Major Depression Disorder detection on EEG-Based with the Convolution Neural Networks approach improved with the Inter-trial phase clustering

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Abstract

Nowadays, Major Depression Disorder is still a concern about human mental health, and there are significant challenges in the diagnosis. There are still limitations in the traditional method used to classify patients from healthy groups and required specialized personnel such as a psychiatrist or psychologist. The aim of this study is to introduce the ability of a deep learning approach to detect abnormalities in EEG (Electroencephalogram) signals of patients with depression. The EEG features are based on the Time-Frequency Analysis of EEG signals from the Morlet wavelet transformation, also known as ERPs (Event-Related Potentials) and ITPC (Inter-trial phase clustering), which is complex and challenging to assess by humans. We proposed a deep learning model that are integrating the two Convolution Neural Networks (CNNs) models to learn both EEG features at the same time to increase efficiency in classification. The result shows that the concatenation CNNs between two input's EEG features received accuracy in classification at 91.60% compared with general CNNs that use single input ERPs with accuracy only 83.33%. Also, we are comparing with a machine learning approach, such as KNN (K-nearest neighbor), that received an accuracy of 67.00%.

Keywords: Electroencephalogram (EEG), Event-Related Potentials (ERPs), Inter-Trial phase clustering (ITPC)

1. Introduction

Major depression disorder is still a grave concern for human mental health. Generally, depression is caused by brain disorders that affect thoughts, emotions, as well as physical health. In several patients who have experience with depression might have symptoms and express symptom [1] such as 1) mood symptoms, 2) somatic symptoms, 3) cognitive symptoms, 4) psychomotor slowness and 5) interpersonal symptoms that cause problems in daily life, such as Insomnia, loss of concentration, eating behavior, working, including living with others in society, and patients suffering in a critical case in depression, may cause suicide. According to the World Health Organization statistics [2], no less than 300 million patients have to live with depression.[1] Hence, if the clinical diagnosis could diagnose the disease and treat those symptoms in an early curable stage, there could save many patients.

Presently, the diagnosis of depression symptoms needs to use a specialist in psychology such as a psychiatrist or psychologist to convince patients in the interview of screening depression patients. The current screening tools mostly used for diagnostic criteria are the international standard criteria such as "Fifth Edition of the Diagnostic and Statistical Manual of Mental Disorders" (DSM-5) [3] and Beck depression inventory (BDI) [4]. Both of these screening tools must have collaborated with the patient because in some patient's cases they avoid in a diagnosis of depression because the nature of mental disorder fear in assistance from another person and the consequence of error diagnosis is that a patient does not receive a correct treatment procedure and might increase the level of mental disorder. According to depression detection, the accuracy in diagnosing it depends on the specialization of personal experience. On the other hand, there is an instrument that is convenient, effective, and reflects directly with brain activity and receives the physiological data in real-time called EEG.

Electroencephalography (EEG) is a noninvasive technique for measures an electrical signal from brain activities. It uses multiple of the electrode that places directly on a scalp to receive a variation of a neuron inside the brain[5]. Recording the brain signal relates to brain activity; it is based on the event set to stimulate brain activity and record it in the experimental time frame. EEG is utilized in medical practice, such as detection in abnormality of brain function, epilepsy detection, and sleep apnea assessment. Generally, an evaluation of the EEG is focused on measure response to a stimulus; the method is called Event-related potentials (ERPs) [6]; it uses an average of EEG signal of each event trial. However, using ERPs just interpretation in the aspect of the time domain in the signal analysis would not be able to observe the dynamic of magnitude in each frequency. Furthermore, receiving both magnitudes of time and frequency is using ERPs in Time-Frequency analysis for interpreting the EEG signal, so it's considered as a type of EEG features.

Moreover, there is another EEG feature in the Time-Frequency domain that correlates with a changing of EEG signal over trials called Inter-trials phase clustering (ITPC) [7], so it is represented as a distribution of vector phase relied on each frequency and each time point that stimulation is onset. So it expresses in the form of magnitude of the average vector phase that shows the interconnectivity of the EEG electrode in the overall stimulus event. The prior evidence about the investigation

The manuscript received July 12, 2020; revised October 1, 2020; accepted November 21, 2020; available online April 8, 2021.
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in ITPC [8] showed that the induction of ITPC as a condition of analysis could enhance observation between the amplitude power and phase with the substantial interference of low-frequency noise in the feedback activity. However, many of the evidence show an analysis relies on the psychological statistics term for excludes a patient out of the control group by observing a response of theta power [9], Using a machine learning to predict abnormality of EEG signal around the Prefrontal cortex region that is center of consciousness activity with conducting handcrafted feature as "Shannon Entropy." [10]. Accordingly, both of those methods require robust techniques for observing a feature from the EEG signal. Finally, we suggest the concatenation of CNN for detecting a symptom in depression disorder without using complex knowledge about the disease.

Convolution Neural Networks (CNNs) is currently an on-trend method for an image and video classification task. Structure of CNNs has comprised two-parts 1) feature extraction layers and 2) classification layers, so an advantage of CNNs is using a convolution filter to extract features from input data and compress features with partial connection for the next classification layer for learning feature in a specific problem. It has considerable evidence about the performance of CNNs in neuroscience fields [11] that substantiate whether CNNs are often successful in performance than the traditional machine learning that uses a handcrafted feature extraction part separated with a classification part. To perform representation of the EEG signals in the 2D images for the CNNs [12], it needs a method for transformation; therefore, morlet wavelet transformation is an implementation tool that is used to convert raw EEG data, especially ERPs data, to become an image to use as input stack in multi-layers CNNs to develop a classification model that can diagnose a depression symptom. To obtain better accuracy more than previous literatures, we propose a multi-input stack that uses ERPs and ITPC spectrograms.

2. Materials

2.1 Dataset

This dataset is provided by "Cognitive Rhythms and Computation Labs [13]." Raw EEG signals were recorded from 121 participants containing the control group and depressed group and had consent in the experiment. EEG signal was measured by using 64 Ag/AgCl electrodes with Synamps2 system (500Hz Sampling rate, bandpass filter 0.5-100, impedances<10 kΩ). The main criteria that is used for separating participants into two groups are based on the beck depression inventory (BDI). Hence, the control group (N=75, 40 female) had stationary low BDI (<7) with no self-reported history of depression and no self-reported indicating in the possibility of Axis 1 disorder. The depressed group (N=46, 34 female) had stationary high BDI(>13), also required to engage criteria Structured Clinical Interview for the DSM-IV, and BDI indicating no difference between current or past MDD group so it capability of combining in a single group.

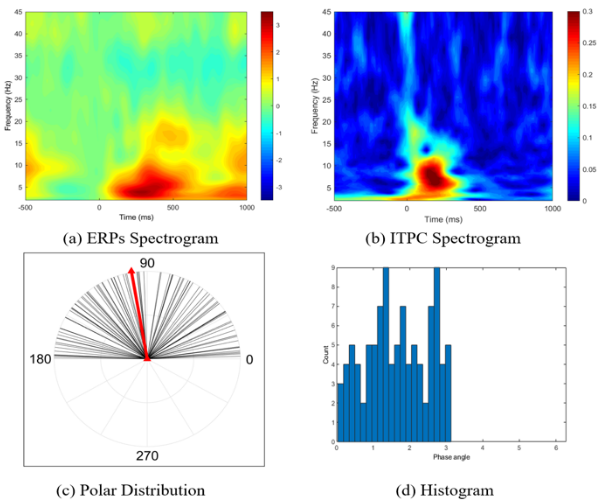
2.2 Data Preprocessing

Pre-processing of EEG signal initiated by an EEGLAB software [14] in Matlab toolbox for Re-references an electrode to mastoids. Bandpass filtered operates in frequency from 0.5 Hz to 50 Hz to eliminate an electrical noise from the powerline and high-frequency noise. Continuous EEG data are extracted in an epoch time for trials. The baseline is correcting at power magnitude from -300 to -200 ms before a stimulus for generating an EPRs and ITPC. Finally, significant artifacts were removed from the signal such as eye movement in a vertical and horizontal axis by Independent Components Analysis (ICA) and is also removed a bad trial in each electrode's channel.

3. Methods

3.1 Time-Frequency Analysis

To perform ERPs and ITPC in the form of a spectrogram image, we propose a complex morlet wavelet transformation (CMW) that calculates an EEG features in the time domain into the time-frequency domain. The process is multiplying a single trial of EEG with the CMW in the frequency domain and using the fast Fourier transform (FFT) to extract a distribution of the power spectrum in each time and frequency. The CMW algorithm is conducted by a Matlab custom equation [15], [16] between Complex sine wave and Gaussian-windowed: $e^{-i2\pi tf}e^{-t^2/(2*\sigma^2)}$ while t is time, f is frequency in logarithmically spaced that frequency is change from 1 to 45 Hz, with the width of each frequency band from 3 to 10. Hence to compare a spectrogram image across the subject, a magnitude power was converted by Baseline Normalization in decibel scale (dB) at an average baseline from -300 to -200 ms pre-stimuli as shown in Fig. **1**(a). In term of ITPC, it is an average in the distribution of vector phase angles at each time-frequency epoch as shown in Fig. **1**(c) and Fig. **1**(d), and we employ the same concept as ERPs to convert them into time-frequency spectrogram as shown in Fig. **1**(b).



(a) ERPs Spectrogram (b) ITPC Spectrogram

(c) Polar Distribution (d) Histogram

Fig. 1 Characteristic of EEG features in expression of time-frequency spectrogram

3.2 Convolution Neural Network

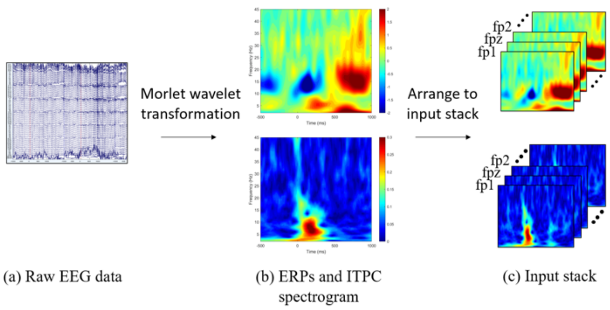


Fig. 2 EEG features input stack generations

To access the ability of Convolution Neural Networks, we start with creating an input stack containing ERPs and ITPC spectrogram images that are resized to 200x200 pixels and rearranged them according to 64 EEG electrodes in each input of CNNs. Finally, an image cube of 200x200x64 is obtained as shown in Fig. **2**. In this study, we proposed a CNNs architecture consisting of two separated convolution layers according to ERPs and ITPC spectrograms which are concatenated to the classification part to predict a different class as shown in Fig. **3**.

To extract a feature, we use standard 2D convolution layers comprising 2 D convolution filters with activation function as a rectified linear unit (ReLU) and sub-sampling to reduce the dimension of the feature following with a fully connected layer to arrange all 2D convolution features in the single dimensionality before training into a classifier in the next layers. The loss function utilizes a binary cross-entropy to obtain an error of binary classes and tuning with RMSprop optimizer with 5e-5 learning rate as shown in Table **1**.

Table 1 Concatenate CNNs configuration

Layer	Layer units/Kernal Size		Output Size
	CNNs (EPRs)	CNNs (ITPC)	
Input layer	64x200x200x3	64x200x200x3	64x200x200x3
Convolution	32/3x3	32/3x3	64x198x198x32
Convolution	64/3x3	64/3x3	64x196x196x64
Maxpool	–/2x2	–/2x2	64x98x98x64
Flatten 2D	–	–	64x614656
Dense layer	128/-	128/-	64x128
Concatenate	–		64x256
Flatten 1D	fully connected		16384
Dense layer	128/–		128
Dense layer	32/–		32
Prediction layer	1		–

4. Results and Discussion

In the assessment of concatenated CNNs that we proposed, firstly a graph is performed an accuracy and loss trend; this is completely performs trends that should be in a training of deep learning. As we observe in a loss trend in Fig. 4, it is immediately overfitting around epoch 19, and after evaluating the model with a testing set, it receives an accuracy of 91.33% with a 0.317 test loss value.

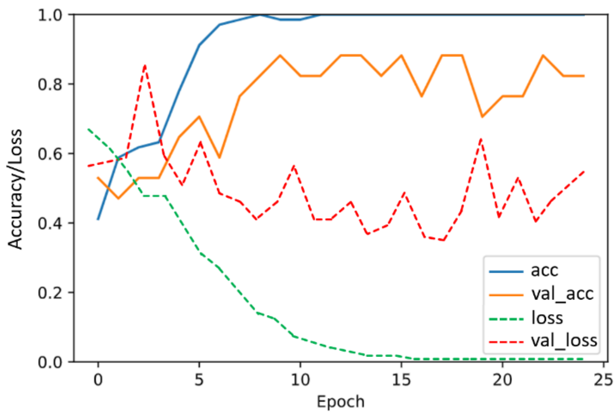


Fig. 4 Accuracy and loss of concatenation CNNs model

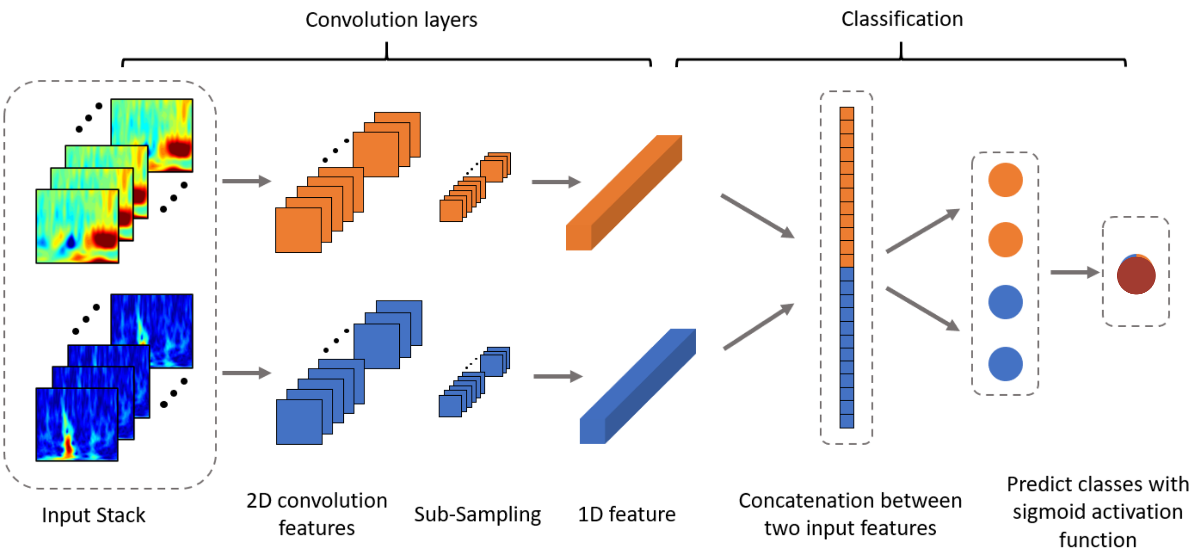


Fig.3 Workflow of Concatenation CNN model

Table 2 shows the comparison of the accuracy from the proposed model to a traditional machine learning, KNN, SVM, and including an original CNNs model that uses only ERPs spectrogram as inputs.

Table 2 Results of KNN, SVM, CNN and Concatenation CNN

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
KNN	50.00	83.33	67.00
SVM	60.00	85.71	75.00
CNN	66.67	100.00	83.33
concat-CNN	80.00	100.00	91.60

According to results, the accuracy of CNNs have improved to 91.60% over the conventional CNNs which is only 83.33%, and a sensitivity and specificity have increased comparing with the ground truth.

5. Conclusion

According to an approach and concept for improving the accuracy of the original CNN that we proposed for detection of the depression patients, The concatenated CNN model that using ERPs and ITPC as the input spectrograms could explain that the model can capture an interconnectivity between two EEG features in proceeding of feature extraction and obtain the improvement of accuracy in classification. Although this robust model receives more accuracy in learning EEG features than the traditional machine learning with a significant number in training parameters, it takes higher time expense in learning of CNNs. Hence, to eliminate the limitation of training parameters, we need more optimization at the convolution layer.

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