

Classification of Brain Functional Connectivity using Convolutional Neural Networks

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Abstract. Abnormalities and alterations in brain connectivity networks as measured using neuroimaging data has been increasingly used as biomarkers for various neuropsychiatric disorders. Schizophrenia (SCZ) is a complex neuropsychiatric disorder associated with dysconnectivity in brain networks. In this paper, we develop a framework for automatic classification of healthy control and SCZ patient based on electroencephalogram (EEG) connectivity and compare the classification performance with conventional artificial neural network (ANN). We propose to use convolutional neural network (CNN) for the classification of brain functional connectivity between healthy control and SCZ groups. Vector autoregression (VAR) model is used to extract connectivity features from schizophrenia EEG signals and directed connectivity at different EEG frequency bands is computed via partial directed coherence (PDC). Results show that the classification with high accuracy is achievable using VAR model. From the result, the performance of CNN reaches 86.9% over five-fold cross validation that considered to be good accuracy for the CNN to do a good prediction. The results also show that time-domain VAR features performed better than frequency domain PDC features. CNN provides a more practical method in classification between healthy and schizophrenic brain connectivity.

1. Introduction

Schizophrenia (SCZ) is a complex neuropsychiatric disorder [1]. Recent attempts have tried to unfold the pathophysiology of SCZ through brain imaging to provide objective diagnosis. The brain imaging techniques that usually used to image the structure of brain were the functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). fMRI able to associate SCZ with functional impairment in sensory and frontal brain areas [2]. EEG studies reported impairment of neural oscillations at both low and high frequencies in schizophrenic cortical network [3]. Functional connectivity estimated from fMRI and EEG also showed dysconnectivity in schizophrenic brain, especially in the frontal region [4]. In this research, we consider the challenges in automatic classification of SCZ which is a complex brain disorder characterize by functional connectivity. The current focus on spectral features of single channel did not extract multivariate connectivity features.

Advancing machine learning has allowed researchers to design automated neuropsychiatric diseases diagnostic algorithms. A few of machine learning algorithms such as kernel discriminant

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analysis (KDA) [5], logistic regression [6], and support vector machine (SVM) [6-11] had been utilized to classify between healthy and schizophrenic brain activity.

The performance of deep neural network (DNN) in classifying schizophrenia brain connectivity have not been well studied, even though the DNN has been implemented to classify brain connectivity of autism spectrum disorder (ASD) with great accuracy [12-14], Results on resting state fMRI study shows that DNN outperformed SVM for classification of schizophrenia brain connectome [5]. Existing studies focused only on the technique of fMRI in evaluating the structure of brain connectivity pattern of SCZ patient [15]. To our knowledge, there is less study evaluated the performance of DNN in distinguishing schizophrenia EEG connectivity. In our recent work [16], we have introduced DNN with deep belief network that achieving remarkable accuracy in classifying EEG-based effective brain connectivity in Schizophrenia.

In this paper, we extract the connectivity patterns between healthy group and SCZ patients from raw EEG signals by using vector autoregression (VAR) model and partial directed coherence (PDC), developed a system for automatic classification of healthy group and SCZ patients based on EEG connectivity using deep neural network (DNN) and to compare the classification performance of convolutional neural network (CNN) with artificial neural network (ANN). We proposed a framework based on deep CNNs for classifying altered EEG-derived brain connectivity patterns in SZ. The performance of CNN in classifying SCZ and healthy groups were evaluated using EEG effective connectivity patterns measured by VAR, PDC and the voting of all two feature sets. We quantify the weighted-directed EEG connectivity by VAR model. Spectral connectivity features are estimated using PDC.

2. Method

The proposed model for classifying schizophrenia and healthy subjects based on EEG-based effective brain networks. EEG datasets were search through online databases. The EEG datasets were published by Moscow State University were chosen. There are two EEG data archives for two state group of subjects which consists of 84 subjects (45 SCZ patients and 39 healthy groups). There are 16 channels numbers of EEG (F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2). Various crafted measures of directed brain connectivity are first estimated from raw EEG data. These extracted connectivity features were used as inputs to the CNN classifier. The convolution layers of CNN will further learn additional features from the crafted connectivity measures, before proceeding for classification in fully connected layer.

2.1. Vector autoregression (VAR) model

VAR model was used in this study to estimate time-domain directed EEG connectivity between various scalp region. The directed functional connectivity in can be characterized via a VAR model of order P, VAR(P):

$$y_t = \sum_{i=1}^p A_{\tau} y_{t-i} + \varepsilon_t \quad (1)$$

y_t is the signal in a given time and A is connectivity coefficient matrix. We find A using least square (LS) method:

$$\hat{\beta} = (X'X)^{-1}X'y \quad (2)$$

VAR coefficients of all lags can be written as linear regression:

$$Y = X\beta + E \quad (3)$$

where,

$$Y = \begin{bmatrix} y'_1 \\ \vdots \\ y'_T \end{bmatrix}, X = \begin{bmatrix} y'_0 & \cdots & y'_{-(p-1)} \\ \vdots & \ddots & \vdots \\ y'_{(T-1)} & \cdots & y'_{(T-p)} \end{bmatrix}, \beta = \begin{bmatrix} A'_1 \\ \vdots \\ A'_p \end{bmatrix} \text{ and } E = \begin{bmatrix} \varepsilon'_1 \\ \vdots \\ \varepsilon'_T \end{bmatrix} \quad (4)$$

2.2. Partial directed coherence (PDC) model

PDC model was proposed to estimate the directional connectivity strength from VAR coefficients in specific frequency f .

$$\pi_{ij}(f) = \frac{|\phi_{ij}(f)|}{(\sum_{k=1}^N |\phi_{kj}(f)|^2)^{1/2}}, 0 \leq |\pi_{ij}(f)|^2 \leq 1 \quad (5)$$

π_{ij} is the directed influence from region i to region j from frequency, f and ϕ are the connectivity matrices. Fourier transform of VAR connectivity matrices, ϕ with sampling frequency f_s is defined as

$$\phi(f) = \ell - \sum_{\ell=1}^p \phi_{\ell}(f) \exp(-i2\pi\ell f/f_s) \quad (6)$$

2.3. Convolutional neural network (CNN)

CNN consists of convolutional layer, pooling layer and fully-connected layer. The main function of convolution layer is to identify spatial invariant features from its input. The input dimension of a typical 2D CNN are height \times width \times colour channel. In this project, the features were extracted at the dimensions of $16 \times 16 \times 5$. The extracted VAR and PDC connectivity features will become the input to train the CNN architecture implemented using MATLAB as shown in figure 1.

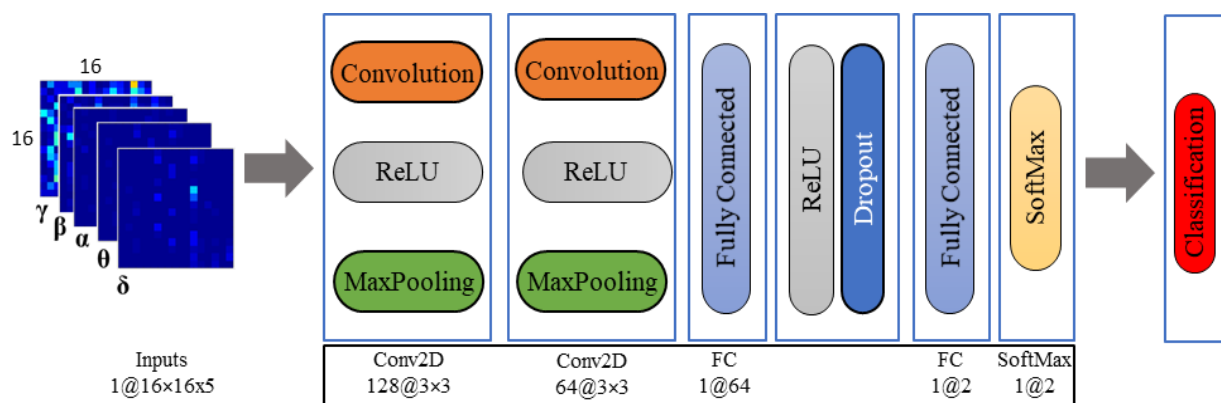


Figure 1. CNN architecture.

The performance of CNN was evaluated by five-fold cross validation. The cross validation also called as rotation estimation. The function of the cross validation is to assess how the result of the statistical analysis will generalize and to estimate how accurately a predictive model will perform in practice. The training set is 67 and the testing is 17. The CNN was trained using Adam optimizer, with learning rate of 0.001 and decay of $1e^{-6}$ for 500 epochs. The classification outputs using VAR and PDC are combined to give final decision.

3. Main results

We evaluated the performance of CNN in classifying schizophrenia and healthy groups on online schizophrenia EEG database published by the Moscow State University.

EEG effective connectivity patterns measured by VAR and PDC matrices were used as input features to the CNN. The connectivity matrices from VAR and the connectivity matrices of five different EEG frequency bands that were stacked as one vector were used to train ANN and CNN. Trials were divided into two sets which are training set and testing set. Training set was used to train the classifier while testing set used to investigate the performance of trained classifier. For the dataset, there were 67 trials in training set and 17 trials in testing set. The training curve of CNN is as shown in figure 2. The objective is to select the epoch when the model has minimal loss.

From the graph, we can see that there is a considerable difference between the training and validation loss. This shows that the convolutional network has tried to memorize the training data and thus, is able to get better accuracy on it. The graph will be trained until 500 epochs which consists of 3000 iteration. The total loss graph, decrease steadily, thus it show that the model train in a good process.

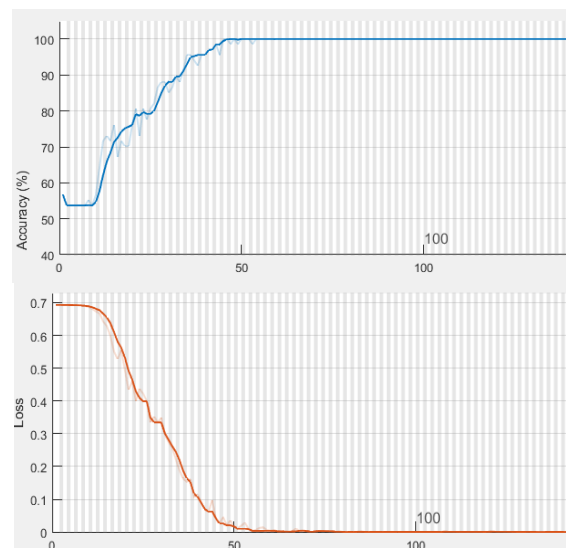


Figure 2. Training curve of accuracy (%) and validation loss of CNN.

The results domain VAR and frequency domain PDC for both the ANN model and CNN model classification as shown in table 1. For of accuracy, specificity, sensitivity and moderate accuracy were computed for time the frequency domain PDC, the results of accuracy for each band, Delta, Theta, Alpha, Beta and Gamma were evaluated.

Table 1. Results of accuracy for ANN model and CNN model.

Classifier	Feature Extraction	Accuracy (%)	Sensitivity (%)	Specificity (%)	Modified Accuracy (%)
ANN	VAR	76.93	95.56	60.00	77.78
	PDC	70.59	80.00	69.29	74.64
CNN	VAR	85.81	79.64	91.12	86.90
	PDC	75.07	80.00	71.14	76.35

The proposed CNN significantly outperforms ANN classifier on resting-state EEG recordings. Voting of between VAR and PDC features showed improvement over individual feature, achieving classification accuracy of 86.90% over five-fold cross validation as shown in figure 3. The results also show that time domain VAR features performed better than frequency-domain PDC features. The classification accuracy (%) for the convolutional neural network (CNN) yield better result than artificial neural network (ANN).

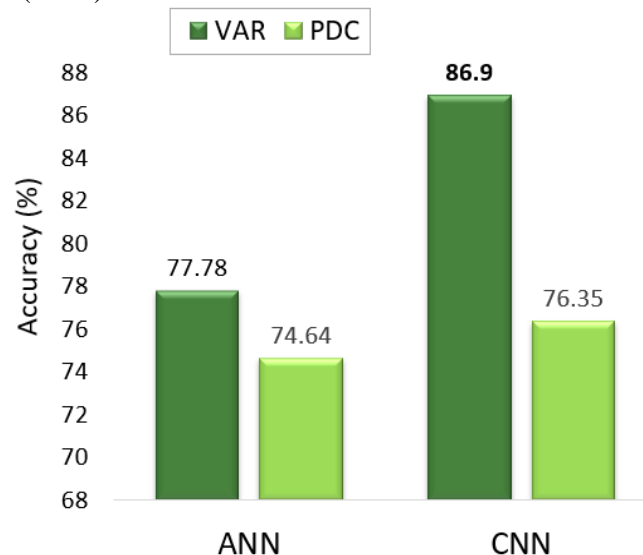


Figure 3. Comparison of accuracy (%) among two different features.

In this research, we did GUI for the CNN connectivity classification toolbox. From the GUI, we can classify the brain connectivity of healthy and schizophrenia patient. The GUI was done in the MATLAB.

4. Conclusion

We developed a framework based on CNN for classifying the EEG brain connectivity between the healthy control and schizophrenia patients. Convolutional neural network (CNN) provides a more practical method in classification between healthy and schizophrenic brain connectivity. The proposed model is useful for future development of automated schizophrenia diagnosis in clinical settings and also generally applicable to other neuropsychiatric disorders besides schizophrenia associated with aberrant connectivity patterns.

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