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

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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.

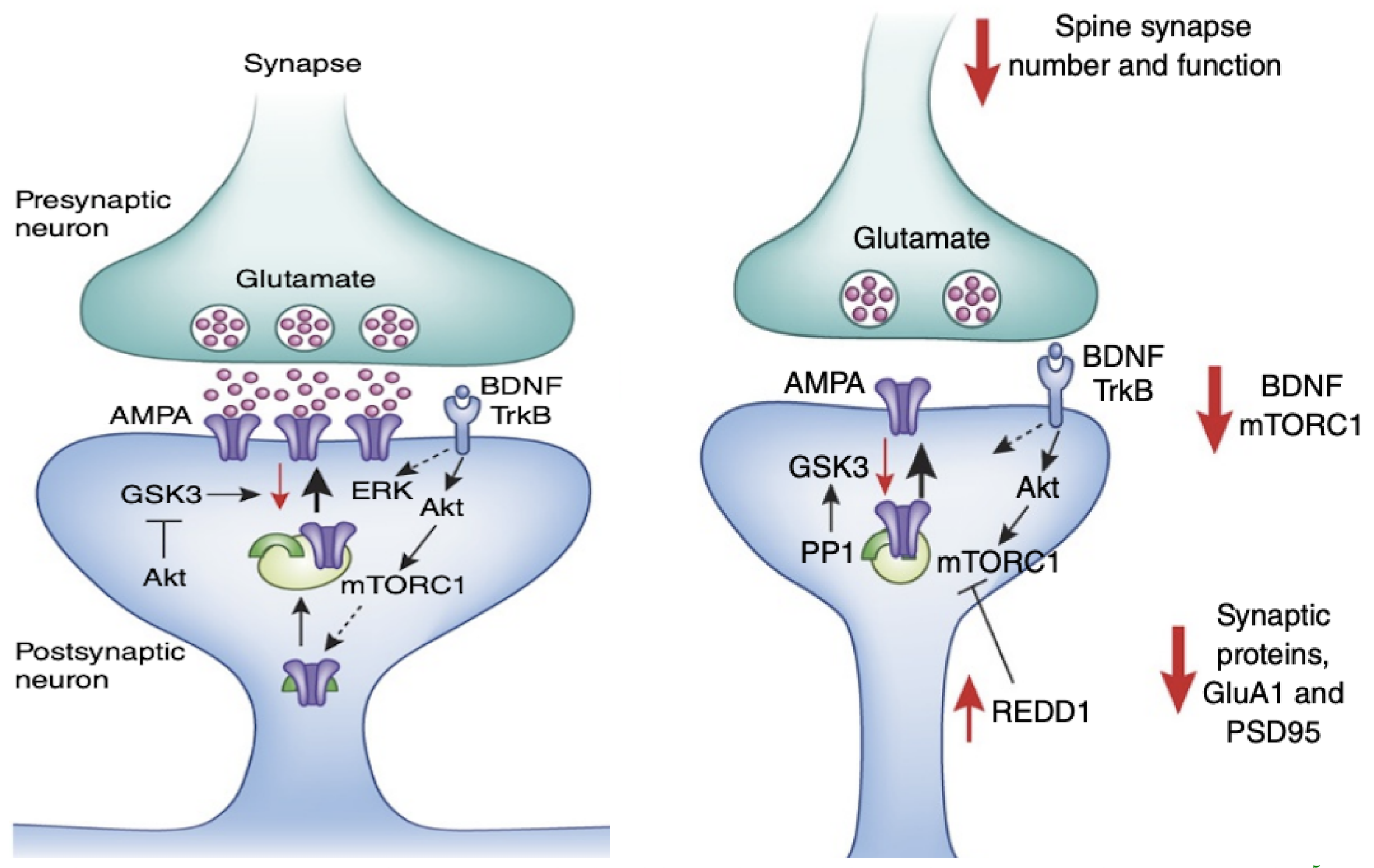

Figure 1: A schematic comparison of synapses of a healthy subject (left) and a depressed patient (right)[5].

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.

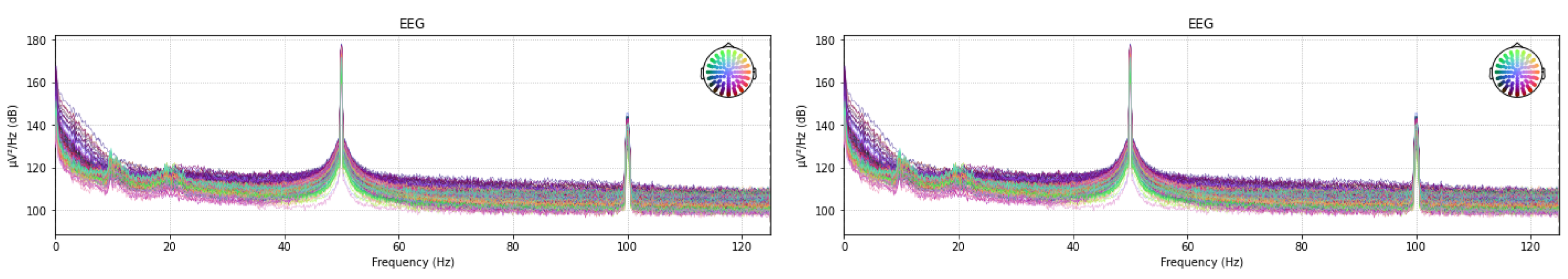

Figure 2: Comparison of power spectral densities of WDD(left) and HC(right).

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

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

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

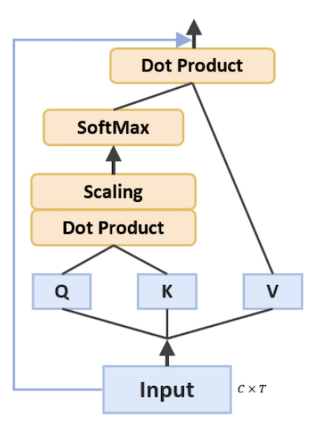

Figure 3: The calculation process of spatial feature-channel attention

We proposed a method of feature channel weighting inspired by the scaled dot-product. 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

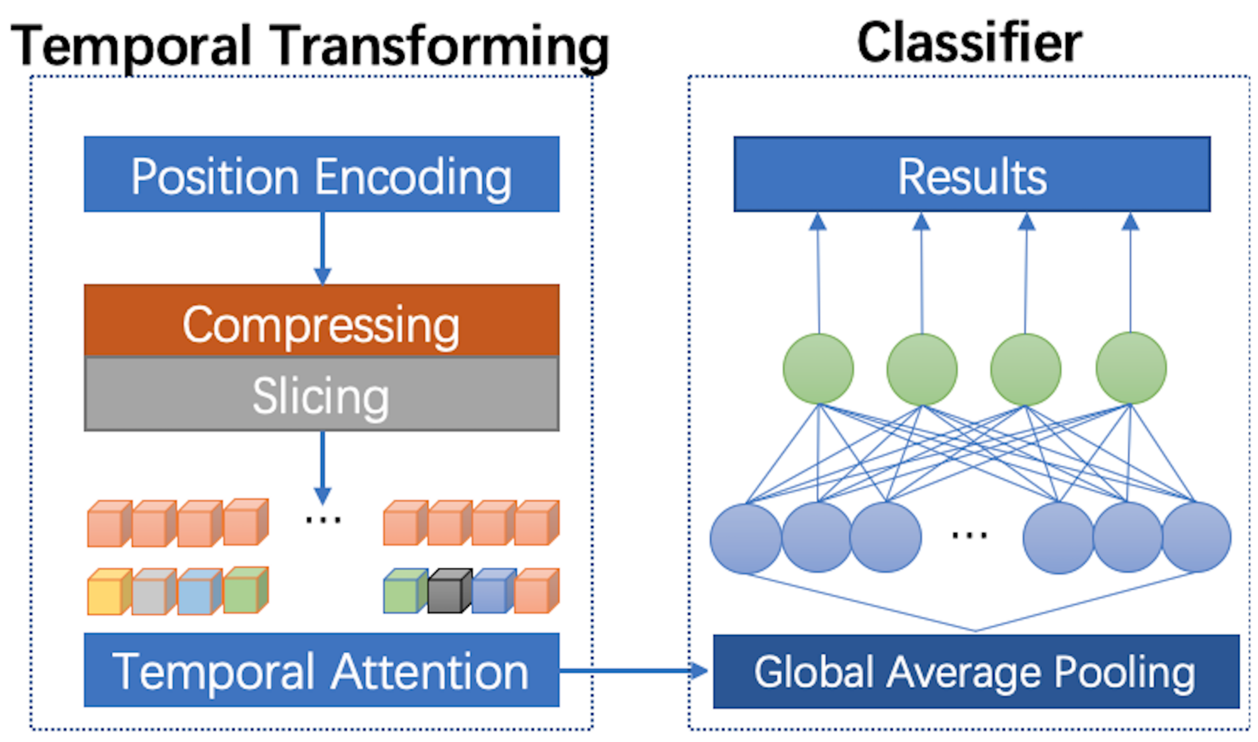

Figure 4: The overall frame of the Spatial-Temporal Transformer

Results

Fig.-?? compares tLorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum 705 valid (CT$\neq$0) improvements in CT.

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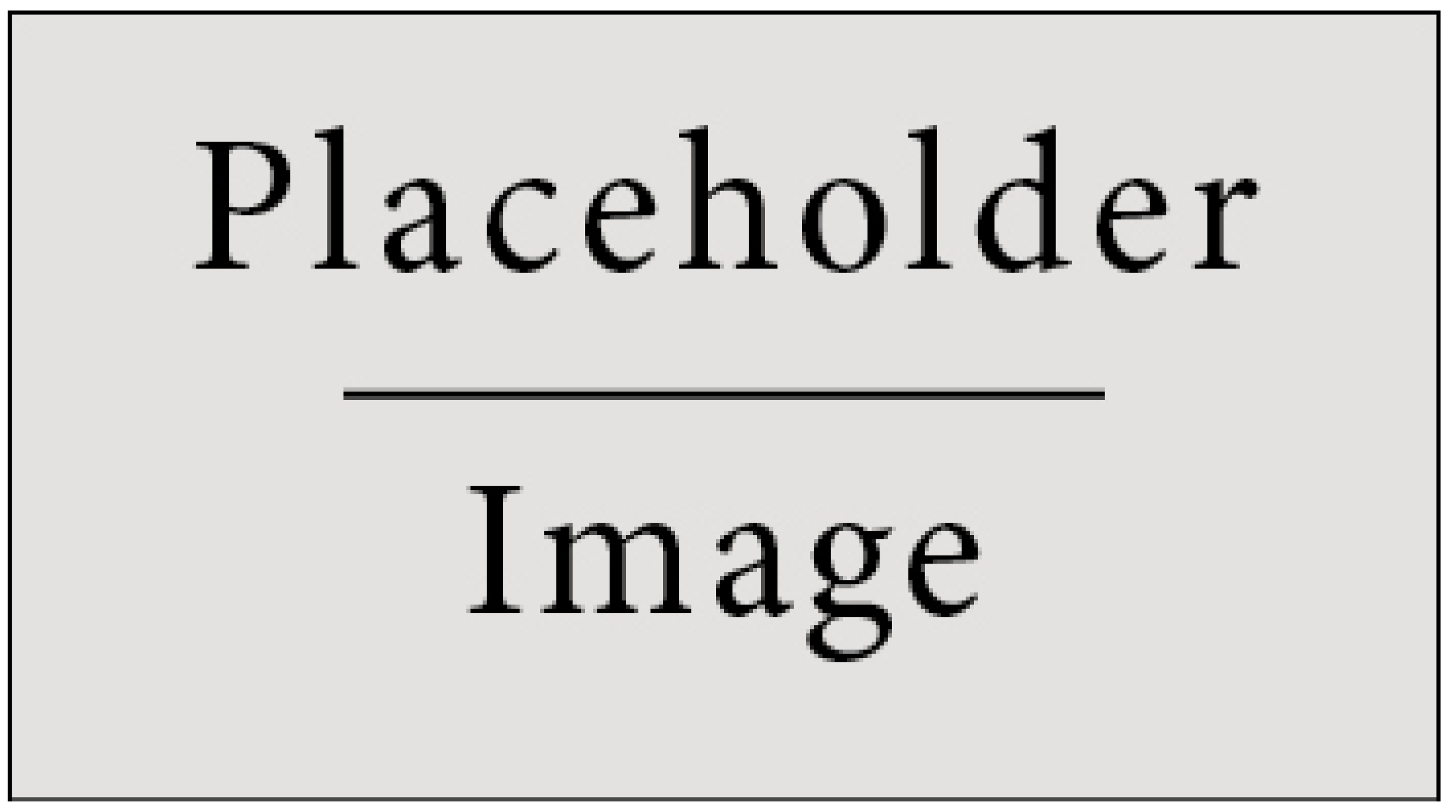

Figure 5: Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor.

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. The most critical step is to slice the data in the time dimension for attention conversion, and finally get a highly distinguishable representation. At this time, use global average pooling and a simple fully connected layer to classify different types of EEG data. 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 30 subjects (15 normal subjects and 15 depressed subjects), the proposed algorithm achieves a 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. In addition, the 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 CNN 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.

Reference

1. Institute of Health Metrics and Evaluation. Global Health Data Exchange (GHDx). http://ghdx.healthdata.org/gbd-results-tool?params=gbd-api-2019-permalink/d780dffbe8a381b25e1416884 9e88b (Accessed 1 May 2021). 2.