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RESEARCH ARTICLE

Automated Rest EEG-Based Diagnosis of Depression and Schizophrenia Using a Deep Convolutional Neural Network

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the West China Medical Ethics Committee of Sichuan University.

ABSTRACT Depression (DP) and schizophrenia (SCZ) are both highly prevalent psychiatric disorders, and their diagnosis depends on the examination of symptoms and clinical tests, which can be subjective. As a measure of real-time neural activity, Electroencephalographic (EEG) has shown its usability to classify people either as normal or as having DP or SCZ, but automatic classification between the three categories (DP, SCZ and the normal) was rarely reported. Here, we propose an automatic diagnostic framework based on a convolutional neural network called the Multi-Channel Frequency Network (MUCHf-Net), which automatically learns feature representations of EEGs that characterize them as normal, DP, or SCZ. Two EEG databases were used in this study, the first one contains EEGs from 300 individuals (DP: 100, SCZ: 100, normal: 100) collecting from our hospital, and the second contains EEGs from 30 individuals (DP: 10, SCZ: 10, normal: 10) from public available datasets, and the spectrum matrices from these multi-channel EEGs were feed into MUCHf-Net. The results showed that: (1) MUCHf-Net accurately distinguished normal EEGs from DP or SCZ EEGs (accuracy: 91.12%; F1 score: 0.8947); (2) low-frequency bands (delta, theta, alpha) contributed the most important information to the classification model; (3) features located in the frontal and parietal lobes contributed more than other regions did; (4) MUCHf-Net fine-tuned on public datasets also had high classification accuracy: 87.71% (triple: normal, SCZ or DP) and 79.27% (binary: psychiatric disorders (DP or SCZ) or normal). Our study shows that deep learning has the potential to become an important tool for assisting in the diagnosis of psychiatric disorders.

INDEX TERMS Electroencephalogram, depression, schizophrenia, deep learning, convolutional neural network, power spectrum.

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I. INTRODUCTION

Depression (DP) is a severe psychiatric disorder that affects about 4.4% of the world's population [1]. It can cause serious emotional abnormalities, such as low spirits, inattention, poor self-esteem, and even suicidal tendencies [2]. Schizophrenia (SCZ) is another chronic and complex psychiatric disorder, whose primary symptoms are hallucinations, speech confusion, and cognitive decline, and which can also lead to suicidal tendencies [3]. DP and SCZ are both psychiatric disorders with high prevalence that can have severely harmful impacts on a person's health. Thus, accurate and timely diagnosis is crucial for their treatment. The most-used international standard is currently the Diagnostic and Statistical Manual of Mental Disorders (Fourth Edition) (DSM-IV), which depends primarily on an examination of patient symptoms by a qualified doctor [4], [5], a process that is inevitably subjective. Additionally, DP and SCZ have many overlapping clinical symptoms, such as lack of energy, social withdrawal, and unhappiness, which makes correct diagnosis particularly difficult [6]. Therefore, finding objective biomarkers for diagnosing DP and SCZ remains an urgent concern.

Neuroimaging methods, such as electroencephalographic (EEG) recordings [7], structural magnetic resonance imaging (sMRI) [8] and functional MRI (fMRI) [9] are all promising resources for diagnosing psychiatric disorders. However, the data obtained from these imaging techniques are complex and high-dimensional, and manual analysis is time consuming. In recent years, researchers have applied artificial intelligence (AI) to the detection of many psychiatric disorders, including DP and SCZ, and the results show that this approach can successfully discover correlations between neuroimaging data and diseases [10], [11], [12]. In one study, researchers used MRI data collected from sMRI scans and a support vector machine (SVM) to distinguish SCZ patients from normal subjects, with an accuracy of 83.5% [13]. In another study, task-related fMRI data were used to distinguish between SCZ and DP in a paradigm that included responses to self-assessment scales. This confirms that it is possible to classify psychiatric disorders using brain signals related to clinical evaluation tests [14].

Although sMRI and fMRI are considered to be good ways to distinguish patients of SCZ and DP from normal subjects, data acquisition is complex and expensive. In contrast, EEG is cheaper, and more convenient to collect, at the same time being just non-invasive and reflecting real-time neural activity. EEG has been widely used in the diagnosis of various neurological diseases. In the past 10 years, analysis of EEG data using machine learning (ML) or deep learning (DL) method to detect neurological diseases, such as epilepsy [15], Parkinson's disease [16], and Alzheimer's disease [17], [18], has attracted an increasing amount of attention. EEG signals contain complex and comprehensive information about the physiological activity of the brain, and the application of AI increases the potential of EEG analysis for disease diagnosis.

In recent years, several studies have proposed computer-aided diagnoses (CADs) and AI-based methods of analyzing EEG to detect DP and SCZ. These studies focus primarily on manually extracting EEG features and then using classifiers for disease diagnosis. Some EEG features that have been commonly used to analyze DP and SCZ include nonlinear measures [19], brain networks [7], and information entropy [20]. ML is the most popular classification method, such as SVM, which is a technique used in many related studies and showed excellent performance [20]. Recently, neural networks (NN) have begun attracting the attention of researchers when dealing with complex neuroimaging data [7], [21], [22]. Compared with ML, DL can more conveniently analyze different forms of data, which can often lead to better classification.

Although young people represent the largest group diagnosed with psychiatric disorders, the majority of studies [7], [9], [20], [21], [22] , [24], [25] have investigated middle-aged groups. Additionally, previous studies have focused on using EEG to distinguish people with either DP or SCZ from those without any psychiatric disorders, but very few have tackled the problem of classifying all three categories (DP, SCZ, and normal) from the same sample. Furthermore, even though DL models with automatic representational learning are usually associated with more flexible analysis methods and stronger adaptability, few researchers have combined spectrograms with DL to classify people as normal or to determine their psychiatric disorder. Therefore, the current study adopted DL, specifically a deep neural network (DNN), as a means to improve classification of EEG signals in a young population as DP, SCZ, or normal.

Here, we developed a DL model for classifying samples of EEG spectra obtained from patients who either had DP or SCZ, or did not have any psychiatric disorders. The relative power spectra of the EEG segments at rest were calculated and used as input to the proposed model for classification. Our contributions are as follows:

1) We propose a DL model that automatically extracts features from EEG spectra and classifies them as DP, SCZ, or normal.
2) Our results indicate that EEG signals combined with deep neural networks (DNN) can be used to classify people as normal or as having DP or SCZ. Additionally, we verified the generalization of the proposed model on data that was not used during model development.
3) We visualized important features in the power spectrum for model decision and found that low-frequency (delta, theta and alpha) EEGs recorded from the prefrontal and parietal lobes provided the most important contribution to classification. Our results are interpretable and provide guidance for clinical diagnosis.
4) We evaluated the generalization of the proposed model on on an EEG database of patients with psychiatric disorders of other ethnicities from abroad, and found our method to be comparable with the latest methods from other studies.

II. RELATED WORK

We focused on studies using DL or ML and EEG to diagnose DP or SCZ, and Table 1 shows some recent studies that have been widely referenced for the diagnosis of psychiatric disorders. At present, traditional ML techniques are still the mainstream to classify EEG of DP and SCZ, researchers use ML classifiers to analyse manual features from EEG recordings and classify them as different categories. The frequency domain information of EEG are often of interest, such as the power of different frequency bands, power asymmetry between hemispheres, etc. Bose *et al.* [23] studied the differences in EEG power spectrum between SCZ patients and healthy subjects under rest, HV and PHV, respectively. They extracted the power of different frequency bands of EEG under the three conditions as features to diagnose SCZ, and found that combined features from rest, HV and PHV produced the highest accuracy of 83.9%. Mumtaz *et al.* [24] and Shalini *et al.* [25] further considered the contribution of power asymmetry for the diagnosis of DP. Mumtaz *et al.* studied using EEG interhemispheric alpha asymmetry and the power of different frequency bands as features to distinguish major depressive disorder (MDD) patients and healthy controls, and Shalini *et al.* used interhemispheric theta asymmetry and different frequency band power for the diagnosis of DP. Their results indicate that power asymmetry is of great value in diagnosing DP. The analysis of EEG entropy features is another important aspect, such as the studies of Acharya *et al.* [19] and Chu et al [20]. Acharya *et al.* proposed a novel Depression Diagnosis Index (DDI) to diagnose DP by combining sample entropy (SampEnt) and other nonlinear features such as fractal dimension (FD), largest lyapunov exponent (LLE), *et al.* They reported the highest classification accuracy of 98% yielded by SVM when feeding these features into the ML classifier. Chu *et al.* calculated three kinds of entropy of five frequency bands of EEG signals to analyze the difference between DP patients and the normal. Other non-linear feature extraction methods, such as Empirical Mode Decomposition (EMD) [26], [27] and high order statistical parameters [28], have also proved valuable to diagnose DP or SCZ.

Recently NN has become increasingly popular among researchers because of its good performance and flexibility in data analysis. Researchers have applied NN to evaluate the performance of using spectral, spatial, and time-domain information to diagnose DP or SCZ [22]. More importantly, NN is able to deal with graph data and sequence data in a more flexible way than ML. Danish *et al.* [7] used 3D Convolutional Neural Network (3D-CNN) to deal with the effective connectivity matrices of the brain to classify subjects as MDD or healthy controls, and Sharma *et al.* [29] used CNN for time domain learning, and long short-term memory (LSTM) structure for sequence learning in their proposed hybrid neural network to screen DP. The time-domain signals of EEG has always been considered difficult to analyze, but some researchers have demonstrated that DNN can learn distinguishable patterns from them, such as Acharya *et al.* [21] and Oh *et al.* [30]. In addition, some studies fused multi-modal features to classify EEG samples based on NN, such as Phang *et al.* [31] who designed a novel DNN architecture called the multi-domain connectome CNN (MDC-CNN) that allows the fusion of the time-domain, frequency-domain and topological measures of brain connectivity for classification SCZ patients and healthy controls.

III. MATERIALS AND METHODS

A. EEG RECORDINGS

1) EEG DATABASE OBTAINED FROM OUR HOSPITAL

The first EEG database were provided by the Mental Health Center in the Second Outpatient Department of West China Hospital at Sichuan University, China. The samples included 100 patients with DP (mean age: 25.38 ± 5.42 years, 50 males), 100 with SCZ (mean age: 25.34 ± 5.40 years, 50 males) and 100 without any psychiatric diseases (normal; mean age: 25.38 ± 5.42 years, 50 males). Each participant was diagnosed by a professional physician according to DSM-IV and signed an informed consent form. A 16-channel EEG collection system (NATION8128W, Shanghai Nuocheng Electric Co., Ltd., China) with a sampling rate of 128 Hz was used to record EEG signals. EEG electrodes were placed according to the international 10-20 electrode positioning system (Fig. 1).

EEG acquisition was carried out in a quiet room. Before data collection, participants were given a 10-s period of quiet and asked to stay relaxed. During collection, they were asked to cyclically keep their eyes open (7 s) and then closed (7 s) according to doctor's prompt. This process was performed three times for each participant, and thus generated six 7-s EEG recordings for each person (2 eye conditions $\times$ 3 repetitions).

2) PUBLICLY AVALIABLE EEG DATABASE

The EEG public database used in this study consists of two open datasets, one containing EEG from patients with paranoid SCZ and healthy controls and the other containing EEG from patients with MDD and healthy controls. The first open dataset [32] is collected from the Institute of Psychiatry and Neurology in Warsaw, Poland, and consists of 14 patients (average age: 28.1 ± 3.7, 7 males) with paranoid SCZ and 14 healthy controls (average age: 27.8 ± 3.2, 7 males). The EEG signals was recorded for 12 min with each participant having their eyes closed and in a relaxed state at a sampling rate of 250 Hz. The second dataset [33] consists of EEG signals of 34 DP patients (17 males and 17 females, mean age: 40.3 ± 12.9) and 30 healthy controls (21 males and 9 females, mean age: 38.3 ± 15.6) and the EEG signals were collected when participants closed their eyes for five minutes. EEG recordings in the two open datasets were collected in accordance with the International 10-20 system and total 19 channels of EEG signals were considered.

Manual screening was performed to removed subjects whose recordings contains too much interference, and EEG

TABLE 1. A list of published works on the automatic diagnosis of DP and SCZ using EEG signals.

Authors	Number of subjects	Method	Conclusion
Bose et al. [23]	● 57 patients with SCZ ● 24 normal subjects	● Absolute band power during rest, hyperventilation and post-hyperventilation ● SVM	Combined features from rest, HV and PHV produces the highest accuracy of 83.9%
Mumtaz et al. [24]	● 33 patients with DP ● 30 normal subjects	● Different frequency band power and alpha interhemispheric asymmetry ● Logistic regression (LR), SVM and Naïve Bayesian (NB)	Ten features from Power and Asymmetry, SVM produces the highest accuracy rate of 98.4%
Shalini et al. [25]	● 34 patients with DP ● 30 normal subjects	● Different frequency band power and theta asymmetry ● Multi-Cluster Feature Selection (MCFS) ● SVM, LR, NB and Decision Tree (DT)	Alpha2 band provides the highest classification accuracy of 88.33% with SVM
Chu et al. [20]	● 17 patients with DP ● 10 normal subjects	● approximate entropy (ApEn), permutation entropy (PE) ,amplitude-aware PE (AAPE) ● SVM	● Normal subjects vs. Obvious disease group: 81.58% ● Normal subjects vs. Moderate disease group: 70.4% ● Obvious disease group vs. Moderate disease group: 67%
Danish et al. [7]	● 30 patients with DP ● 30 normal subjects	● Brain default mode network (DMN) ● 3D-CNN	Highest accuracy: 100%
Acharya et al. [19]	● 15 patients with DP ● 15 normal subjects	● Nonlinear features ● SVM	Average accuracy: 98%
Bairy et al. [28]	● 15 patients with DP ● 15 normal subjects	● Linear prediction coding and nonlinear features ● Bagged tree	Highest accuracy: 94.3%
Siuly et al. [27]	● 49 patients with SCZ ● 32 normal subjects	● Empirical mode decomposition (EMD), Kruskal Wallis Test ● DT, k-NN, SVM and ensemble bagged tree	EBT produces a classification accuracy of 93.21%
Shen et al. [26]	● Dataset 1: 81 patients with DP, 89 normal subjects ● Dataset 2: 160 patients with DP, 116 normal subjects ● Dataset 3: 105 patients with DP, 109 normal subjects ● Dataset 4: 105 patients with DP, 70 normal subjects	● Improved EMD method ● SVM	● Accuracy of dataset 1: 83.27% ● Accuracy of dataset 2: 85.19% ● Accuracy of dataset 3: 81.98% ● Accuracy of dataset 4: 88.07%
Acharya et al. [21]	● 15 patients with DP ● 15 normal subjects	● Time domain signal ● CNN	Highest accuracy of 95.96% using EEGs from right hemisphere
Sharma et al. [29]	● 21 patients with DP ● 24 normal subjects	● Time domain signal ● CNN and LSTM	Highest accuracy: 99.10%
Li et al.	● 24 patients with DP ● 27 normal subjects	● Spectral, spatial, and time-domain information ● CNN	Highest accuracy: 85.62%
Phang et al. [31]	● 45 patients with SCZ ● 39 normal subjects	● Time-domain vector auto-regressive (VAR) model coefficients, the frequency-domain partial directed coherence (PDC), the complex network (CN) measures ● CNN	CNN based on the weighted-averaged fusion achieved the best accuracy of 91.69%
Oh et al. [30]	● 14 patients with SCZ ● 14 normal subjects	CNN	● Non-subject based testing: 98.07% ● Subject based testing: 81.26%

recordings of 10 SCZ patients and 10 healthy subjects were retained. In order to balance the numbers of subjects in different categories, 10 DP patients were selected. The EEG data of these 30 subjects (DP: 10, SCZ: 10, Normal: 10) formed a new dataset. All EEG recordings were manually preprocessed described as section III (B) and segmented into

7s EEG segments. In order to balance the number of samples of different types, EEG recordings only between 1 and 6 minutes (5 minutes in total) were reserved and transformed to frequency domain described as section III (C) for SCZ patients. We randomly selected samples of three subjects from each category to form a test set, and those of the other subjects form a training set.

B. EEG PRE-PROCESSING

Raw EEG recordings were first segmented according to eye state (open/closed), which generated 1800 EEG segments (eyes open: 3 × 300, eyes closed: 3 × 300). Subsequently, we only considered the 900 eyes-closed segments for analysis. The average reference at each electrode was calculated for each EEG segment, and a 0.3–45 Hz band-pass filter was then applied to remove frequencies that we were not our focus. When dealing with artifacts in EEG segments, we used independent component analysis (ICA) and manually checked each EEG segment to ensure that the obvious artifacts (eye movements and head movements) were removed. The entire process is shown in Fig. 1.

C. POWER SPECTRA

After manual cleaning, EEG segments were transformed into frequency spectra. The Welch method (1-s window length, 50% overlap) was used to obtain the 1–45 Hz spectra for each electrode channel, which generated a 45 × 16 spectrum matrix (45 frequencies × 16 electrodes) for each EEG segment. Because individual variation in the range of spectrum values can be high, we calculated the relative power spectrum of each channel to reduce this imbalance, according to formula 1:

$$P'_{ci} = \frac{P_{ci}}{\sum_{i=1}^{F} P_{ci}} \tag{1}$$

where P_{ci} represents the value in the spectrum of the i-th frequency of the c-th channel. After data processing and spectrum calculation, we obtained 825 spectrum samples from the 300 participants (DP: n = 277, SCZ: n = 271, normal: n = 277). All samples were processed in the same way using Brainstorm software [34]. Among the 825 samples, we randomly chose 130 samples from 45 participants (n = 15 for DP, SCZ and normal, respectively) for testing the generalization of the Multi-Channel Frequency Network (MUCHf-Net) model after training. The other 695 samples were used for model training and validation.

D. MODELS

MUCHf-Net is a neural network developed by the authors. It comprises five convolutional layers, two average pooling layers, and two fully connected layers (Fig. 2), and was designed to extract distinguishable patterns from the spectra of multi-channel EEG signals. Assuming that the spectrum of a multi-channel signal was X ∈ (F, C), F represents the frequency dimension and C represents the channel dimension. The output of the MUCHf-Net was Y ∈ N, where N is the number of predicted categories. The structure of the MUCHf-Net can be divided into four parts:

1) The frequency convolutional layer: This layer deals with the spectra of all channels, with 1D convolution being applied to each channel's spectrum. The convolution kernels slide in each channel from low frequency to high frequency to aggregate frequency features. For each input X ∈ (F, C), a feature map X_1 ∈ (K_1, F, C) was obtained after frequency convolution, where K1 is the number of feature extractors in the frequency convolutional layer.
2) The spatial convolutional layer: Correlation usually exists between multiple channels of a signal, and spatial convolution builds relationships between multichannel features by combining them. The size of the convolution kernel was set to (1, C) to cover all channels, where C is the number of channels. For input X_1 ∈ (K_1, F, C), a feature map X_2 ∈ (K_2, F, 1) was obtained after spatial convolution, where K_2 is the number of feature extractors.
3) The feature integration layer: Deeper feature extraction can usually discover more complex patterns. Here, successive 2D convolution was applied to obtain more advanced patterns. For each input feature map X_2 ∈ (K_2, F, 1), X_2 was first reorganized into a new feature map of size (1, F, K_2) and then processed further with successive convolution filters. The successive convolution filters were applied to increase the range of the receptive field.
4) The classification layer: This layer comprised two densely connected layers, which generated prediction scores for each category by feeding in the feature maps obtained from previous feature extractors.

To sum up, the frequency convolutional layers learn the power features by sliding over the spectrum of each channel using 1-dimensional convolution, and the spatial convolution layer aggregates features from different channels by the cross-channel convolution. A feature integration layer is used to further extract features from the output of spatial convolution and feed them into the classification layer. We chose the best network structure and parameters by trial-and-error strategy, the number of neurons in each layer, filter size, and step length are summarized in Table 2.

E. MODEL TRAINING

Samples from 255 (85 × 3) subjects were involved during model training, and five-fold cross-validation was used to test the performance of the model trained after each run. Subjects from each category were randomly divided into 5 parts. In each run, four parts of them were used to train the model, and the remaining was used to test the performance of the model.

The initial learning rate of the MUCHf-Net was set to 1×10^{-4}, the fixed epoch decay strategy and a batch size of

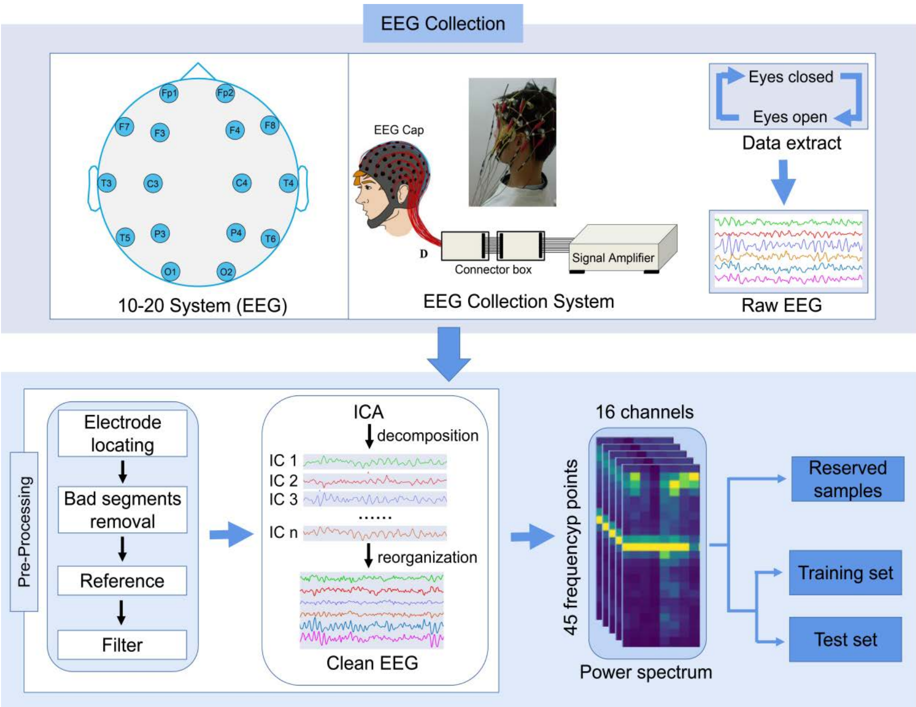

FIGURE 1. EEG collection and preprocessing flow diagram. EEG signals were collected using a 16-channel EEG collection system. For each channel, we removed bad segments from the raw EEG by visual inspection. Average references were calculated at all electrodes for each EEG segment, and then a 0.3–45 Hz band-pass filter was applied to the EEG segments to remove frequencies that were not our focus. We performed ICA using Brainstorm software to remove artifacts from the signal, and finally transformed the cleaned EEG segments to frequency spectra to generate power spectrum matrices (45 × 16).

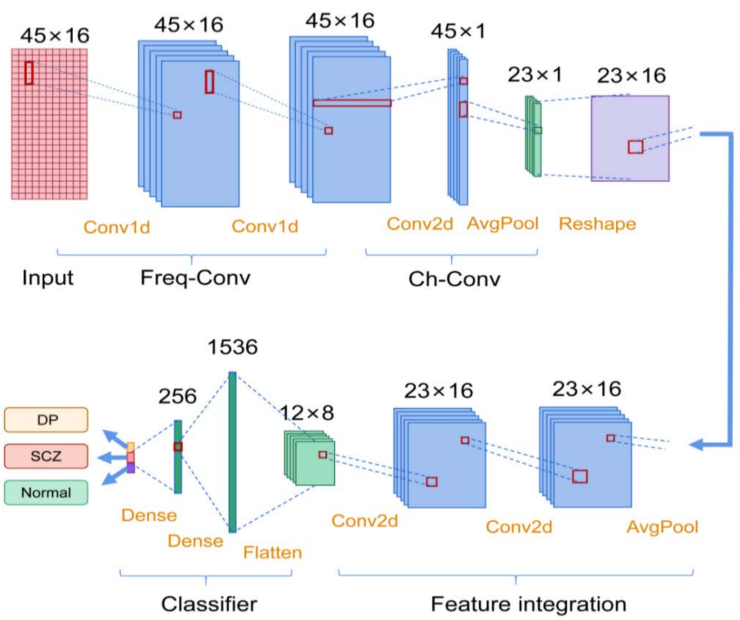

FIGURE 2. MUCHf-Net frame diagram.

32 were applied to the learning rate adjustment when training the model. A cross-entropy cost function was applied to evaluate the performance of the model, the Adam optimizer was used to adjust the parameters of the network, and five-fold cross-validation was applied to train the model. L2 regularization is applied to the parameters of the model during training, and the most appropriate number of iterations was chosen by observing training cost function curves of the model to reduce over-fitting caused by over-training.

F. EVALUATION METRICS

Accuracy, F1 score, sensitivity and specificity were calculated separately as measures of test performance. Accuracy was calculated as the proportion of samples that were

TABLE 2. Network framework of MuMUCHf-Net.

Block	Layers	Output size	Note
Input	—	(1, F, C)	F: Frequency dimension, set to 45 C: Number of channels, set to 16
Frequency convolution layer	Conv2d_3×1	(K_1, F, C)	K_1: Number of convolution filters, set to 16
	ReLU	(K_1, F, C)	
	Conv2d_3×1	(K_1, F, C)	
	BatchNorm	(K_1, F, C)	
	ReLU	(K_1, F, C)	
Spatial convolutional layer	Conv2d_1×C	(K_2, F, 1)	K_2: Number of convolution filters, set to 16
	BatchNorm	(K_2, F, 1)	
	ReLU	(K_2, F, 1)	
	AvgPool_2×1	(K_2, F/2, 1)	
Feature integration layer	Reshape	(1, F/2, K_2)	K_3, K_4: Number of convolution filters, set to 32 and 16
	Conv2d_3×3	(K_3, F/2, K_2)	
	ReLU	(K_3, F/2, K_2)	
	DropOut	(K_3, F/2, K_2)	Dropout rate: 0.4
	Conv2d_3×3	(K_4, F/2, K_2)	
	ReLU	(K_4, F/2, K_2)	
	AvgPool_2×2	(K_4,F/4,K_2/2)	
Classification layer	Flatten	K_4×F/4×K_2/2	
	Dropout	K_4×F/4×K_2/2	Dropout rate: 0.4
	Dense	256	
	Dense	3	
	Softmax	3	

correctly classified. The F1 score can be regarded as a harmonic average of the model's precision and recall, which can be written as:

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}, \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{4}$$

where TP is the true positive, FN is the false negative, FP is the false positive, and TN is the true negative. Sensitivity and specificity reflect the model's ability to predict positive and negative samples, respectively. Sensitivity is calculated the same as recall, and specificity can be written as:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{5}$$

G. VISUALIZATION OF IMPORTANT INPUT REGIONS FOR MODEL PREDICTION

To explore how the model used inputs to generate decisions, Gradient-weighted Class Activation Mapping (Grad-CAM) [35] was applied to generate visual heat maps of input regions that were important for model prediction. This process employs visual explanation technology for decisions made by CNN-based models and uses the back-propagated gradient of the predicted scores for the specified category to generate a location map that highlights the input regions that are important for the decision.

Grad-CAM uses the gradient information that flows into the last convolutional layer of the CNN to understand the importance of each neuron in making the decision. Given an image and a target category, the model generates a prediction score for this target category through forward propagation. Then, the scores of the target category are backpropagated to the feature maps of the last convolutional layer of the model to calculate the gradients of these feature maps, and the gradient value indicates the importance of the feature map for classification. Combining the feature maps and gradients can generate a rough positioning heat map, which indicates the important regions in the input.

In this study, each sample of dataset from 300 subjects were fed to MUCHf-Net to generate a prediction score for the sample, and the score was backpropagated to the last convolutional layer of the model to generate a Grad-CAM. We calculated Grad-CAMs for all samples separately, and then calculated an average Grad-CAM for each category. These average Grad-CAMs were used to visualize important regions in the inputs for model predictions.

IV. RESULTS

A. MODEL TRAINING AND TESTING

Following a five-fold cross-validation protocol, MUCHf-Net was fed with training samples and then its performance was validated on the validation samples. In each run, the model was trained for 100 epochs because it has been observed to converge after 100 epochs. Fig. 3(a) shows one of the training and validation cost-function curves that was obtained after one repetition. Fig. 3(b) shows validation accuracy after each cross-validation repetition; the average accuracy for the validation set is about 76%. Additionally, accuracy differed for the three categories, with normal samples being identified with the highest accuracy (95.76%), and both DP and SCZ with accuracy slightly less than 75%.

One-hundred and thirty spectrum samples (DP: 44, SCZ: 41, HC: 45) from test set were used to test how well the

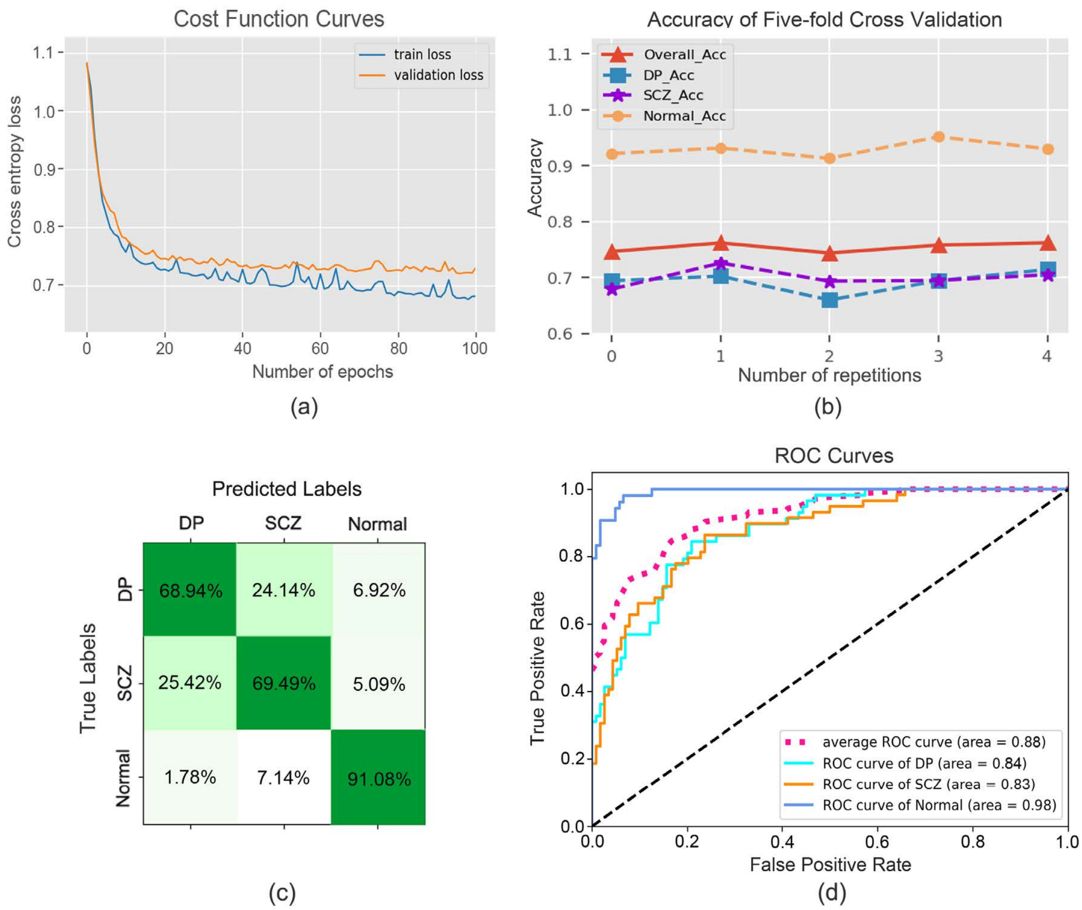

FIGURE 3. (a) Training cost curves produced by the MUCHf-Net. (b) Classification accuracy of five-fold cross-validation. The dotted lines show the classification accuracy for each sample type (normal, DP, SCZ) and the solid line shows the overall accuracy after each repetition. (c) Confusion matrix for the classification of the test set. (d) ROC curves for the classification on the test set.

TABLE 3. Classification performance of the MUCHf-Net on the training, validation and test set.

	Models	Labels	Sensitivity	Specificity	F1 score	Overall accuracy
Training	MUCHf-Net	DP	0.8027±0.021	0.8928±0.014	0.7931±0.015	0.8410±0.018
		SCZ	0.8011±0.029	0.9044±0.013	0.8094±0.018	
		Normal	0.9441±0.012	0.9644±0.009	0.9354±0.011	
Validation	MUCHf-Net	DP	0.7045±0.027	0.8837±0.017	0.7233±0.014	0.7574±0.023
		SCZ	0.7173±0.021	0.8426±0.014	0.7318±0.018	
		Normal	0.8972±0.025	0.9287±0.010	0.9006±0.016	
Test	MUCHf-Net	DP	0.6818	0.8604	0.7046	0.7769
		SCZ	0.7073	0.8426	0.7149	
		Normal	0.9112	0.9565	0.8947	
	RF classifier	DP	0.4772	0.7816	0.4999	0.6412
		SCZ	0.5476	0.7977	0.5542	
		Normal	0.8889	0.8837	0.8420	

Note: The performance of MUCHf-Net on the training and validation sets during the five-fold cross-validation is reported as the mean ± std.

proposed system could generalize to new participants. The trained MUCHf-Net was used to predict whether any of the 45 individuals from test set had DP, SCZ, or did not have any psychiatric disorder. At the same time, an RF classifier was trained on the training samples with grid search technology and tested on the same test set to make a comparison with the performance of MUCHf-Net.

Table 3 reports the performance of MUCHf-Net and RF classifier on the training samples, validation samples, and test set. The performance of MUCHf-Net on the training samples is significantly better than that on the validation samples and the test set, which may be caused by individual specificity of EEG. Many studies have reported the impact of individual differences on EEG classification [36], [37], but we have observed that the classification between normal subjects and those with psychiatric disorders has not been greatly affected. In validation sets and the test set, MUCHf-Net can distinguish between normal samples and

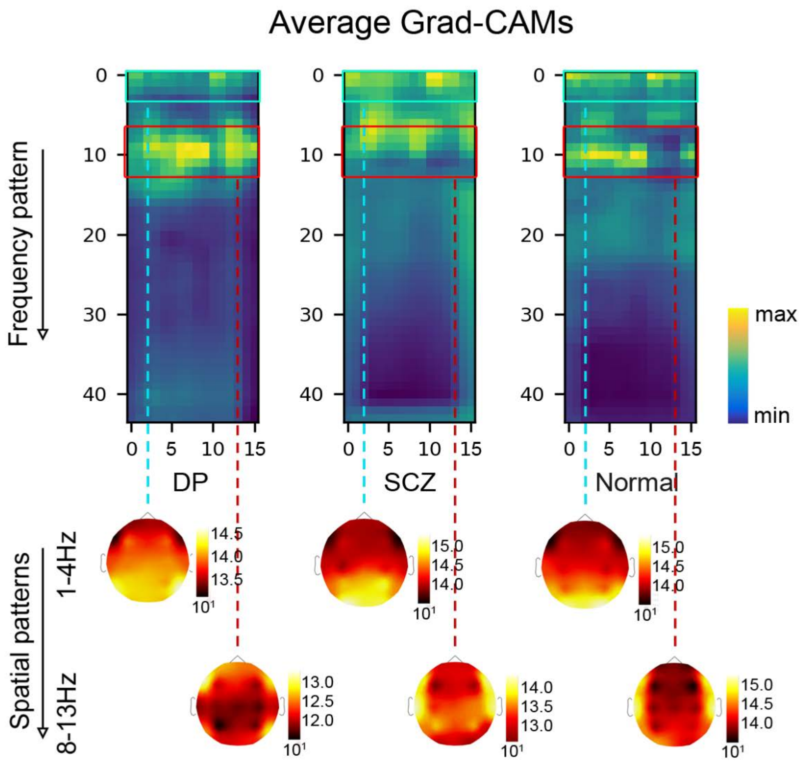

FIGURE 4. The average Grad-CAMs and distribution of important regions in brain topology. Average Grad-CAMs for the samples in each category (top). The color scale represents importance for classification, with brighter yellow regions indicating more importance (bottom). The average importance scores for each channel in the alpha and delta bands were calculated and are displayed on the topographic map of the brain (bottom).

those with psychiatric disorder with high accuracy in most cases. Figure 3(d) shows the receiver operating characteristic (ROC) curves of MUCHf-Net on the test set. It can be seen that the normal samples reaches an area under curve (AUC) of 0.98. In addition, the low accuracy for DP and SCZ both on validation samples and test set indicates that the classification between the two categories is more difficult. This phenomenon can be seen more clearly in the confusion matrix produced from the test performance (Fig. 3c) that misjudgments are more likely to occur between DP and SCZ. Table 3 shows the performance of the RF classifier on the same test set, what can be found is that MUCHf-Net shows a significant advantage (more than 13% accuracy) over RF classifiers when analyse samples from new individuals.

B. VISUALIZATION OF IMPORTANT FREQUENCY AND BRAIN REGIONS

Fig. 4 shows the average Grad-CAMs and the distribution of classification importance by brain topological region for each category. From this analysis of the Grad-CAMs, we found that the low-frequency bands of the EEGs (delta, theta, and alpha) produced high importance scores, with delta and alpha frequency bands being the highest. Brain topology maps of classification importance showed higher scores for that signals from prefrontal and parietal lobe channels. Thus, the prefrontal and parietal lobes may be of great significance in the diagnosis of DP and SCZ.

C. CLASSIFICATION PERFORMANCE OF DIFFERENT FREQUENCY BANDS

To determine the classification performance of each frequency band, an RF classifier was used to classify the three sample types using the spectral features of different frequency bands. The whole spectrum was divided into five parts according to five frequency bands (delta, theta, alpha, beta, and gamma), and the multi-channel spectrum for each frequency band was reorganized to a one-dimensional vector and input into the RF classifier.

Fig. 5 shows the accuracy of RF classifier for each of the five frequency bands. In all frequency bands, classification of normal samples was highly accurate (up to 91.53%). In contrast, accuracy for SCZ and DP was unsatisfactory (less than 50% in most frequency bands). Nevertheless, the dotted line in Fig. 5 indicates an obvious increase in accuracy as the frequency band expands from delta to alpha. It is easy to infer that the spectra of low-frequency bands might contribute more significantly to the classification than do the other frequency bands. This phenomenon confirms the importance of the low-frequency bands in distinguishing these three types of EEGs from each other. Another interesting phenomenon was that as the frequency increased, accuracy at classifying DP

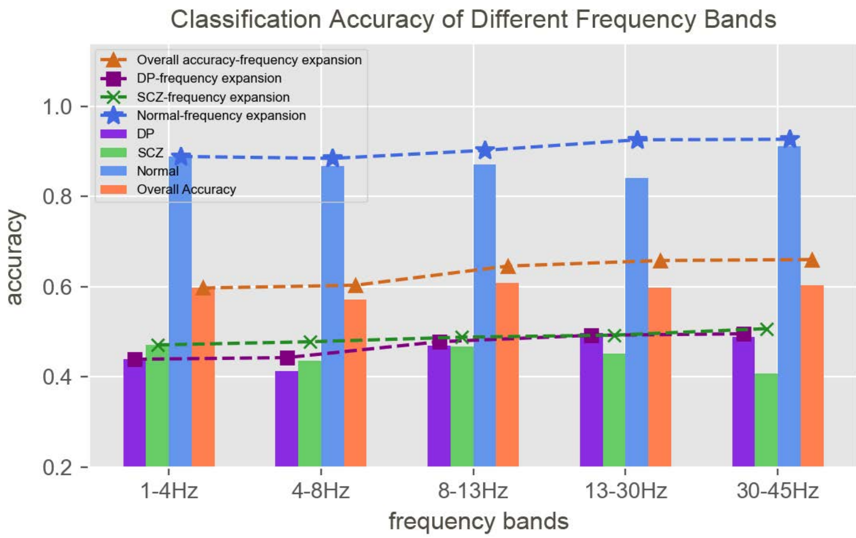

FIGURE 5. **The accuracy of RF classifier for different frequency bands. The histogram shows the accuracy for each sample type and the overall accuracy. Dashed lines show the accuracy for each category and the overall accuracy as the frequency band expands (combining features of more frequency bands).**

followed an upward trend, while SCZ classification accuracy decreased.

D. PERFORMANCE ON PUBLIC EEG DATABASES

Two experiments were performed to test the performance of MUCHf-Net on the new test set: 1) Test the classification performance of the earlier MUCHf-Net trained in Section IV(A) on the new test set. 2) Fine-tune the parameters of earlier trained MUCHf-Net on the new training set, and then test its performance on the new test set. Table 4 shows the test accuracy of MUCHf-Net in the two experiments, together with classification accuracy of some latest studies to identify DP on the identical public dataset for DP or to identify SCZ on the identical public dataset for SCZ.

The overall accuracy of MUCHf-Net in experiment 1 is only 70.15%. This result is not satisfactory because we have observed that similar studies on the same public database show classification accuracy of even exceed 90%. But it is worth emphasizing that the model had never been trained on public datasets in experiment 1. We know that EEG signals are complex, and many factors, such as individual specificity and differences in acquisition equipment, will affect the results of this study. Despite the low accuracy, we still gain from it: 1) Similar to the results in section IV(A), the accuracy of samples from normal subjects is significantly higher than that from patients with DP or SCZ, which means that normal subjects is easier to distinguish from patients with psychiatric disorders. 2) The classification accuracy of samples from patients with DP or SCZ was still significantly higher than the random probability (33.3%), implying that MUCHf-Net is helpful in predicting whether a patient has DP or SCZ. As expected, the results of experiment 2 have been significantly improved compared to experiment 1, which proves that further optimization of the model's parameters on the dataset can improves the overall accuracy, as it may mitigate the impact of differences in devices and acquisition paradigms. In addition, the accuracy between the normal samples and those from patients who has psychiatric disorder is up to 87.71%, which is close to the results of binary classifications between normal subjects and patients with DP or between normal subjects and patients with SCZ in some studies reported in Table 4. It is worth mentioning that the experiment of triple classification is more difficult than that of binary classification, because the added category will significantly increase the probability of misjudgment, especially between DP and SCZ. Nevertheless, we still obtained performance close to binary classification. Among Table 4, it can be observed that our results are better than Mahato's who used frequency band power and power asymmetry as classification features and ML classifiers, indicating that MUCHF-Net is superior to ML algorithms.

V. DISCUSSION

As two highly prevalent psychiatric disorders with overlapping symptoms, the clinical diagnosis of DP and SCZ has always been a challenge. The standard diagnosis depends on patient self-reports and examination by a psychiatrist. However, this method depends on doctor experience and lacks objective standards. Because EEGs reflect brain activity, it has the potential for use in an objective method for diagnosing psychiatric disorders. Comparative studies of psychiatric disorders including DP and SCZ [44], [45] have focused on analyzing EEG differences at the group level, and distinguishing between different disorders has rarely been considered. In this study, we fed DP, SCZ, and normal EEG spectra into a DL model and tested its ability to classify them. The results indicate that our model can efficiently and accurately distinguish the spectra of healthy individuals from those with either DP or SCZ.

TABLE 4. Summary of automated diagnosis of DP and SCZ on public dataset.

Authors	Number of participants	Techniques	Accuracy
Ke et al. [38]	● 34 DP patients ● 30 normal subjects	● CNN	98.59%
Mahato et al. [39]	● 34 DP patients ● 30 normal subjects	● Linear features and non-linear features ● Multi Layered Perceptron Neural Network (MLPNN), Radial Basis Function Network (RBFN), Linear Discrimination Analysis (LDA) and Quadratic Discriminant Analysis	93.33%
Mahato et al. [25]	● 34 DP patients ● 30 normal subjects	● Power spectrum and power asymmetric ● SVM, LR, NB and DT	88.33%
Saeedi et al. [40]	● 34 DP patients ● 30 normal subjects	● Brain network analysis ● CNN and LSTM	99.24%
Jahmunah et al. [41]	● 14 SCZ patients ● 14 normal subjects	● Non-linear features ● DT, LDA, k-NN, Probabilistic NeuralNetwork (PNN) and SVM	92.91%
Oh et al. [31]	● 14 SCZ patients ● 14 normal subjects	● CNN	81.26%
Buettner et al. [42]	● 14 SCZ patients ● 14 normal subjects	● Power spectrum ● RF	100%
Krishnan et al. [43]	● 14 SCZ patients ● 14 normal subjects	● Multivariate empirical mode decomposition (MEMD) ● SVM	93%
Ours (experiment 1)	● 3 DP patients ● 3 SCZ patients ● 3 normal subjects	● Power spectrum ● CNN	Overall accuracy: 70.15% (DP: 63.72%, SCZ: 64.87%, Normal: 80.44%)
Ours (experiment 2)	● 14 DP patients ● 14 SCZ patients ● 14 normal subjects	● Power spectrum ● CNN	Overall accuracy: 79.27% (DP: 77.67%, SCZ: 75.38%, Normal: 87.71%)

DL has become an attractive tool for developing automatic methods of diagnosing psychiatric disorders because it can process complex medical data better than traditional ML. In the current study, we developed a DL model that learned the characteristic features of EEG spectra taken from three types of individuals. We found that DL model performed about 13% better than ML. A DNN performs adaptive representation learning and can discover more discriminative patterns. It can be seen from the classification of new samples that our DL model was more adaptable than the ML classifier. The DL model still achieves good performance on dataset from public databases, and test results show that the proposed model of tripe classification is competitive compared to methods of binary classification proposed in other studies.

From the average Grad-CAMs depicted in Fig. 4, we can see that the low-frequency bands (delta, theta, and alpha) were more important for classification than the higher frequency bands (beta and gamma), particularly the delta and alpha frequency bands. Previous studies have shown that psychotic disorders may be related to changes in low-frequency power [44], [45]. Thus, we can infer that differences in low-frequency bands might have particular significance when diagnosing DP and SCZ. Although the MUCHf-Net distinguished normal participants and those with psychiatric disorders very accurately, it was prone to mistakes when judging g between DP and SCZ.

There are also many disadvantages: 1) The amount of data is not sufficient. The EEG database from our hospital contains only 100 subjects per category, and more seriously, the amount of data for a single individual is grossly insufficient, with only 21s (3×7s) of resting-state EEG recordings being available. 2) The EEG feature analyzed are relatively single. In this study we only considered the power information of subjects' EEG, however, the differentiated EEG features of psychiatric disorders are complex and using only power information may not be sufficient to diagnose diseases. 3) Although the algorithm proposed in this study is able to accurately classify normal individuals and patients with psychiatric disorders, the classification between DP and SCZ is still a challenge as it can not accurately classify the power information of both using EEG. 4) In the results section we explored brain regions with high contribution to classification, such as the prefrontal and parietal lobes. However, we have not explored the neural mechanisms involved more deeply, nor have we integrated these findings with the clinical analysis of these diseases.

In future studies, we hope that multi-center EEG data can be utilized to study in depth the differences between schizophrenia and depression. It is necessary for disease diagnosis to consider combined features such as abnormal functional connections between brain regions, EEG power asymmetry and other popular EEG features. In addition, incorporating the insights of senior clinicians is beneficial, we hope to use clinician knowledge to guide the development of AI diagnostic algorithms and interpret the findings of AI algorithms.

VI. CONCLUSION

EEG power spectra can be very useful for analyzing abnormal states of the brain. In this study, we input EEG power spectra into a DL model, which then learned how to classify the samples as DP, SCZ, or normal. We tested how well the model could generalize by observing how it classified EEG data from previously unknown participants. Results showed that the proposed model can accurately classify samples as normal or not normal, but was less accurate at distinguishing between DP and SCZ samples. We also analyzed the EEG frequencies and found that the MUCHf-Net classification relied more on information from the low-frequency bands (delta, theta, and alpha) than from the high-frequency bands. Analysis of brain topology then revealed that MUCHf-Net deemed the EEG spectral information from the prefrontal and parietal lobes of the brain to contain critical information for classification that was not present in the other regions of the brain.

DP and SCZ are two psychiatric disorders with high prevalence and similar symptoms. A multi-classification model involving DP, SCZ, and normal EEGs should be developed instead of using two binary classification models that distinguish between normal and DP and between normal and SCZ. AI-assisted diagnosis is a rapidly developing technology and has considerable potential for diagnosing psychiatric disorders.

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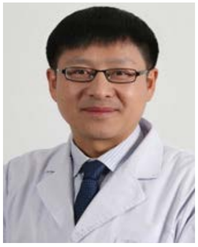

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