ORIGINAL ARTICLE

The Reliability of Diagnosing Schizophrenia Using the GRU Layer in Conjunction with EEG Rhythms

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Abstract

Purpose: At resting state, the human brain releases cycles of Electroencephalography (EEG), which has been proven aberrant in persons with schizophrenia. Deep learning methods and patterns found in EEG of brain activity are helpful features for verifying schizophrenia. The proposed study demonstrates the applicability of alpha-EEG rhythm in a Gated-Recurrent-Unit-based deep learning model for studying schizophrenia.

Materials and Methods: This study suggests Rudiment Densely-Coupled Convolutional Gated Recurrent Unit (RDCGRU) for the EEG rhythm (gamma, beta, alpha, theta, and delta) based diagnoses of schizophrenia. The model includes multiple 1-D-Convolution (Con-1-D) folds with steps greater than 1, which enables the model to programmatically and effectively learn how to reduce the incoming signal. The Con-1-D layers and numerous Gated Recurrent Unit (GRU) layers comprise the Exponential-Linear-Unit activation function. This powerful activation function facilitates in-deep-network training and improves classification performance. The Densely-Coupled Convolutional Gated Recurrent Unit (DCGRU) layers enable RDCGRU to address the training accuracy loss brought on by vanishing or exploding gradients. This makes it possible to develop intense, deep versions of RDCGRU for more complex problems. The sigmoid activation function is implemented in the digital classifier's output nodes.

Results: The RDCGRU framework performs efficiently with alpha-EEG rhythm (88.06%) and harshly with delta-EEG rhythm (60.05%). The research achievements: In EEG rhythm-based schizophrenia verification, GRU cells with the RDCGRU deep learning model performed better with alpha-EEG rhythm.

Conclusion: The α-EEG rhythm is a crucial component of the RDCGRU deep learning model for studying schizophrenia using EEG rhythms. In our investigation of RDCGRU deep learning architectures, we noticed that Con-1-D layers connected special learning networks function well with the α-EEG rhythm for the EEG rhythm-based verification of schizophrenia.

Keywords: Gated Recurrent Unit; Rudiment Densely-Coupled Convolutional; Densely-Coupled Convolutional; 1-D-Convolution Layer.

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1. Introduction

Schizophrenia (SZ) is a neurocognitive condition that affects just under 0.35% of the wider public, asserts the World Health Organization [1]. In adults, this percentage is 0.45%. Hallucinations are one symptom of SZ, along with thought problems, illusions, thinking disturbances, misunderstandings, negative moods, cognitive deficits, and intellectual disability. A physical assessment is a part of the SZ investigation (to solve issues with related symptoms), an evaluation process (to determine whether or not signs are due to alcohol or drugs), and examination therapy (if feasible, to identify whether concerns are brought on by brain injury or other abnormalities with the brain); finally, the expert evaluation, which entails a licensed psychiatrist speaking with participants in-depth and meeting with people who have connections to SZ sufferers, is the last step. Such conventional therapies may occasionally be incorrect due to SZ patients' propensity to hide genuine illnesses and trained psychotherapists' difficulty distinguishing SZ from various situations.

Therefore, to demonstrate the precision of SZ diagnosis, several clinicians have attempted to develop quantifiable biomarkers employing "Electroencephalography (EEG) signals." A patient's ability to recover from SZ depends on when they begin psychotherapy. This demonstrates the importance of early SZ treatment in improving patients' health and reducing their propensity for self-harm or violence, relieving them of depression. To surpass the drawbacks of standard therapy and enhance the accuracy of initial SZ assessment, an intelligent diagnostics system that uses signal processing, deep learning methods, and brain EEG rhythms as a marker is required. Mind connection networks derived from EEG rhythms must be analyzed to determine human cognition in health and disease. Mind engagement pattern shifts are beneficial as "biomarkers for clinical therapy" since they have been associated with various psychiatric illnesses. SZ is called a "dysconnectivity illness," EEGs can show changes in how the brain works.

This paper discusses the significant research on SZ identification. M. Agarwal *et al.* [2] suggested a precise and simple-to-use method for SZ detection utilizing EEG. The signal is separated into sub-band ingredients by a Fourier-based method that can be done in real-time utilizing rapid Fourier transform. These ingredients are then used to determine statistical characteristics. In addition, a feature called the look ahead pattern is created to record regional differences in the EEG. The EEG signal analysis is made possible by the combination of these two unique approaches. The Kruskal-Wallis test is used to identify essential traits. By utilizing the boosted trees classifier on two different datasets, the suggested method identifies SZ patients with an accuracy of 98.62% and 99.24%.

Moreover, an increasing array of methods aimed at enhancing model interpretability and causal reasoning may enable deep learning to emerge as a potent instrument for revealing the mechanisms behind SZ. J. A. Cortes-Briones *et al.*'s [3] proposed essay aims to familiarize SZ researchers with deep learning and highlight some of its most recent uses in SZ research. Overall, the study has produced remarkable outcomes in problems involving outcome prediction and classification.

F. Li *et al.* [4] used the resting-state EEG network topology to identify multi-class SZ. Their motivation stems from the significant potential of resting-state networks to explain the varying degrees of brain impairments observed in SZ groups. The researchers created a multi-class feature retrieval technique that combined network structure-based supervised learning with an orchestra co-decision procedure to determine the spatial network topology and recognize SZs. In the alpha band, the recommended model had the best classification accuracy, scoring 71.58%.

Alpha-EEG (8-16Hz) rhythms are consistently identified as prominent in human EEG. These oscillations are most reliably seen in recordings made of conscious, relaxed, and with their eyes-closed subjects. During rest, persons with schizophrenia exhibit aberrant changes in their cognitive function [5, 6]. There is proof that certain features of psychosis-spectrum [7-9] SZ may be caused by abnormal α-EEG rhythms linked to disturbed cognitive functions [10, 11]. The occipital and parietal brain areas exhibit the strongest α-EEG rhythm while the eyes are closed at the "individual α-peak frequency," as determined by EEG during relaxation [12]. Functionally, A repressive alpha rhythm's timing and phase are associated with the brain's generalized onset of electrical activity [13, 14]. Consequently, declines in α-power may indicate the proportion of neuronal activities committed to cognitive functioning (for instance, in circumstances of event-related desynchronization), and increases in "individual α-peak frequency" may affect oscillatory timing managed across neurological groups and networks that are critical for governing sensory stimulation [12]. Psychophysiological studies have shown that "individual α-peak frequency" is linked to sensory stimuli, demonstrating that subjects with higher "individual α-peak frequency" can discern between visual stimuli with different stimuli start asynchronies [15]. The cross-modal sound-induced flash illusion was also more likely to occur at quicker stimulus onset asynchronies in subjects with greater "individual α-peak frequency" (and consequently faster alpha cycles), suggesting faster emotive timing [16]. In a network of brain regions that are essential for attention, higher "individual α-peak frequency" has been linked to more regional cerebral blood circulation, according to neuroimaging studies [17].

In the investigated research for the verification of SZ, we trained our applied deep learning model with the normal and abnormal resting state EEG rhythms. The following information is included in the research article: (a) The methodology: In the methodology part, we illustrated the RDCGRU model, DCGRU, activation function, GRU, the performance metric of the deep learning model, and "Software & libraries, and Computer Specifications" in subsection 2.1-2.8, (b) result, (c) discussion, and (d) the conclusion.

2. Materials and Methods

Figure 1 displays the analysis methodology of the Rudiment Densely-Coupled Convolutional Gated Recurrent Unit (RDCGRU) deep learning model. The 2.1–2.8 subheadings represent the deliberate methodology for studying SZ.

2.1. Preprocessing

To validate SZ, we utilized the normal and abnormal resting-state EEG rhythms (those of SZ patients and healthy control participants) to train and test the RDCGRU model. The current study compares the EEG rhythms of SZ with those of healthy control patients, particularly gamma, beta, alpha, theta, and delta, as well as a mixture of all of these rhythms. The EEG rhythms were separated by the applied bandpass filter of the different ranges [γ~32-64Hertz, β~16-32Hertz, α~8-16Hertz, θ~4-8Hertz, and δ~0.5-4Hertz]. The duration of the preprocessed EEG is 5 seconds, and the sampling rate is 250 Hz.

2.2. The Rudiment Densely-Coupled Convolutional Gated Recurrent Unit Deep-Learning (RDCGRU) Framework

The model shown in Figure 1 is intended to classify SZ EEGs. Rudiment Densely-Coupled Convolutional Gated Recurrent Unit (RDCGRU) deep-learning architecture is prepared by stacking several 1-D-Convolution (Conv-1-D) layers and numerous Gated-Recurrent-Unit (GRU) layers. The model includes various Con-1-D folds with steps greater than 1, which enables the model to programmatically and effectively learn how to reduce the incoming signal. In a feed-forward fashion, the piled GRU cells are densely connected, and each Con-1-D layer contains a variety of filters of differing lengths. The numerous filters in the Con-1-D layers allow RDCGRU to separate and incorporate features from various timeframes. The task that a Con-1-D layer was assigned and its location in the network usually determines the ideal filter size for that layer. Users of the RDCGRU can test out various filter widths for each Con-1-D layer. The other side is that DCGRU layers enable RDCGRU to address the training accuracy loss brought on by "exploding or vanishing gradients;" This might make it possible to develop intense deep versions of the RDCGRU for more complex problems. Additionally, densely coupled GRU layers improve feature propagation and encourage feature reuse. This model has a batch size of ten times that of the GRU layer.

2.3. The Densely-Coupled Convolutional Gated Recurrent Unit (DCGRU)

The Convolutional-Recurrent Neural Network (C-RNN) model is not impervious to the demotion problem, which can slow or stop the training of more complex neural networks. The optimizer causes more training errors for basic scenarios that don't call for the overall model diversity that a C-RNN model offers [18]. To address this problem, we omit links in the stacked Gated Recurrent Unit (GRU) cells of the C-RNN to design the Densely-Coupled Convolutional Gated Recurrent Unit (DCGRU) model motivated by the DenseNet model proposed by G. Huang *et al.* [19] for CNNs. Each GRU layer is feed-forward connected to every other GRU layer. In Figure 1, the DCGRU is symbolized by blue boxes with feedback 1, 2, and 3. Experientially, convolution layers will bypass GRU layers when the data requires less model complexity than the network offers.

2.4. Activation Function

The Con-1-D layers and numerous GRU layers consist of an "Exponential Linear Unit (ELU) activation function," and a "sigmoid activation function" is applied for the final categorization (healthy control person and SZ) for the reasons mentioned:

2.4.1. The Exponential Linear Unit (ELU) Activation Function

D.A. Clevert *et al.* [20] developed the Exponential Linear Unit (ELU), a powerful activation function that facilitates in-deep-network training and improves classification performance. Unlike traditional activation methods, ELU adds a saturation function to manage the negative section. ELUs can bring mean unit activations closer to zero, lowering batch normalization's computing complexity because they include negative values. Learning is accelerated by shifts towards zero, which brings the average gradient nearer to the unit-natural gradient due to a lesser bias shift effect. Deactivating the unit lowers the activation function, allowing ELU to operate more quickly in noisy environments. The ELU activation function's mathematical definition is summarized in Table 1.

Table 1. Definition of Deep Learning's Nonlinear Activation Function

Serial Number	Activation Function Name	Expression of the Activation Function in Mathematics
1	ELU	$f(x) = \frac{1}{1+e^{-x}}$
2	Sigmoid	$f(x) = \begin{cases} \alpha\,(e^{-x} - 1), & x \le 0 \\ x, & x > 0 \end{cases}$

2.4.2. The Sigmoid Activation Function

It is an output-producing function that is effortless and continuously differentiable after activation [21]. This function has a nonlinear, S-shaped curve. The sigmoid function's activation value ranges from 0 to 1 and is the standard justification for using it. The sigmoid function must be implemented in the output layer of the binary classifier. In the presented research, only two cases are possible: SZ or a Healthy Control (HC) [HC→0, SZ→1]. Table 1 summarizes the mathematical expression of the Sigmoid activation function.

2.5. The Gated Recurrent Unit (GRU)

In recent years, the Gated Recurrent Unit (GRU) has seen extensive use in processing time series data. The GRU automates the Long-Short-Term-Memory (LSTM) architecture by removing the memory unit mechanism and replacing the input and forget gates with an update gate. Numerous studies have demonstrated that GRU achieves equal accuracy to LSTM while requiring minimal computations [22]. Figure 2 depicts the configuration of the GRU structure, primarily of reset and update gates. Both gates impact the prior hidden state S_{t-1} and the current input y_t. The reset gate R_t specifies how much the last hidden state is filtered before using the filtered information and the current input y_t to generate the new hidden state $\hat{S}$. Again, the following GRU structure will receive the foremost valuable knowledge due to the update gate U_t, which regulates the ratio of the previous hidden state S_{t-1} to the newly updated state $\hat{S}$ in the next hidden state S_t.

If we take y_t as the input units, S_{t-1} as the previous hidden state, $\hat{S}$ as the newly updated state Equation 1, S_t as the new hidden state Equation 2, R_t as the reset gate Equation 3, and U_t as the update gate Equation 4, the GRU convergence equations state the following [23]:

$$\hat{S} = \sigma\,[ZS\,yt + Rt \odot (TS\,St - 1) + bS] \quad (1)$$

$$St = (1 - Ut) \odot St - 1 - Ut \odot \hat{S} \quad (2)$$

$$Rt = \sigma\,[ZR\,yt + TR\,St - 1 + bR] \quad (3)$$

$$Ut = \sigma\,[ZU\,yt + TU\,St - 1 + bU] \quad (4)$$

T_S, T_R, and T_U are the weight matrix of the three layers for the previous short-term state S_{t-1}. Z_S, Z_R, and Z_U are the weight matrices of the three layers concerning the input y_t. The weight matrices Z_R, Z_U, and Z_S are utilized to determine the gates R_t and U_t and the new hidden state $\hat{S}$. The symbol $\odot$ denotes the elementwise multiplication of vectors. Sigmoid (σ) is an example of an activation function used to simulate a gate mechanism and normalize the input. The sigmoid (σ) activation function is applied in Equation 1 for the binary classification.

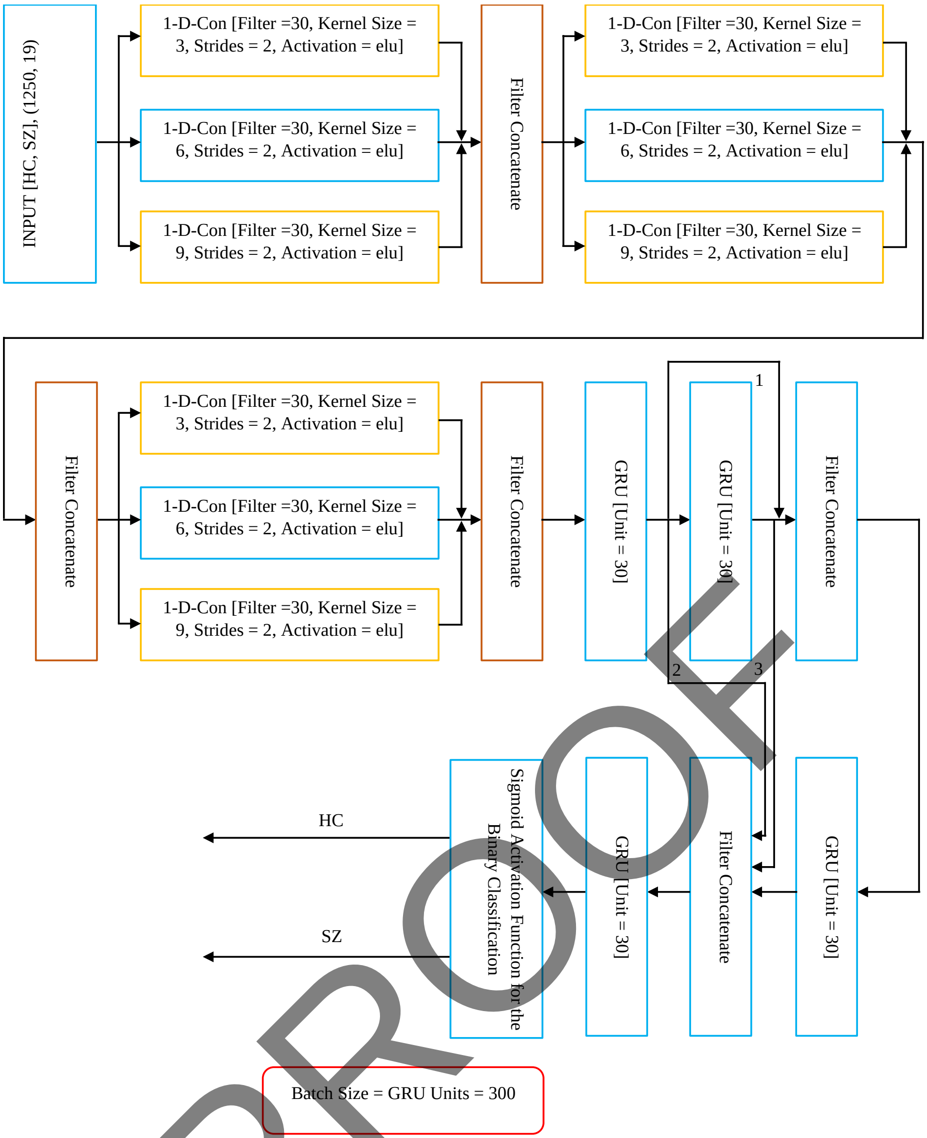

Figure 1. Architecture of the RDCGRU deep learning model

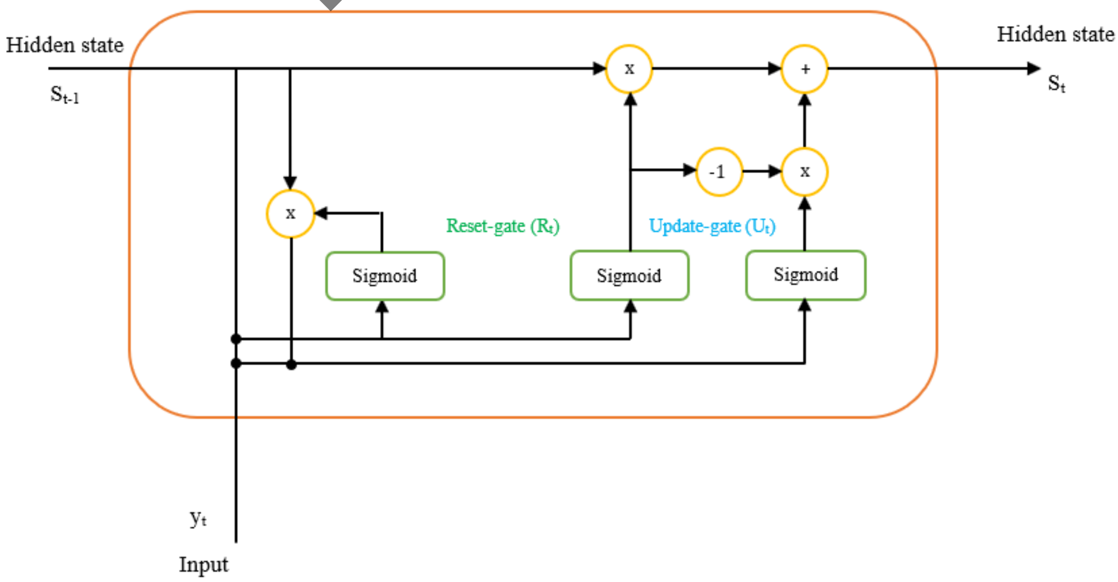

Figure 2. The GRU cell architecture in the RDCGRU deep learning model

2.6. The performance Metric of the RDCGRU Deep Learning Model

The f1-score, precision, recall, and accuracy metrics are used to evaluate the RDCGRU model's diagnostic performance for SZ. The applied deep learning model uses the Leave One Subject Out (LOSO) cross-validation method.

2.7. The Dataset

The dataset was sourced from the Institute of Psychiatry and Neurology in Warsaw, Poland [24, 25]. The positioning of the electrodes followed the 10-20 international rule. The EEG dataset were acquired at a sampling rate of 250Hz over 19 channels (i.e., Fz, F3, F4, F7, F8, Fp1, Fp2, Pz, P3, P4, O1, O2, T5, T6, Cz, C3, C4, T3, T4). The respondents relaxed with their eyes closed for an average of 15 minutes while collecting the data. The collected EEG data are described in further detail in Table 2. It includes EEG signals of 14 normal individuals and 14 subjects with schizophrenia who do not have neurological conditions. The control group was chosen considering factors such as gender and age. This research included subjects with an ICD-10 condition F20.0 who were over 18. These people did not take drugs for at least seven days before data collection. Pregnant women with biological-cognitive dysfunction, severe neurological diseases, a general medical condition, or those under 18 were not allowed to participate in the study. Additionally, patients with the disease's early stages, such as those experiencing their first attack, were excluded from the study.

2.8. Software & Libraries, and Computer Specifications

Software and libraries: Anaconda Packages, MNE-Python, Python, Jupyter Notebook, Spyder IDE. Computer specifications: Dell G15-5515, AMD-Ryzen-7, VRAM-6GB, RAM-16GB, Memory clock speed-3200MHz, Processor speed-3.2GHz.

Table 2. Dataset Information [Notations: SZ is the Schizophrenia subject, and HC is the Healthy control subject]

Serial No.	Contains	Significance
1.	Form of Biomedical Signal	Electroencephalogram
2.	Count of Electrodes	19
3.	Naming of Electrodes	Fz, F3, F4, F7, F8, Fp1, Fp2, Pz, P3, P4, O1, O2, T5, T6, Cz, C3, C4, T3, T4
4.	Normative Electrode	FCz
5.	The mood at the recording session	The eye is closed and relaxing.
6.	Sampling frequency	250Hz
7.	Recording duration	Fifteen minutes
8.	Total number of segments	5550
9.	Length of each segment	5 sec (250 x 5 = 1250)
10.	Total sample point in a segment for a single channel	1250
11.	Total sample point in a segment with 19 channels	19 x 1250 = 23750
12.	overall participants	28 [14-HC (7 Males, 7 Females), and 14-SZ (7 Males, 7 Females)]
13.	Eligibility conditions	ICD-10 condition F20.0, the age requirement of 18, and seven-day medication interval.
14.	Exemption standards	SZ treats neurological illnesses in their very early stages (i.e., Alzheimer's, Epilepsy, Parkinson's disease), pregnancy, and biological-cognitive dysfunction.
15.	The average age of HC participants	7 HC Male [Age: 26.8 ± 2.9year] 7 HC Female [Age: 28.7 ± 3.4year]
16.	The average age of SZ participants	7 SZ Male [Age: 27.9 ± 3.3year] 7 SZ Female [Age: 28.3 ± 4.1year]
17.	Exemption standards	SZ treats neurological illnesses in their very early stages (i.e., Alzheimer's, Epilepsy, Parkinson's disease), pregnancy, and biological-cognitive dysfunction.
18.	The average age of HC participants	7 HC Male [Age: 26.8 ± 2.9year] 7 HC Female [Age: 28.7 ± 3.4year]
19.	The average age of SZ participants	7 SZ Male [Age: 27.9 ± 3.3year] 7 SZ Female [Age: 28.3 ± 4.1year]

3. Results

Compared to other EEG rhythms, the RDCGRU deep learning model performs better with α-EEG (resting-state healthy and unhealthy α-EEG) rhythm because of the GRU unit's improved learning ability. The RDCGRU model was tested with each EEG rhythm, and it achieved the highest accuracy, 88.06%, with the α-EEG rhythm. The research findings are depicted in Table 3. The RDCGRU framework works effectively with α-EEG rhythm (88.06%) and poorly with δ-EEG rhythm (60.05%). The accuracy of the RDCGRU model with γ-EEG, θ-EEG, and β-EEG rhythms are 76.87%, 62.05%, and 60.19%, respectively.

4. Discussion

The RDCGRU deep learning model, Convolutional Neural Network-Complex Network (CNN-CN) [26], and Convolutional Neural Network-Partial Directed Coherence (CNN-PDC) [26] are examples of convolutional deep learning networks that follow the special deep learning networks. The most critical and helpful characteristic in automatic feature extraction for the EEG-based verification of SZ using convolutional deep learning networks is the resting-state normal and aberrant α-EEG rhythm. Table 4 provides evidence supporting the validity of the α-EEG rhythm in the GRU-based diagnosis of SZ. Table 4 compares the work discussed to the most recent deep-learning framework for EEG rhythm-based SZ assessment.

Table 3. The validity of the RDCGRU framework with different EEG rhythms

Serial Number	The EEG rhythms and their frequency interval (Hz)	Performance of the RDCGRU Deep Learning Framework			
		Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1.	δ-EEG (0.5-4 Hz)	60.05	52.11	86.53	65.05
2.	θ-EEG (4-8 Hz)	62.05	50.48	78.23	61.36
3.	**α-EEG (8-16 Hz)**	**88.06**	**78.28**	**92.44**	**84.77**
4.	β-EEG (16-32 Hz)	60.19	50.92	81.55	62.69
5.	γ-EEG (32-64 Hz)	76.87	72.75	97.05	83.16
6.	All EEG rhythms (δ, θ, α, β & γ)	81.81	61.24	76.38	67.97

Table 4. An analysis of the newly developed deep learning model used to evaluate SZ based on EEG rhythms

Serial Number	Research	Model Name	Raw EEG Rhythm	Accuracy (%)
1.	Present work, 2023	Applied RDCGRU deep learning model	Raw δ-EEG Rhythm	60.05
			Raw θ-EEG Rhythm	62.05
			Raw α-EEG Rhythm	**88.06**
			Raw β-EEG Rhythm	60.19
			Raw γ-EEG Rhythm	76.87
			Raw All EEG Rhythms (δ, θ, α, β & γ EEGs)	81.81
2.	D. Ahmedt-Aristizabal *et al.* [27], 2021	2D-CNN-GRU	Raw All EEG Rhythms (δ, θ, α, β & γ EEGs)	69.78 (Test Accuracy)
		2D-CNN-LSTM	Raw All EEG Rhythms (δ, θ, α, β & γ EEGs)	72.54 (Test Accuracy)
		R-CNN	Raw All EEG Rhythms (δ, θ, α, β & γ EEGs)	69.80 (Test Accuracy), 89.98 (Validation Accuracy)

The RDCGRU outperforms in comparison to 2D-CNN-GRU [27] and 2D-CNN-LSTM [27]. The R-CNN [27] validation accuracy is slickly high (89.98%) compared to the RDCGRU deep-learning model (88.06%).

The RDCGRU deep learning architecture relies on the α-EEG rhythm to verify SZ automatically. Figure 3 displays the usual α-EEG rhythm of the healthy control subject at rest. Figure 4 displays the aberrant α-EEG rhythm of the SZ patient at rest. Compared to the α-EEG rhythm of the healthy control subjects, the α-EEG rhythm of the SZ patient is slower. The EEGs of the O1, O2, T5, and T6 electrodes differ significantly between healthy controls and SZ patients.

5. Conclusion

For EEG-based SZ confirmation in the RDCGRU deep learning model, GRU cells connected to Conv-1-D layers responded better with α-EEG rhythm. The RDCGRU model relies heavily on the α-EEG rhythm for studying SZ using EEG data.

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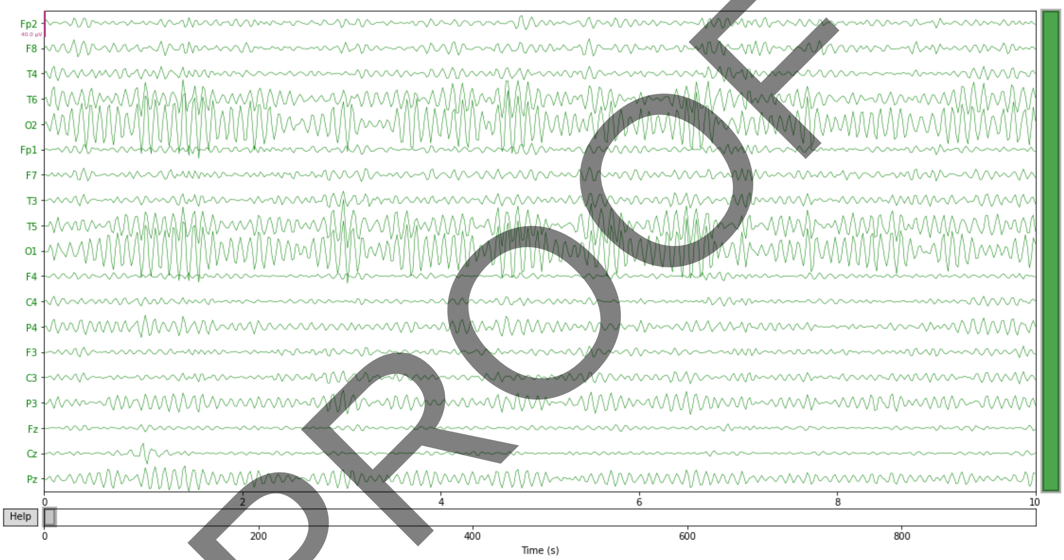

Figure 3. The resting-state normal α-EEG rhythm of the healthy control person

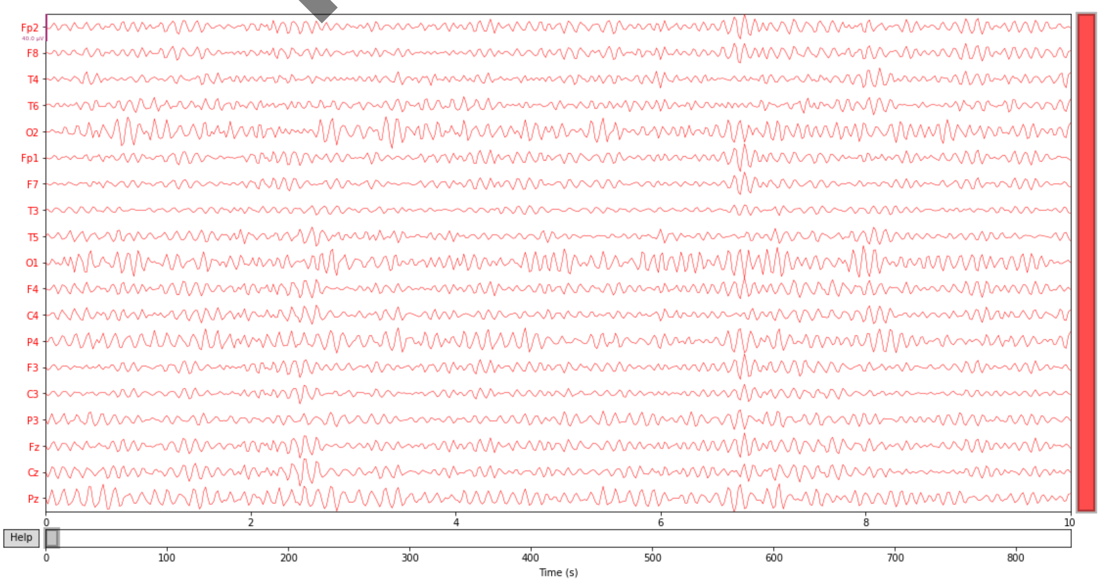

Figure 4. The resting-state abnormal α-EEG rhythm of the SZ patient

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