Conducting a study on the classification of EEG signals in the high-risk population of schizophrenia using the 1DCNN-LSTM algorithm

Shenghui Ying[a], Yutong Luo[b], Yuesheng Zhao*[a], Ya Wang[c,d], Xiaoling Wang[a]
[a]School of Automation, Guangxi University of Science and Technology, Liuzhou, 545006, China; [b]Student Mental Health Education Center, Guangxi University of Science and Technology, Liuzhou, 545006, China; [c]School of Psychology, Capital Normal University, Beijing, 100089, China; [d]CAS Key Laboratory of Mental Health, Institute of Psychology, Chinese Academy of Sciences, Beijing, 100101, China
*Email: zhyuesheng@126.com

ABSTRACT

The research employs EEG in combination with the 1DCNN-LSTM algorithm for the purposes of identifying and classifying people with varying risks of schizophrenia. This collection of data for schizophrenia's high-risk and low-risk groups comprises EEG signals from 98 people, the division was made between a group of 50 with normal EEG signals and another group of 48 with high-risk indicators for schizophrenia. The duration of measurement for every participant stood at 12 minutes. The data set was processed in advance, encompassing tasks like channel exclusion, re-referencing, dividing the dataset, performing independent component analysis (ICA), windowing, normalizing, and segregating it into the testing, training, and validation sets. Subsequently, the processed EEG data was integrated into the 1DCNN-LSTM classification model, where post-extensive learning, the model's weights were derived. The categorization system attained a 94.26% precision rate in the identification of the complete-channel EEG data collection. This research utilized the 1DCNN-LSTM algorithm to classify and identify high-risk and low-risk groups for schizophrenia, showcasing an adequate recognition capability that satisfies real-world application criteria. The system precisely categorizes populations at varying risk levels for schizophrenia through comprehensive EEG data, thus facilitating precise schizophrenia detection and offering prompt diagnosis and treatment for those at high risk for the condition.

Keywords: Schizophrenia, classify, EEG data, 1DCNN-LSTM, algorithm

1. INTRODUCTION

Schizophrenia is a severe mental illness characterized by hallucinations, delusions, and mental disorders [1]. Schizophrenia is a serious mental disorder with serious health effects [2]. Accurate and objective identification is crucial for the treatment and intervention of patients. While our understanding of schizophrenia still has many limitations, algorithms and techniques can be used to predict the probability of developing schizophrenia, identify at-risk populations, and intervene in the early stages of the disease. Early intervention can help patients better manage symptoms, improve social skills, increase confidence and self-esteem, and adapt more effectively to life and work. Therefore, it is particularly important to research and develop algorithms and techniques to identify people at high risk of schizophrenia.

To accurately diagnose schizophrenia, researchers utilized characteristics such as total gray matter loss in the brains of schizophrenia patients over the past decade. They used MRI and fMRI imaging to distinguish the brains of healthy and schizophrenic patients, and used functional magnetic resonance imaging (fMRI) datasets to train deep learning models to schizophrenia diagnosis [3-15]. However, due to the existence of motion artifacts, imaging equipment is costly and the image fusion quality of different devices is poor, presenting a challenge to image fusion [16].

With the development of electroencephalogram (EEG) analysis techniques, they have also been employed in schizophrenia research [17-19]. EEG analysis involves electrodes being placed on the scalp to record the electrical activity of neurons in the brain, which are then analyzed by data analysis techniques to extract information about brain activity. Since 2018, the application of deep learning algorithms in EEG analysis has been at research frontier of schizophrenia analysis. Many researchers have combined EEG analysis techniques with deep learning algorithms to identify schizophrenia patients [20-29], with promising classification accuracy. The 1DCNN-LSTM algorithm was used

International Conference on Future of Medicine and Biological Information Engineering
(MBIE 2024), edited by Yudong Yao, Xiaoou Li, Xia Yu, Proc. of SPIE Vol. 13270,
132700G · © 2024 SPIE · 0277-786X · doi: 10.1117/12.3035466

to study people at high risk of schizophrenia and people at low risk. The classification of people at high risk of schizophrenia and those at low risk is of great significance for the treatment and rehabilitation of schizophrenia.

2. EEG SIGNAL DATASET AND ITS PREPROCESSING

The high-risk population dataset for schizophrenia used in this study collected EEG signal data from 126 individuals. Invalid data from 38 individuals, caused by various reasons during the data collection process, were excluded. The remaining dataset consists of EEG signal data from 98 individuals, including 48 individuals from the high-risk population for schizophrenia and 50 individuals from the low-risk population for schizophrenia. The data was sampled at a frequency of 1000Hz.

As shown in Figure 1, the preprocessing of the dataset includes channel rejection, re-referencing, data segmentation, ICA, windowing, normalization, Dataset Splitting. Channel rejection, re-referencing, data segmentation, and ICA were performed using the EEGLab toolbox in MATLAB software. Windowing, normalization, Dataset Splitting were performed on the MATLAB platform. The normalization process involved the assistance of Jupyter for certain tasks.

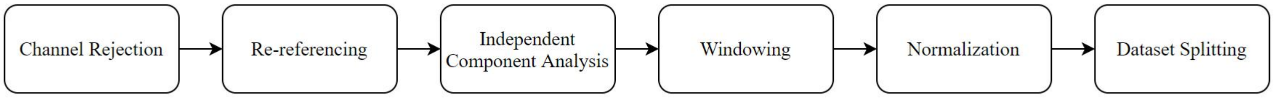

Figure 1. Data Preprocessing Workflow.

2.1 Channel rejection, re-referencing, data segmentation, and independent component analysis (ICA)

Channel Rejection: As shown in Figure 2, the EEG dataset consists of a total of 66 channels. And the figure below shows the distribution of EEG electrodes, where each electrode corresponds to a channel. Among these channels, two channels capture horizontal eye movement signals and vertical eye movement signals. Both of these signals are caused by eye movements and not generated by brain activity. Therefore, it is necessary to first remove the eye movement signals.

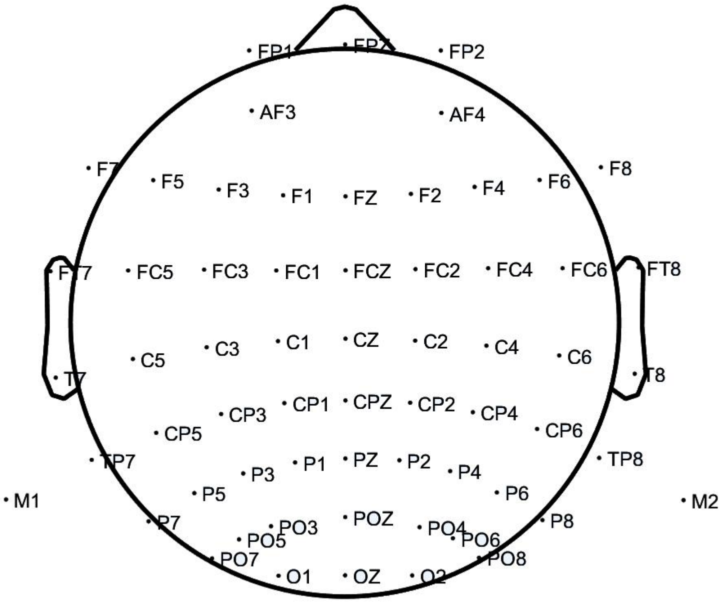

Figure 2. Distribution of EEG Electrode Channels.

Re-referencing: The values obtained from EEG data collection do not have a specific unit of measurement. Essentially, they represent electrical potentials. However, there are variations in electrical conductivity among different individuals, and there is no standardized reference. The purpose of re-referencing is to eliminate the effects of individual differences and address common-mode interference. In EEG signal re-referencing, a reference point is selected, and the differentials of the data can be obtained. In this study, the M2 channel, specifically the mastoid EEG signal, was chosen as the reference point. This channel is located away from the cerebral cortex and is relatively stable.

Independent Component Analysis (ICA): Independent Component Analysis is an abbreviation for Independent Component Analysis. It is used to remove artifacts such as eye movement and muscle activity from the EEG signals, by decomposing mixed signals into multiple mutually independent components. For example, the sample data consists of $\alpha = \{\alpha_1, \alpha_2 \cdots \alpha_n\}$, which represents n mixed signals. And $\beta = \{\beta_1, \beta_2 \cdots \beta_n\}$ represents a vector of n independent and non-interfering signals in the ideal state. In order to extract independent component data from the sample data, it is necessary to pass through a mixing matrix. As shown in formula 1:

$$\tau^{-1}\alpha = \beta \tag{1}$$

The key to obtaining independent component data lies to adjust the mixing matrix. The ICA algorithm can approximate the ideal hybrid matrix. There are various ICA algorithms, and the algorithm selected in this paper is FasICA, which is implemented using the pop_runica function in EEG Lab. Based on the maximum non-Gaussianity, the algorithm has the advantages of fast operation speed, fast convergence speed, good stability and easy realization.

2.2 Windowing, normalization, dataset splitting

Windowing: Divides input data into periodic segments using a specific time window. This process involves partitioning relatively long time series into shorter segments. In this study, a one-second window was used. Windowing can help reduce computational complexity, improve the model's local perception ability, increase the number of data samples, and mitigate overfitting problems.

Normalization: Because the range and distribution of data sets are often not ideal, significant differences between data points can affect training speed, convergence rate and generalization ability. Therefore, there is a need to normalize data, which involves scaling the value range of a dataset to a specific range. There are several normalization methods, such as Min-Max normalization, Z fraction normalization and mean variance normalization. In this study, a Min-Max normalization method was used, which scales the data down to [0, 1]. As shown in formula 2:

$$x_i^{'} = \frac{x_i - \min(X)}{\max(X) - \min(X)} (X = \{x_1, \ x_2 \cdots x_i\}) \tag{2}$$

Dataset Splitting: In machine learning, the division of data into training, validation, and test sets is essential. The training set is used for model training, the test set is used for evaluating the model's performance, and the validation set is used for optimizing the model during the training process. In this study, experiments were conducted on both the 63-channel full dataset and the commonly used 3-channel dataset for eyes-open, eyes-closed, and combined "eyes-open & eyes-closed" data.

After the previous data preprocessing steps, the obtained dataset for eyes-open, eyes-closed, and combined "eyes-open & eyes-closed" data has the following channel-wise sample counts: 70364, 70364, and 140728, respectively. Each sample contains 1 second of data. For dataset splitting, 60% of the data is allocated as the training set, 15% as the validation set, and 25% as the test set. The dataset splitting is performed using random sampling, where each sample is chosen with an equal probability. The samples are independent and not mutually exclusive, ensuring a reduced sample bias and improving the representativeness and reliability of the dataset. This approach guarantees the rationality of the recognition results.

3. ALGORITHM INTRODUCTION

After the data preprocessing stage, this study's recognition algorithm employed a combined 1D CNN (Convolutional Neural Network) model and LSTM (Long Short-Term Memory) model known as the 1D CNN-LSTM model. The 1D CNN model and LSTM model are two commonly used and well-established models in the field of deep learning.

3.1 1DCNN algorithm

The main feature of Convolutional Neural Networks (CNNs) lies in the first words: convolution. CNNs typically consist of an input layer, convolutional layers, activation function layers, pooling layers, normalization layers, and fully connected layers. They are commonly used to process data such as images, videos, and audio. 1DCNN is a type of Convolutional Neural Network that excels in time series classification tasks. It inherits the convolutional nature of CNNs but is specifically designed to handle one-dimensional sequential data. It has proven to be highly effective in the field of time series classification.

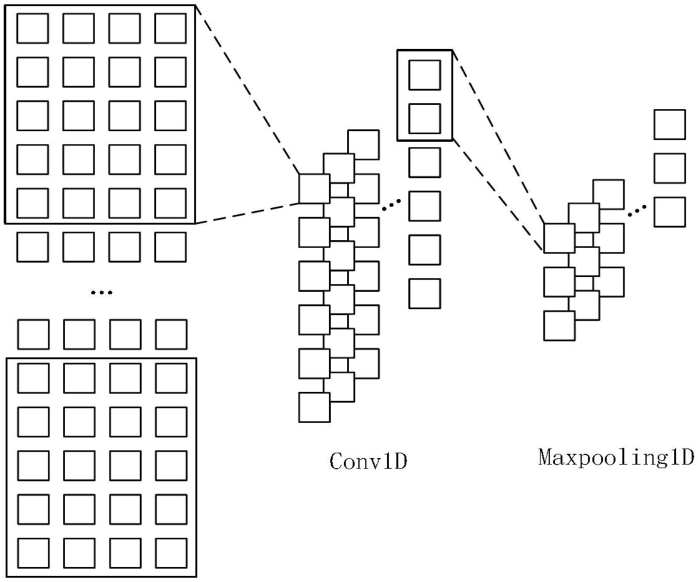

Figure 3. The schematic diagrams for the 1D Convolutional Layer and the Max Pooling Layer.

When performing convolutional operations in 1DCNN, the convolutional kernel convolves only in one dimension, hence the name "1D Convolutional Neural Network". As shown in Figure 3, the 1D convolution starts from the position of the rectangular box in the top left corner and moves downwards with a specified stride until it reaches the bottom left rectangle. This process is repeated across the input data to compute the convolved features. The max pooling layer, on the other hand, operates independently on each feature map or channel, selecting the maximum value within non-overlapping regions.

3.2 LSTM algorithm

LSTM is a recursive neural network initially proposed by Hochreiter & Schmidhuber in 1997. Over the years, it has made some advancements and has evolved into a comprehensive and well-developed framework. LSTM aims to address the limitations of traditional RNNs by introducing memory and forgetting mechanisms to improve learning and capture long-term dependencies. As a deep learning network, LSTM is widely used in various fields, thanks to its ability to model continuous data and process long-term dependencies.

As shown in Figure 4, LSTM consists of an input gate, a forgotten gate, an output gate, and a memory unit. The input gate controls the flow of new information into the storage unit. Oblivion Gate regulates the flow of old information from memory units. The output gate controls the flow of output information from the storage unit. Memory cells store and maintain state information for input sequences.

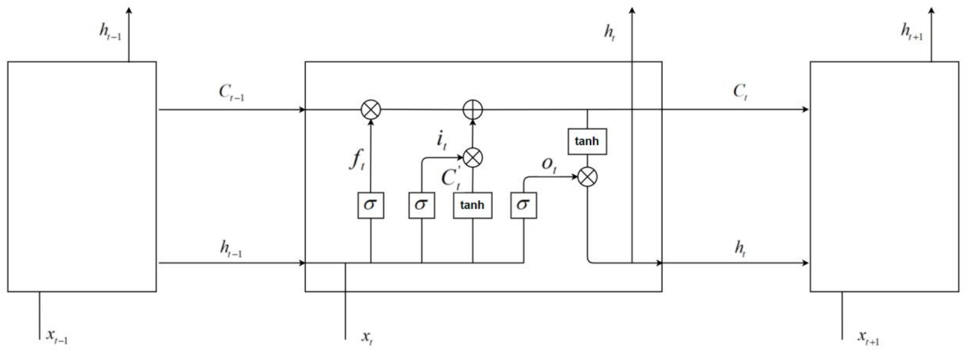

Figure 4. LSTM Algorithm Structure Diagram

The specific formulas for the input gate, forget gate, output gate, and memory cell in LSTM are as shown in formula 3-6:

$$InputGate : i_t = \sigma(x_t w_{xi} + h_{t-1} w_{hi} + b_i) \tag{3}$$

$$ForgetGate : o_t = \sigma(x_t w_{xo} + h_{t-1} w_{ho} + b_o) \tag{4}$$

$$OutputGate : f_t = \sigma(x_t w_{xf} + h_{t-1} w_f + b_f) \tag{5}$$

$$MemoryCell : C_t = \tanh(x_t w_{xc} + h_{t-1} w_{hc} + b_c) \tag{6}$$

4. IDENTIFICATION OF INDIVIDUALS AT HIGH RISK FOR SCHIZOPHRENIA BASED ON LSTM-1DCNN

LSTM and 1DCNN are two deep learning algorithms with fundamentally different principles. This study suggests that LSTM can extract temporal features, while 1DCNN can extract spatial features. The combination of 1DCNN-LSTM allows for the simultaneous extraction of both temporal and spatial features. When dealing with continuous measurements of EEG signals, extracting both temporal and spatial features using 1DCNN-LSTM yields more precise identification results compared to solely extracting spatial or temporal features. Therefore, this study adopts the parallel structure of the 1DCNN-LSTM algorithm.

As shown in Figure 5, the overall structure of 1DCNN-LSTM is in a Q-shaped configuration. It starts from the input layer and branches into two separate paths. These paths are then connected to fully connected networks. In the diagram, the naming convention for the functions follows Matlab conventions and differs in capitalization from LSTM, CNN, and other terms.

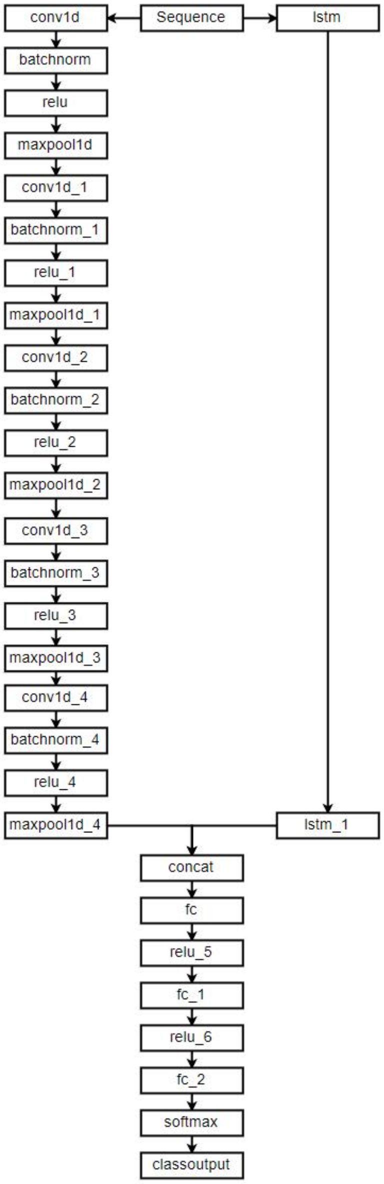

Figure 5. 1DCNN-LSTM Algorithm Structure Diagram

Researchers have used three-channel data (Fp1, Fp2, Fz) for EEG signal analysis, while others have used data from all channels. To compare the differences between the two approaches, the input layer's input data size was set to 3 and 63, respectively. In the LSTM-1DCNN architecture, the first branch after the input layer is the 1DCNN branch, which consists of five convolutional layers, batch normalization layers, activation function layers, and pooling layers. The size of the convolutional kernel is 9, and the number of kernels is sequentially set as 32, 64, 128, 256, and 512. Batch normalization layers can accelerate the training process and improve the model's generalization ability. The specific formula is as shown in formula 7:

$$x_{\mathrm{i}}^{'} = \gamma \frac{x_i - \mu_B}{\sigma_B} + \beta(B = \{x_1,\ \ x_2 \cdots x_{\mathrm{m}}\} \text{且} 1 \leq i \leq m) \tag{7}$$

Whereas, $x_i^{'}$ represents the batch-normalized data, μ_B represents the mean of the batch samples, and σ_B represents the sample variance.

The activation function layer in the LSTM-1DCNN architecture uses the ReLU (Rectified Linear Unit) activation function. ReLU is a piecewise linear function that sets all negative input values to zero while leaving positive values unchanged. This activation function accelerates the convergence speed and is commonly used in deep learning models. For the pooling layer, there are several common types such as max pooling, average pooling, global pooling, and adaptive pooling. In this study, the max pooling layer is used. It uses a window size of 2 and a stride of 2 to reduce computational complexity and improve the robustness of features. The max pooling operation selects the maximum value within each pooling window, thereby downsampling the feature map.

In this study, the commonly used flatten layer at the end of the 1DCNN branch has been replaced with a global average pooling layer. This modification retains the flatten layer's dimensionality reduction characteristic while mitigating overfitting to some extent. It also provides more flexibility in terms of input size, as the global average pooling layer can handle inputs of varying dimensions.

The second branch after the input layer in LSTM-1DCNN is the LSTM branch, consisting of two LSTM layers. Each layer has 100 neurons. The outputs from the first and second branches are then merged and fed into the fully connected network. First, a concatenation layer is created to combine the inputs from the two branches, serving as the input layer of the fully connected network. The fully connected network consists of three fully connected layers and three activation function layers. The neuron numbers in the fully connected layers are 128, 64, and 2, respectively. The activation function layers use ReLU, ReLU, and Sigmoid functions, respectively. The Sigmoid function is expressed as shown in formula 8:

$$\sigma(t) = \frac{1}{1+e^{-t}} \tag{8}$$

During the training process of the algorithm, the Adam optimizer was used in the optimizer settings. The batch size was set to 256, which means that 256 samples were used in each iteration. The number of epochs was set to 100, indicating that the training process went through 100 iterations over the entire dataset.

5. EXPERIMENTAL RESULTS ANALYSIS AND DISCUSSION

After training the LSTM-1DCNN model, it is necessary to evaluate its performance to assess the effectiveness of the training. There are several metrics used for evaluating classification performance. In this study, metrics such as accuracy, precision, recall, and F1 score are employed. These metrics provide a comprehensive evaluation of the model's performance, even in situations where the sample distribution is imbalanced, ensuring the accuracy of the evaluation results.

Accuracy, precision, recall, and F1 score calculations are all dependent on the confusion matrix. The confusion matrix, as shown in Table 1, represents the classification results. In this context, the positive class corresponds to the high-risk samples for schizophrenia, while the negative class corresponds to the low-risk samples for schizophrenia:

Table 1. Confusion Matrix.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive(TP)	False Negative(FN)
Actual Negative	False Positive(FP)	True Negative(TN)

Accuracy refers to the percentage of correctly predicted samples by the trained model on the test set, calculated as shown in formula 9:

$$acc = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{9}$$

Although accuracy is a good metric for measuring overall correctness, it may not be a reliable indicator when dealing with imbalanced datasets. In extreme cases, such as when the ratio of high-risk to low-risk samples for schizophrenia reaches 99:1, a model that predicts all test samples as high-risk for schizophrenia would achieve an accuracy of 99%. However, this accuracy value loses its interpretability and usefulness in such imbalanced scenarios.

Precision, concerning either positive or negative predictions, refers to the percentage of correctly predicted samples among all samples of that particular class. Taking positive precision as an example, the formula is as shown in formula 10:

$$precise = \frac{TP}{TP + FP} \times 100\% \tag{10}$$

Recall, concerning either positive or negative predictions, refers to the percentage of correctly predicted samples among all samples of that particular class. Taking positive recall as an example, the formula is as shown in formula 11:

$$recall = \frac{TP}{TP + FN} \times 100\% \tag{11}$$

Precision and recall are indeed valuable metrics, but it is often challenging to improve both simultaneously in practical applications. To balance precision and recall, the F1 score is used as a combined evaluation metric. The formula for calculating the F1 score is as shown in formula 12:

$$F1 = \frac{2 \times precise \times recall}{precise + recall} \times 100\% \tag{12}$$

The paper conducted experiments on open-eye data, closed-eye data, and "open & closed-eye" data for both full-channel and commonly used three-channel data. The evaluation indicators are shown in Table 2:

Table 2. The overall table of common evaluation metrics for a model trained based on experimental data.

		Acc	High risk of schizophrenia			Low risk of schizophrenia		
			Precision	Recall	F1 score	Precision	Recall	F1 score
Full-channel	open-eye	94.86%	94.30%	95.60%	94.94%	95.44%	94.09%	94.76%
	closed-eye	94.26%	93.90%	94.79%	94.35%	94.63%	93.71%	94.17%
	open & closed-eye	95.30%	94.81%	96.00%	95.40%	95.81%	94.57%	95.18%
Three-channel	open-eye	77.93%	77.90%	78.63%	78.26%	77.95%	77.21%	77.58%
	closed-eye	59.21%	58.58%	65.80%	61.98%	60.03%	52.47%	55.99%
	open & closed-eye	70.70%	69.88%	74.46%	72.10%	66.81%	71.66%	69.15%

Based on the provided data, it can be observed that there is a significant difference in performance between the model trained on three-channel data compared to the model trained on full-channel data. However, the performance difference is relatively small when comparing models trained on open-eye, closed-eye, and open & closed-eye data. The model trained on full-channel open & closed-eye data exhibits the best overall performance, while the model trained on three-channel closed-eye data shows the poorest performance. Models trained using the full-channel open-eye, closed-eye, and open & closed-eye data can meet the standards for everyday applications, considering their overall performance.

6. CONCLUSION

Schizophrenia is a severe mental illness characterized by symptoms such as hallucinations, delusions, and disorganized thinking. With millions of schizophrenia patients and an even larger number of individuals at high risk in China, accurate diagnosis and differentiation are necessary. With the development of EEG measurement technology, EEG techniques have also been used for differentiation and diagnosis of schizophrenia. In this study, EEG data from 98 individuals were used to classify and identify individuals at high and low risk of schizophrenia, achieving an accuracy rate of over 94%.

From the experimental results of this study, it can be observed that the performance of the three-channel model differs significantly from the full-channel data-trained model, while the performance difference is smaller between the models trained with eyes open, eyes closed, and combined eyes open & closed data. Therefore, the correlation between schizophrenia identification and eyes open/closed is relatively small, and when identifying individuals at high and low risk of schizophrenia, the factor of eyes open/closed may not need to be considered. On the other hand, the full-channel data contains much more information than the three-channel data, which aligns with information theory, as a larger dataset with more data points tends to improve the accuracy of model classification. Therefore, increasing the amount of data can be one way to differentiate individuals at high and low risk of schizophrenia more accurately.

This study proposes the use of the 1DCNN-LSTM algorithm for the identification and classification of individuals at high and low risk of schizophrenia. The recognition performance of this algorithm meets the requirements of practical applications, accurately classifying individuals at high and low risk of schizophrenia based on full-channel EEG measurement data. This approach enables accurate identification of schizophrenia and provides early diagnostic services for individuals at high risk of schizophrenia.

ACKNOWLEDGEMENTS

We would like to express our gratitude to Guangxi University of Science and Technology for providing the library resources and financial support. We would also like to thank the reviewers for their valuable feedback. The following are the specific details of the funding project.

1. The 2023 Guangxi University young and middle-aged teachers' basic scientific research ability improvement project (No.2023KY0352, Research on the Recognition of Psychological Abnormalities in College Students Based on the Fusion of Pulse and EEG Techniques, Yutong Luo)

2.National Science Foundation of China (32071062)

REFERENCES

[1] JinChi Z, XiaoLan W, JinYi W, et al., "Diagnosis of Schizophrenia Based on Deep Learning Using fMRI[J]," Computational and Mathematical Methods in Medicine, 2021.
[2] Jihoon O, Baek-Lok O, Kyong-Uk L, et al., "Identifying Schizophrenia Using Structural MRI With a Deep Learning Algorithm[J]." Frontiers in psychiatry, 2020,11.
[3] Giraldo-Chica M, Woodward D N, "Review of thalamocortical resting-state fMRI studies in schizophrenia[J]." Schizophrenia Research, 2016,18058-63.
[4] Briend F, Marzloff V, Brazo P, et al., "Social cognition in schizophrenia: Validation of an ecological fMRI task[J]," Psychiatry Research: Neuroimaging, 2019, 28660-68.
[5] Mwansisya E T, Hu A, Li Y, et al., "Task and resting-state fMRI studies in first-episode schizophrenia: A systematic review[J]," Schizophrenia Research, 2017, 1899-18.
[6] Indranath C, Manoj A, Bharti R, et al., "Bi-objective approach for computer-aided diagnosis of schizophrenia patients using fMRI data[J]," Multimedia Tools and Applications, 2018, 77(20):26991-27015.
[7] Qureshi I N M, Oh J, Lee B., "3D-CNN based discrimination of schizophrenia using resting-state fMRI[J]," Artificial Intelligence In Medicine, 2019, 9810-17.
[8] Qiu-Hua L, Yan-Wei N, Jing S, et al., "SSPNet: An interpretable 3D-CNN for classification of schizophrenia using phase maps of resting-state complex-valued fMRI data[J]," Medical Image Analysis, 2022, 79102430-102430.
[9] Oh K, Kim W, Shen G, et al., "Classification of schizophrenia and normal controls using 3D convolutional neural network and outcome visualization[J]." Schizophrenia Research, 2019, 212186-195.
[10] Wang Z, Sun Y, Shen Q, et al., "Dilated 3D Convolutional Neural Networks for Brain MRI Data Classification[J]," IEEE Access, 2019, 7134388-134398.

[11] Shradha V, Tripti G, M. T, et al., “Machine learning techniques for the Schizophrenia diagnosis: a comprehensive review and future research directions[J],” Journal of Ambient Intelligence and Humanized Computing, 2023, 14(5).

[12] Weizheng Y, Linzhen Y, Dandan L, et al., “Multi-scale convolutional recurrent neural network for psychiatric disorder identification in resting-state EEG[J],” Frontiers in psychiatry, 2023, 14.

[13] Jie H, Yanli Z, Wei Q, et al., “Automatic recognition of schizophrenia from facial videos using 3D convolutional neural network[J],” Asian Journal of Psychiatry, 2022, 77.

[14] H A A, F R A, A M R, et al., “Feature and decision-level fusion for schizophrenia detection based on resting-state fMRI data[J],” PloS one, 2022, 17(5): e0265300-e0265300.

[15] Pantea M, O K L, I T N. “Data Driven Classification Using fMRI Network Measures: Application to Schizophrenia[J],” Frontiers in neuroinformatics, 2018, 1271.

[16] L C A, M A P, Kirstin R, et al., “EEG functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer’s disease and schizophrenia[J],” Journal of Physics: Complexity, 2022,3(2).

[17] Dario G, Ramos J C D, Eka C, et al., “The EEG multiverse of schizophrenia[J],” Cerebral cortex (New York, N.Y.: 1991), 2022,33(7).

[18] Kyungwon K, Thanh N D, Min C, et al., EEG microstate features for schizophrenia classification[J],” PloS one, 2021, 16(5): e0251842-e0251842.

[19] Aadith V, Nicholas M, Atul M, et al., “Understanding Cortical Dysfunction in Schizophrenia With TMS/EEG[J].” Frontiers in neuroscience, 2020, 14554.

[20] Shradha V, Tripti G, M. T, et al., “Machine learning techniques for the Schizophrenia diagnosis: a comprehensive review and future research directions[J],” Journal of Ambient Intelligence and Humanized Computing, 2023,14(5).

[21] David A A, Tharindu F, Simon D, et al., “Identification of Children At Risk of Schizophrenia via Deep Learning and EEG Responses[J],” IEEE journal of biomedical and health informatics, 2020.

[22] DongWoo K, JungJin Y, “EEG-Based Schizophrenia Diagnosis through Time Series Image Conversion and Deep Learning[J],” Electronics, 2022, 11(14).

[23] Manish S, Kumar R P, Akshat G, et al., “Automated detection of schizophrenia using deep learning: a review for the last decade[J],” Physiological measurement, 2023, 44(3).

[24] Rinku S, Parthasarathi S, Prasun C., “A deep learning based model using RNN-LSTM for the Detection of Schizophrenia from EEG data[J],” Computers in biology and medicine, 2022, 151(Pt A).

[25] Ahmad S, Sara B, Arash M., “Transfer learning with deep convolutional neural network for automated detection of schizophrenia from EEG signals[J],” Physical and engineering sciences in medicine, 2020, 43(4).

[26] Sebamai P, Mrutyunjaya S, Ranjeeta B, et al., “Autoencoder-based improved deep learning approach for schizophrenic EEG signal classification[J],” Pattern Analysis and Applications, 2022, 26(2).

[27] Sara B, Sadat M S, Ahmad S., “Detection of schizophrenia using hybrid of deep learning and brain effective connectivity image from electroencephalogram signal[J],” Computers in biology and medicine, 2022, 146.

[28] Jie S, Rui C, Mengni Z, et al., “A hybrid deep neural network for classification of schizophrenia using EEG Data[J],” Scientific Reports, 2021, 11(1).

[29] Hanife G., “1D-convolutional neural network approach and feature extraction methods for automatic detection of schizophrenia[J],” Signal, Image and Video Processing, 2023, 17(5).