Lab 2 EEGNet

YingJhi Lin 411551007

1 Introduction

This is a binary classification task using deep learning approach on EEG Data. We implement the classic EEG model: EEGNet and tried different settings to seek for the best performance. Furthermore, we plotted the figures containing training/testing accuracy and loss.

2 Experiment setups

2.1 The detail of the model

2.1.1 Introduction of EEGNet

EEGNet is a compact convolutional neural network for EEG-based BCIs that can generalize across different BCI paradigms in the presence of limited data and can produce interpretable features. EEGNet introduced the use of depthwise and separable convolutions for EEG signal classification task. Furthermore, the author compared the proposed model EEGNet, both for within-subject and cross-subject classification to current state-of-the-art(SOTA) approaches across four BCI paradigms: P300 visual-evoked potentials, error-related negativity responses (ERN), movement-related cortical potentials (MRCP), and sensory motor rhythms (SMR). The results suggested that EEGNet was robust enough to learn a wide variety of interpretable features over a range of BCI tasks. One of the most important things in practice is that is, neurophysiologically interpretable features can be extracted from the EEGNet model as it is a critical component to understanding the validity and robustness of CNN model architectures not just for EEG.

2.1.2 Architecture of EEGNet

EEGNet is composed of two blocks. In the block 1, the author performed 2 convolutional steps including a 2D convolution and a depthwise convolution. Applied batch normalization along the feature map dimension before applying exponential linear unit(ELU) nonlinearity. In the block 2, they performed a seperable convolution, which is a depthwixe convolution followed by a pointwise convolutions. The model architecture is showed as below.

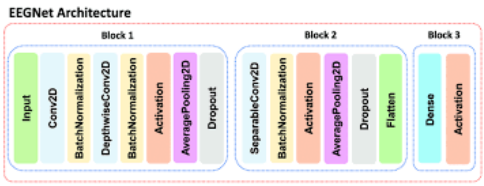

Fig. 1 Architecture of EEGNet

2.2 Explain ELU function

ELU was first proposed in the paper: Fast and Accurate Deep Network Learning by Exponential Linear Units (ELUs). ELU is defined as:

$$ELU(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha * (exp(x) - 1), & \text{if x} \leq 0 \end{cases}$$

ELU is a function that tend to converge cost to zero faster and produce more accurate results. Different to other activation functions, ELU has a extra alpha constant which should be positive number. ELU has the advantages of (1)ELU becomes smooth slowly until its output equal to $-\alpha$ whereas ReLU sharply smoothes (2)ELU is a strong alternative to ReLU (3)unlike to ReLU, ELU can produce negative outputs. On the contrast, ELU has disadvantages that for all x larger than 0, it can blow up the activation with the output range of [0, inf].

3 Experiment Results

3.1 Highest testing accuracy

The setting of hyperparameters is showed in table1. We got the best accuracy of 0.8231 doing the EEG classification task.

Table 1 Hyperparameters setting and highest testing accuracy

Epochs	Batch size	Optimizer	Learning rate	Highest accuracy
300	32	Adam	0.001	0.8731

Fig. 2 Screenshot of accuracy

3.2 Figure of Accuracy and loss

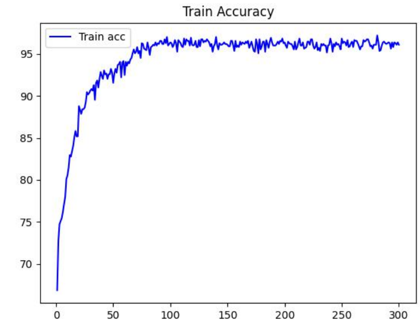

Fig. 3 Training accuracy

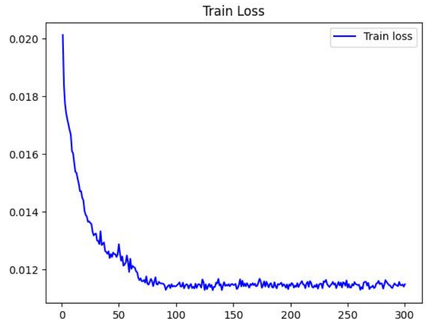

Fig. 4 Training loss

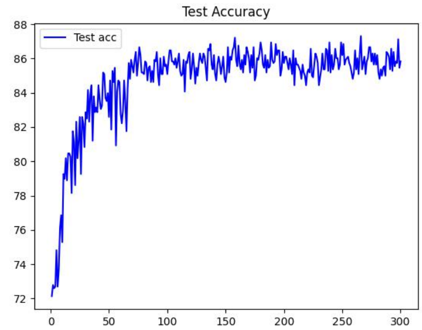

Fig. 5 Testing accuracy

3.3 Result of different alpha value in ELU

We experimented different α in ELU to see how it influenced the performance(table 2). One can observe that the performance showed the best when the α is set to 1.0.

3.4 Result of different dropout probability

We experimented different dropout probability to see how it influenced the performance(table 3). One can observe that the performance showed the best when the dropout probability is set to 0.25.

Table 2 Testing performance related to different alpha of ELU

Model	Alpha	Accuracy
EEGNet	0.2	0.7851
	0.6	0.7926
	1.0	0.8194
	1.4	0.8028
	1.8	0.7026

Table 3 Testing performance related to different dropout rate

Model	Dropout Rate	Accuracy
EEGNet	0.25	0.8185
	0.5	0.7917
	0.75	0.7093

3.5 Other experiments

We experimented different activation function to see how it influenced the performance(table 4). One can observe that the performance showed the best when the activation function is set to ELU.

Table 4 Testing performance related to different activation function

Model	Activation function	Accuracy
EEGNet	ELU(alpha = 1.0)	0.8231
	ReLu	0.7269
	LeakyReLu	0.75

4 Discussion

We had done some experiments to seek for the best setting of the hyperparameters. Looking upon table 2, we can see that the right α value of the ELU function is very important while it may influence the performance no matter it is high or low. Nonetheless, the more the dropout rate is, the worse the performance is. However, a well rate of dropout could make a model more robust and prevent overfitting. We finally test the 3 activation functions to discuss why the authors choosed ELU. The result showed that ELU performed the best certainly. From the testing accuracy plot, we can observe there the training status is stable and without overfitting , we furthermore save only the best model while training.

5 Github Link

URL: https://github.com/xup6YJ/Medical-Image-Analysis