Neural network in EEG Classification

ABSTRACT

EEG is a one of the major tools used in detection of pathology – for example it can be used to detect the seizure and epilepsy diagnose. Unfortunately, while EEG is a common practice in diagnostic it still requires a trained professional to analyze the result and produce interpretation of the signal. The solution for this problem can be use of Machine Learning approach. Multiple research projects focused on use of ML for this problem – from most simple like regression to more complicated methods like neural networks. However, most of this research focused on one application of EEG in diagnose, like most popular – pre-ictal classification in seizure detection. This project is focused on four different neural networks which provided good accuracy in seizure classification to check if exist networks that can provide good prediction for another application of EEG classification.

INTRODUCTION

Electroencephalogram (EEG) is used the recording electrical brain activity. Neurons create voltage fluctuations that EEG can measure. These types of results are used to diagnose multiple neurological diseases. It is done with the different number of electrodes on the scalp surface, that record voltage fluctuations, usually in the 10-20 system (name from the distances between adjacent electrodes on the skull surface).

The EEG is used in multiple diagnoses, from sleep disorders to ADHD or brain tumors. It is one of the most popular tools used in the diagnosis of epilepsy. Today EEG is slowly being replaced by the newer technique, but thanks to low costs, tolerance to motion from subjects and no radiation exposure risk EEG is still a popular tool in medicine.

Nowadays EEG recording is interpreted manually by a trained doctor. That has several disadvantages – it is time-consuming and required trained staff. Hence, it has been important to automate the process – for years new automated solutions were proposed. Since EEG contains multiple results from electrodes over long periods of time it is important to preprocess results to more readable and light data – most represented as one or two-dimensional array of fluctuations in time, usually preprocessing like differential window and feature extraction (for example with phase correlation). Preprocessing is an important step in handling the EEG data and has a high influence on the final results of classification [1].

EEG classification problems can be solved with multiple tools. The research shows that depending on the application of machine learning solutions, data, and data preprocessing even the simpler classification methods – like k-Nearest Neighbor can achieve high accuracy on the data. The problem is the solutions are usually focused on one problem – the most common is seizure detection (classification of ictal and pre-ictal phase on EEG), with different accuracies depending on the data. For more complex problem and less preprocess data research are directed more toward neural networks.

MATERIALS AND METHODS

Data

Data were obtained from the Kaggle dataset [2, 3]. It contains the EEG record from 500 different subjects and activities, which were recorded for 23.6 seconds. Each of the samples is divided into 4097 data points, which hold the value of EEG at different points in time. These points were divided so each column of the dataset contains 180 points representing 1 second of EEG recording, giving the dataset matrix of 11500 x 180 in size. As the label of the data, it can contain one of 6 different activities:

- 1 - seizure activity
- 2 - EEG from the area where the tumor was located
- 3 - EEG activity from the healthy brain area
- 4 - eyes closed
- 5 - eyes open

Depending on the classification the label could change (labels 2-5 get label 1 for seizure classification), and for others, the dataset was shrunk to fit the description of classification. The data were divided into 4 different subsets:

- Seizure vs non-seizure data (Seizure classification)
- Eyes-closed vs eyes-open data (Eyes classification)
- Tumor-area vs health area data (Tumor classification)
- Non-shrink data (original dataset) (Multi classification)

Since the data contains large range of value all data were scaled.

Methods

4 different neural networks were used, based on the other research [4]. The publication was based on non-processed EEG, and the data used in this project are already processed, where one sample is presented as a one-dimensional list. For this, it is important to change the architecture of the neural networks so they will be fitting the processed data as input.

Multi Layer Perceptron

Multi-Layer Perceptron (MLP) is the simplest of presented networks. MLP is characterized by at least three layers: input, hidden, and output with a nonlinear activation function. The number of hidden layers can change, the same as the number of neurons (units) in each layer.

This network is based on 4 hidden layers with decreasing number of units. The first one has 300 units, and the next ones: are 100, 50, and 20. All of the hidden layers have ReLU activation. Depending on classification different output layer is used. For multi-classification problems, the output layers have 6 units with SoftMax activation. For binary classification, the output is 2 units with sigmoid activation.

Convolution Neural Network

Another architecture is based on Convolutional Neural Network (CNN). While it is usually used in image analysis the CNN has good accuracy in a lot of classification problems, including the EEG data [5].

This architecture is based on the 4 Convolutional 1D layers with Max Pooling between. The kernel size is 3 for Conv1D and pool size of 2 in each Pooling layer. The input layer has 32 filters, the next 16, the next 32 with the last Conv1D layer with 64 filters.

Bi-directional LSTM Network

Bi-directional Long-Short Term Memory (Bi-LSTM) is a recurrent neural network (RNN), which, compared to LSTM is characterized by having two independent RNNs working together, with allowance to putting information both backward and forward. Thanks to that, Bi-LSMT can preserve information from both the past and the future. Bi-LSTM is used commonly in Natural Language Processing.

The Bi-LSTM network needed additional regularization layers – which were provided in the article [4]. The first Dropout layer with 10% factor was applied before the Bi-LSTM layer and the Dropout layer with a factor of 50% was applied after Bi-LSTM. A bidirectional layer was chosen with the 20 units.

Convolution Neural Network + Bi-directional LSTM Network

CNN + Bi-LSTM network was based on the previous CNN and Bi-LSTM architecture. First, the data go through CNN layers, with the same number of filters and pool size as mentioned previously, then through Bi-LSTM layers with the intact Dropout layer and number of units.

All changes in networks were based on the classification of seizure and non-seizure EEG. For other applications even if the network was interpreted as overfitting there were no changes in architecture – the purpose of this project is to find the best architecture for all of the mentioned applications, so the changes in only one application would eliminate the purpose of this project.

All networks are trained with a training set and validation set, that contains 15% of the training set. The number of epochs is 20.

RESULTS

All network has results represented in 3 types: training accuracy in time, validation accuracy in time, and test accuracy.

Table 1 The training and validation accuracy of networks for different type of application

Type of classification	MLP		CNN		Bi-LSTM		CNN + Bi-LSTM	
	Train	Vali	Train	Val	Train	Vali	Train	Val
Seizure	0.9760	0.9594	0.9711	0.9572	0.9688	0.9594	0.9717	0.9457
Eyes	0.8331	0.7663	0.8072	0.8243	0.8149	0.8243	0.8200	0.8207
Tumor	0.5802	0.5851	0.5473	0.5688	0.5796	0.5580	0.6049	0.5670
Multi	0.4754	0.4645	0.6830	0.6500	0.6954	0.6746	0.7219	0.6754

Train – training accuracy, Val – validation accuracy

All of the presented architecture accuracy for seizure classification are comparable with its alternatives in the mentioned research for non-processed EEG data. The architecture of CNN + Bi-LSTM has worse validation accuracy and can be considered slightly overfitting the data, but the additional Dropout layers prevent the higher overfitting. The best accuracy in most applications has the CNN + Bi-LSTM network. It is only slightly worse than MLP for eyes application. The accuracy for seizure classification and eyes-closed classification has visibly higher accuracy than the tumor and multi-categorical classification. However, the Table 2 shows the test accuracy for architectures with Bi-LSTM is highly worse than for training and validation sets.

Table 2 Test accuracy of networks for different type of application

Type of classification	MLP	CNN	Bi-LSTM	CNN + Bi-LSTM
Seizure	0.954	0.966	0.41	0.548
Eyes	0.769	0.793	0.535	0.485
Tumor	0.519	0.501	0.502	0.490
Multi	0.467	0.662	0.178	0.193

For most classifications, the best training accuracy shows the CNN network. For the tumor, it's the MLP with similar results for architectures with Bi-LSTM, which is comparable to the training and validation accuracy.

DISCUSSION

The aim of this project was to determine if there is one universal neural network architecture fit for the classification of different EEG data. Based on different research there were 4 different neural networks taken into consideration – MLP, CNN, Bi-LSTM, and CNN + Bi-LSTM. Based on research MLP and CNN provide good accuracy in multiple EEG classification, especially based on seizure detection [6], but the other research suggests that additional Bi-LSTM layers should provide even more accuracy [4]. Considering the preprocessing of the data the networks were fit to get a one-dimensional array as inputs. It is unknown if these changes were the reason why some networks overfit the data. It was impossible to recreate the accuracies of the networks – Bi-LSTM networks get only better accuracies in the training and validation data, but never in the testing subset. The number of Dropout layers was provided to correct the overfitting. The Dropout layers improved (decreased) the overfitting in the networks but did not eliminate it. Additional layers of regularization could further decrease the overfitting, but it was impossible to do this in this project.

For the different applications of the classification on EEG, it can be seen 2 different types of results. The best results yield the Seizure Classification and Eyes-closed detection. The seizure classification could be high due to the source of provided networks – they were used in pre-ictal phase detection. The eyes-closed classification is harder to interpret – the eyes-closed EEG has more fluctuation (and higher differences between the two closest points in time) than eyes open, but it is hard to explain why tumor-area vs health-area of brain detection yield much lower accuracy since the EEG is similar to the one of the eyes-closed subsets. The possible explanation can be the wider range of differences between samples. It would be useful to check the provided architectures on different types of data, from different studies to provide additional information.

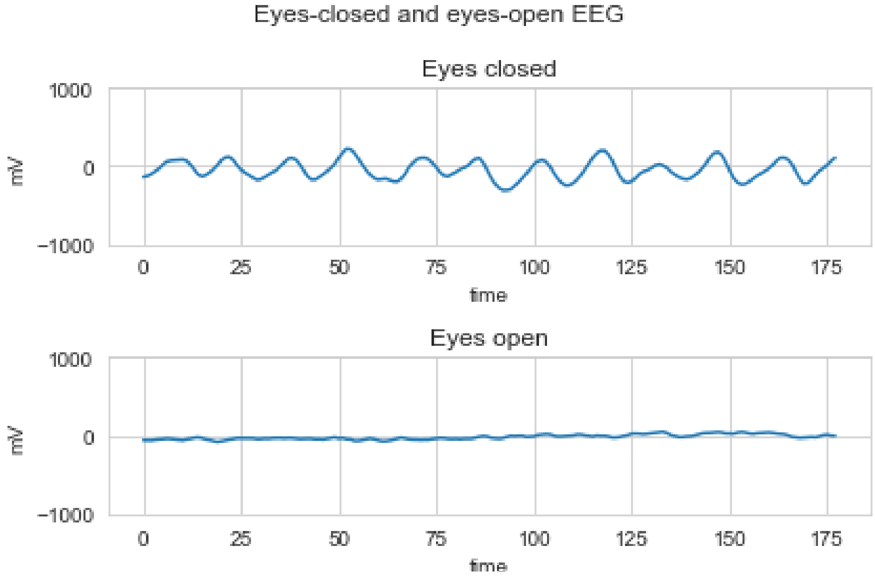

Figure 1The example of Eyes-closed EEG and eyes-open EEG

Based on the 4 different architectures it is impossible to choose the architecture that will provide good results for all possible EEG classifications. However, the most promising results are yielded by the CNN mostly due to avoiding overfitting with average or high accuracy in all classifications and it should be focused on enhancing this network to find if it is possible to get better results.

REFERENCES

1. Hosseini, M., Hosseini, A. and Ahi, K., 2021. A Review on Machine Learning for EEG Signal Processing in Bioengineering. *IEEE Reviews in Biomedical Engineering*, 14, pp.204-218.
2. Kaggle.com. 2022. *Epileptic Seizure Recognition*. [online] Available at: <https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition> [Accessed 26 June 2022].
3. Andrzejak, R., Lehnertz, K., Mormann, F., Rieke, C., David, P. and Elger, C., 2001. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, 64(6).
4. Daoud, H. and Bayoumi, M., 2019. Efficient Epileptic Seizure Prediction Based on Deep Learning. *IEEE Transactions on Biomedical Circuits and Systems*, 13(5), pp.804-813.
5. Craik, A., He, Y. and Contreras-Vidal, J., 2019. Deep learning for electroencephalogram (EEG) classification tasks: a review. *Journal of Neural Engineering*, 16(3), p.031001.
6. Gemein, L., Schirrmeister, R., Chrabąszcz, P., Wilson, D., Boedecker, J., Schulze-Bonhage, A., Hutter, F. and Ball, T., 2020. Machine-learning-based diagnostics of EEG pathology. *NeuroImage*, 220, p.117021.