is the padding for plots that appear in the image.

B. Max Pooling Layer

Down samples the input representation by taking the maximum value over the window defined by "pool_size" for each dimension along the feature's axis. The window is shifted by strides in each dimension.

C. Dense Layers

The first experiment's neural network is made up entirely of dense layers as it is a linearization. Each layer uses a relu activation function and has 128, 64, 32, 16, 8, 1 fully connected node respectively. The second experiment utilizes only two fully connected layers; the first one having 16 nodes and the later having only 1 node.

D. Equations

$$y = \begin{cases} 0 \; for \; x > 0 \\ x \; for \; x < 0 \end{cases} \quad (1)$$

Rectified Linear Activation

This function is responsible for mapping an input that is positive to the output node. If the input in less than or equal to zero, the then a zero is mapped to the output node.

$$\sigma(z) = \frac{1}{1+e^{z}} \quad (2)$$

Sigmoid Activation

The sigmoid function transforms the input value into a value that is between the 0 and 1.

IV. Findings

A. Training results

For the first experiment the, the neural network was trained on 14,980 data points with a 90/10 validation split. The network trained on 11984 samples, validated on 2996 samples. The neural network is set to run for 200 epochs but averaged 10-15 epochs to reach its optimum weight values. once the network was trained it would then proceed to predict whether the eye was open of closed for 2996 instances. The values must be rounded to the corresponding eye state values as the network did not have binary predictions.

The neural network model was trained on 46 EEG plots that were save in the JPG format. The images with passed through the CNN in batch sizes of 10 for 100 epochs. The resulting weights were saved if they produced the highest accuracy. Although the data was small it overall received poor accuracy. The 100th epoch's values are indicative of the most recent run of the training process and they are as follows: loss: 0.6421 - accuracy: 0.6585

B. Validation results

The validation spilt for the Eye State dataset is 10%. Although there were many data points available for use, the validation loss and accuracy of the neural network are poor. The third trail of this experiment is most indictive of the overall results. The validation loss (val_loss) is .4754 and the validation accuracy (val_acc) is .5541.

The validation split was 10% of the Localize MI dataset. In the future. This will be more valuable with more data. The 100th epoch's values are indicative of the most recent run of the training process and they are as follows: val_loss: 0.6809 val_acc: 0.6000

C. Weights

The weights are represented as the multiplicative factor of the filters. Simply put, the weights determine how much influence the input node of a neural network will have on the output node. Once desirable nodes weights are achieved for both experiments, they can be used to train a new neural network with similar data. After the performance of the neural network is assessed, the weights will be altered in an attempt to improve accuracy for the training and the validation data. The current weights used in the experiments are shown in the table below.

D. Figures and Tables

TABLE I. Experiment 1

Trial	**Weights**				
	Loss	***Accuracy***	***Validation Loss***	***Validation Accuracy***	***RMSE***
1	5370.5988	0.4981	1.0429	0.4910	0.7947
2	436.3758	0.5456	0.5590	0.5467	1.078
3	3731.9720	0.5419	0.4754	0.5541	0.6274
4	4129.0023	0.5224	0.7102	0.4566	0.7339

Figure 3.

TABLE II. Experiment 2

Trial	**Weights**			
	Loss	***Accuracy***	***Validation Loss***	***Validation Accuracy***
1	0.6577	0.6389	0.6389	0.7
2	0.0182	1.0	0.2710	0.9
3	0.6756	0.6389	0.6648	0.7
4	0.0567	0.9722	0.0641	1.0

Figure 4.

V. Conclusions

The Convolutional Neural Networks are a viable candidate for the training for source localization of EEG waves. This project has proven to be very insightful in many ways and there are many uses for such technology in and out of the medical realm. The network trained requires a larger data set to train on to bring it accuracy up. There were only 46 samples to be source from the given data set. The current python script used for the data processing was directly for the Localize MI dataset. The python script needs to be updated so that it may be integrated more seamlessly with other data sets.

In the future, the two experiments will be combined in order to evaluate a machines ability to identify the source localization of different stimuli. There will be a continuation of updates to the code using preprocessing capabilities of the MNE library and accompanying Python script to develop a script that can easily be integrated. There will also be the inclusion new EEG data that will be tested based on the previously trained models

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ACKNOWLEDGMENT

Thank you to Dr. Sumit Chakravarty for being a mentor through these experiments. Thank you to the Mr. Tom Boyle and Mr. Hunter Edison for their assistance with the use of the Kennesaw State HPC.