Automated EEG-based major depress disorder detection through transformer-based network

Ziyan Zhang[1], Zhe Cao[1], Weiqi Ruan[1]
1. Institute for Quantum Science and Engineering, SUSTech, Shenzhen, China
Correspondence: 12132873@mail.sustech.edu.cn
12132834@mail.sustech.edu.cn
1023104572@qq.com

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Introduction

In recent years, deep learning has been extensively used for arbitrary diagnosis of many mental diseases based on EEG or fMRI, including epilepsy[1], seizure prediction[2], Alzheimer's disease[3], etc. Simultaneously, depression is a common illness worldwide, with an estimated 3.8% of the population affected, including 5.0% among adults and 5.7% among adults older than 60 years. Over 700,000 people die due to suicide caused by the depression every year. [4] However, it can be effectively diagnosed and treated in early period. A schematic comparison of synapses from a healthy subject and a depressed subject is presented in Fig. 1.

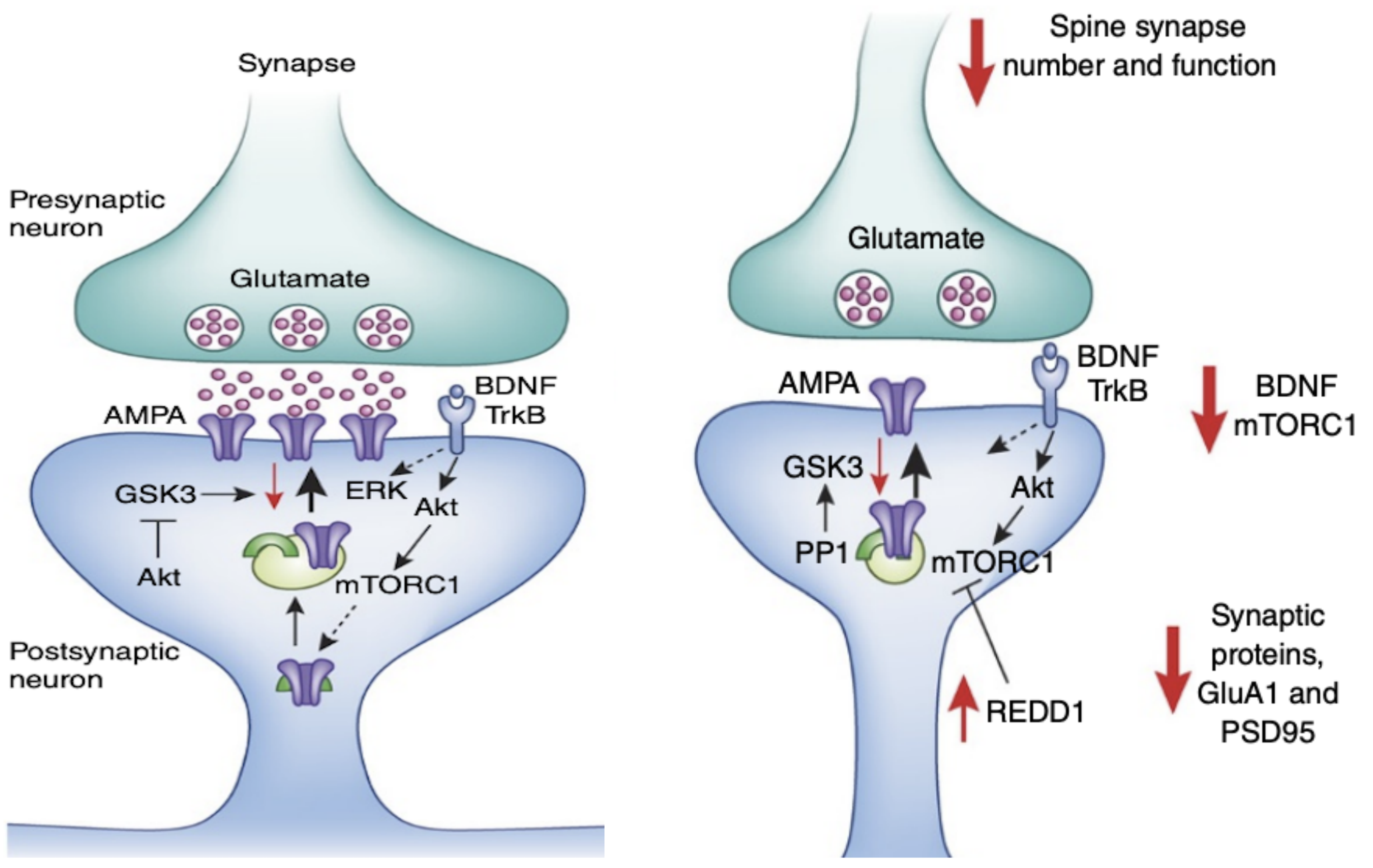

Figure 1: A schematic comparison of synapses of a healthy subject (left) and a depressed patient (right)[5].

In this work, we presented an EEG-based major depress disorder detection neural network based on transformer. It takes EEG signal as input and outputs its predication graded with None, Mild, Moderate and Severe based on the severity of symptoms. We trained this network with 128 channels resting signal obtained 24 major depressive disorder subjects and 29 healthy control subjects, ranging from 16 - 52 years old[6]. This model was tested by various public datasets, the accuracy and f1 score can reach over 0.8. Additionally, we compared our network with naive CNN and RNN, it can be inducted that our model performs better.

Data and Methods

The data being used in this work is an open-source EEG dataset from UAIS Lab, Lanzhou University, China[6]. The dataset contains traditional 128-electrodes EEG signals as well as audio data from clinically depressed patients and matching normal controls. The EEG signals of 53 subjects were recorded in resting state & under stimulation.

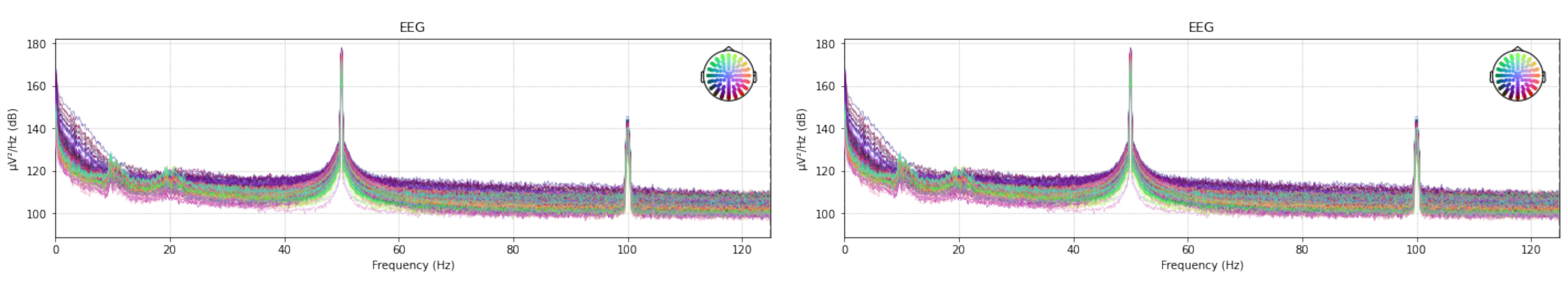

Figure 2: Comparison of power spectral densities of WDD(left) and HC(right).

The pre-processing of the raw EEG signal contains 3 parts,

1. Segmenting
2. Band-pass filtering
3. Standarlization

The data is segmented into trials as $C_{eeg} * T$, where C_{eeg} is the number of EEG channels and T is the sample points. Then we add band-pass filter data to $[4, 40]Hz$ to remove high and low-frequency noise. After that we apply standard normalization to relive the fluctuation and non-stationarity as

$$X = \frac{x - \mu}{\sqrt{\sigma^2}}$$

Additionally, we give a feasible way based on CSP usage to improve the difference of the original signal and maintain the temporal information.

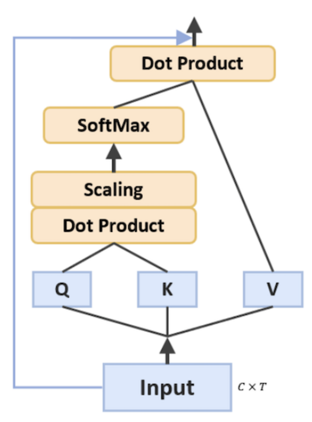

Figure 3: The calculation process of spatial feature-channel attention

We proposed a method of feature channel weighting inspired by the scaled dot-product[7]. As illustrated in Fig.3. The input data is first linearly transformed into vectors, queries(Q), and keys(K). The whole process can be expressed as

$$Attention(Q, K, V) = \frac{QK^T}{d_k}V$$

Additionally, we perceiving global temporal dependencies of EEG signals using the attention mechanism. In the beginning, the data is compressed to one dimension $1 \times T$ to reduce the computational complexity, since the feature channels have been weighted in the previous step. Therefore, we divide the data into multiple slices with a shape of $1 \times d$ for attention training. After that, we simply apply global average pooling to generate the results. We showed the whole process in Fig.4

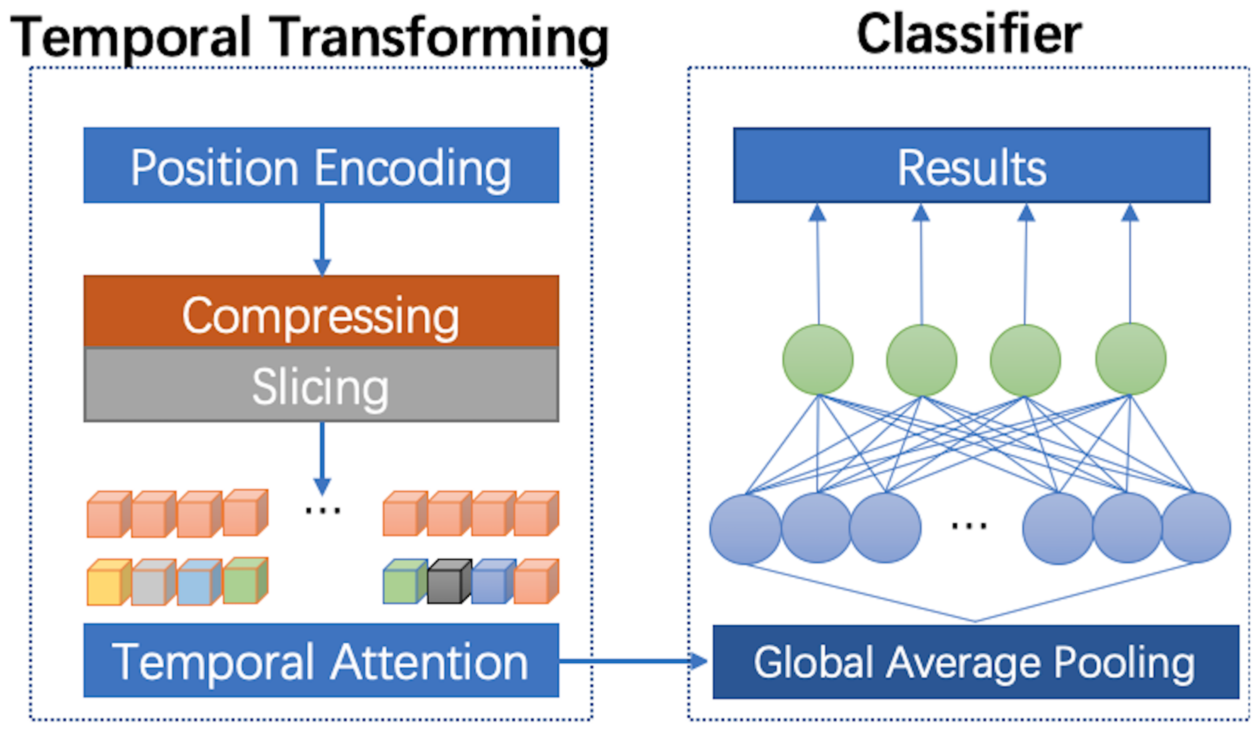

Figure 4: The overall frame of the Spatial-Temporal Transformer

Results

We train this model under Google Colab environment with GPU Tesla T4. The slice size, h, k_c, and N_f were 10, 5, 41, and 4. Additionally, in this model, we use Adam Optimizer with a learning rate of 0.0002. We also set our batch size to be 50, a dropout of 0.5 in temporal transforming and 0.3 in spatial transforming to avoid overfitting. Still, we compared the F1 score under different epoch while training, specific data are listed in Table 1. F1 score can be calculated as

$$F1\_score = 2(Recall * Precision)/(Recall + Precision)$$

Table 1: Epoch's influence on F1 score

Epoch	Accuracy	Precision	Recall	F1-score
9	90.83	76.84	84.27	84.38
10	91.94	83.75	80.14	82.91
11	91.61	86.78	81.18	85.94
12	91.62	82.23	81.29	81.76

We can find the better result is always obtained by 11 epochs. Then to evaluate our model, we made comparative experiments with some other baselines. Brief descriptions are given as follows.

1. EEGNet[8], designs a compact and practical CNN with depthwise and separable convolutions to classify EEG.
2. CNN+LSTM[9], segments the original signal for OVR-CSP processing and extracts features with CNN, and the output is passed through an LSTM for temporal features.

Through our investigation, we can conduct that under this scenario, our proposed model performs better.

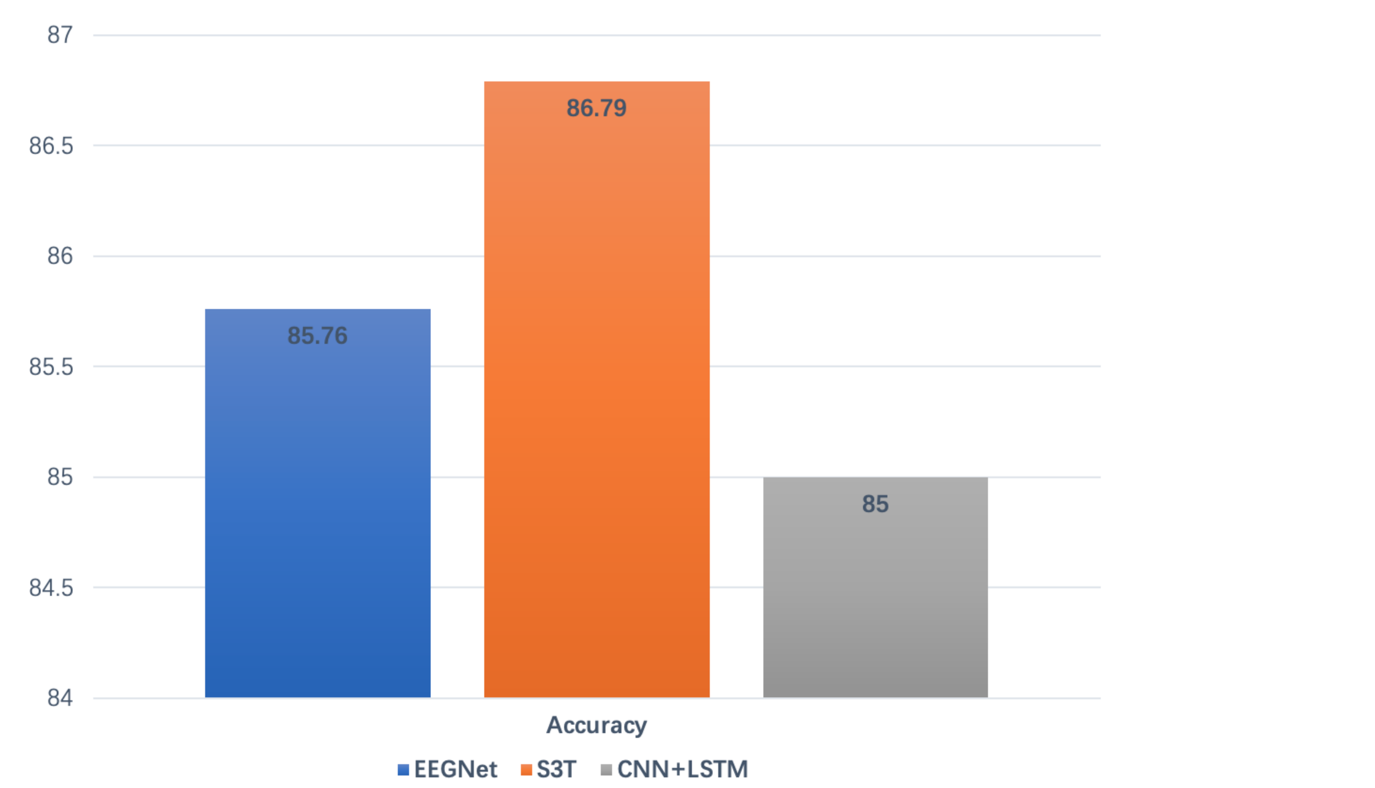

Figure 5: The study results of 3 models

Summary

At present, people usually use some convolutional neural network (CNN)-based methods for electroencephalogram (EEG) decoding. However, CNNs have limitations in perceiving global dependencies, which is insufficient for the common EEG paradigm with strong overall relationships. The EEG decoding method we proposed mainly relies on the attention mechanism. The EEG data is first preprocessed and spatially filtered. Then, we apply attention transformation on the feature channel dimension so that the model can enhance more relevant spatial features.

Our model considers the spatial characteristics and timing of EEG signals on the basis of Convolutional Neural Network (CNN), and this is indeed an advantage of the proposed model. Although this study is based on a limited number of EEG signals obtained from 53 subjects, the proposed algorithm achieves about 90% accuracy rate and takes into account The spatial characteristics and timing of EEG signals. The proposed model can be used as a tool to objectively diagnose depression using EEG signals. In current clinical practice, the diagnosis of depression is based on questionnaire surveys and the patient's physical emotions. We hope this system can be used remotely by non-professional clinicians. Once the EEG signals are obtained from the patient, they will be sent to a server in the cloud (located in the hospital), where the proposed model can be used for diagnosis. The diagnosis result can be sent to the clinic immediately, as a reference for the diagnosis of professional clinicians.

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