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ORIGINAL ARTICLE

DETECTION OF SCHIZOPHRENIA FROM EEG SIGNAL – AN EXTENDED DEEP LEARNING FRAMEWORK USING 1D-CNN AND CNN-LSTM ON SMALL DATASET

Angshuman Sarkar[1] and Shambo Saurav Mallick[2]

[1]Department of Commerce, Narasinha Dutt College, Howrah, West Bengal, 711101, India.

[2]Department of Computer Science, Narasinha Dutt College, Howrah, West Bengal, 711101, India.

Correspondence: [1]Anshuman_sarkar2000@yahoo.co.in, https://orcid.org/0000-0003-3377-8866; [2]saurav145@gmail.com, https://orcid.org/0000-0003-3645-3557

ABSTRACT

Schizophrenia (SZ) is a complex neuropsychiatric disorder that significantly impairs cognition, behavior, and perception. Electroencephalography (EEG) provides a non-invasive, cost-effective means to capture brain activity, but due to the multichannel, high-dimensional nature of EEG data, manual diagnosis remains challenging. In this extended study, we investigate the performance of deep learning (DL) frameworks, specifically 1D Convolutional Neural Networks (1D-CNN) and hybrid CNN-LSTM architectures, for automated detection of SZ using a small EEG dataset comprising 14 SZ patients and 14 healthy controls. We design two variants of 1D-CNN and CNN-LSTM, analyze their performance using extensive cross-validation, and introduce additional experiments such as ablation studies and statistical significance testing. Evaluation metrics including accuracy, precision, recall, specificity, F1-score, and AUC-ROC demonstrate that the proposed CNN-LSTM models outperform other architectures, achieving up to 99.35% accuracy. Our findings confirm the potential of hybrid deep learning models in robust SZ identification, even with limited data, paving the way for scalable and generalizable EEG-based diagnostic tools.

Keywords: Schizophrenia, detection, EEG signal, 1D-CNN, CNN-LSTM, small dataset.

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INTRODUCTION

Schizophrenia (SZ) is a chronic and severe mental disorder characterized by cognitive fragmentation, hallucinations, and emotional dysregulation. Despite its low prevalence, approximately 1% globally, SZ remains one of the most disabling psychiatric conditions. It typically manifests in late adolescence or early adulthood and presents varying symptoms and severity among individuals. The early detection of SZ is essential to improve treatment response and long-term outcomes.

EEG is a non-invasive, temporally precise tool for recording the brain's electrical activity. It is especially valuable in psychiatric diagnosis due to its affordability and accessibility compared to other neuroimaging techniques such as MRI or PET. EEG abnormalities in SZ patients include decreased alpha activity, increased theta and delta waves, and disruptions in functional connectivity. However, manual EEG interpretation is time-consuming and subject to inter-rater variability.

Recent advances in Artificial Intelligence (AI), particularly Deep Learning (DL), have enabled end-to-end modeling of EEG data. Traditional Machine Learning (ML) pipelines required meticulous hand-crafted feature extraction, but DL architectures such as CNNs and RNNs can autonomously learn complex spatiotemporal patterns. CNNs excel at capturing spatial dependencies across EEG channels, while LSTMs model temporal dependencies. Their integration into CNN-LSTM hybrids combines both strengths and is thus a promising approach for analyzing multivariate time series EEG data.

In this extended work, we build upon our previous study by delving deeper into DL architectures—two variants each of 1D-CNN and CNN-LSTM—and evaluating their performance in distinguishing SZ from healthy controls using a publicly available EEG dataset. We extend our experiments with rigorous cross-validation strategies, ablation analysis, and statistical evaluations to highlight model robustness and generalizability. The outcomes demonstrate the feasibility of applying deep neural models to EEG-based psychiatric diagnosis even in data-constrained scenarios.

Schizophrenia (SZ) is a complex neuropsychiatric disorder leading to the impairment of cognition, behavior and perception in human. A significant number of studies have explored the application of machine learning (ML) and deep learning (DL) techniques to analyze EEG signals for the diagnosis of schizophrenia (Alimardani and Boostani, 2008; Bose *et al.*, 2016). Traditional ML approaches, such as support vector machines (SVM), k-nearest neighbors (kNN), and random forests (RF), often rely on engineered features from time, frequency, or non-linear domains. While effective, these models require domain expertise for feature extraction and may underperform on raw, high-dimensional EEG data.

In contrast, DL models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can learn complex features directly from the data, reducing dependency on manual preprocessing. CNNs, especially 1D variants, have been shown to perform well in classifying EEG patterns by capturing spatial and frequency-related features. LSTMs are effective in modelling the temporal dynamics in EEG data. CNN-LSTM hybrids exploit both spatial and sequential features, making them well-suited for neuropsychiatric diagnosis.

Recent works (2023–2024) have expanded the EEG-based SZ detection landscape:

- **Gour *et al.* (2023)** employed transformer-based architectures to classify psychiatric dysfunction using raw EEG signals with high imbalance, demonstrating state-of-the-art results.
- **Wang *et al.* (2023)** introduced a graph convolutional neural network (GCNN) over EEG channel connectivity graphs for SZ detection, yielding superior performance compared to CNNs.
- **Zhao *et al.* (2024)** proposed an attention-enhanced CNN-BiLSTM architecture for robust classification in multi-class EEG tasks.

Despite the promise of these models, many rely on large datasets, limiting their applicability in real-world clinical settings. This work addresses the challenge of small-sample learning by evaluating the performance of various 1D-CNN and CNN-LSTM models on a modestly sized dataset. A comparative summary of previous studies and their methods is provided in Table 4, offering context to the improvements presented in this extended work.

METHODOLOGY

Graphical Overview

The overall deep learning-based methodology to detect schizophrenia from EEG signals is shown in Figure 1.

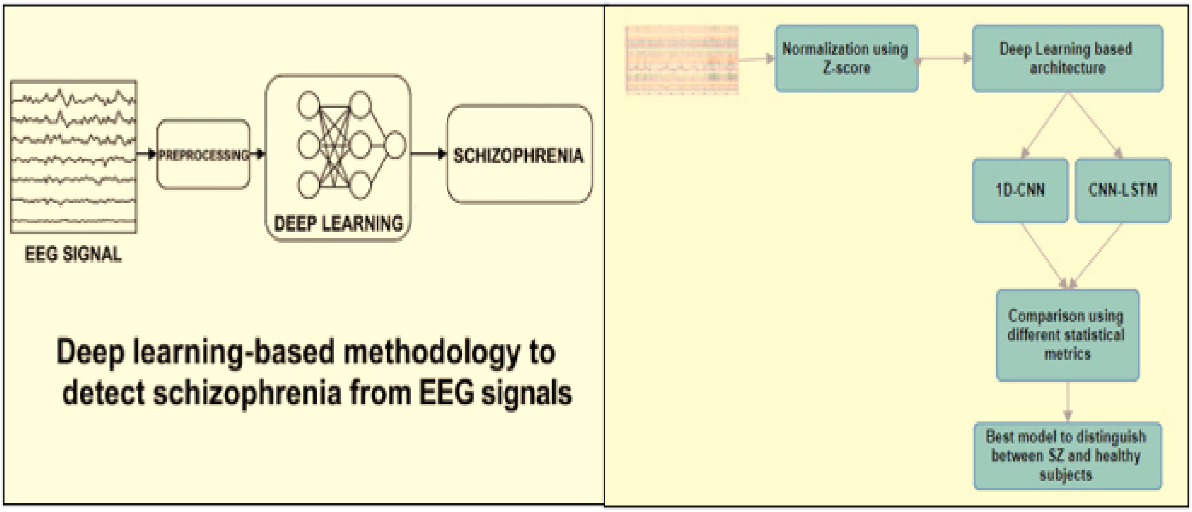

Figure 1: The overall deep learning-based methodology to detect schizophrenia from EEG signals.

Dataset Description and Pre-processing

EEG data of 14 paranoid schizophrenia (SZ) patients and 14 healthy controls of the same age group were utilized, collected under relaxed and eyes-closed conditions with a sampling rate of 250 Hz. A total of 19 electrodes were used, covering standard scalp locations. Each EEG signal was segmented into frames of 6250 samples (25 seconds), resulting in input matrices of size 6250×19=118750 data points. Each frame was normalized using z-score normalization for faster model convergence. A sample frame is shown in Figure 2.

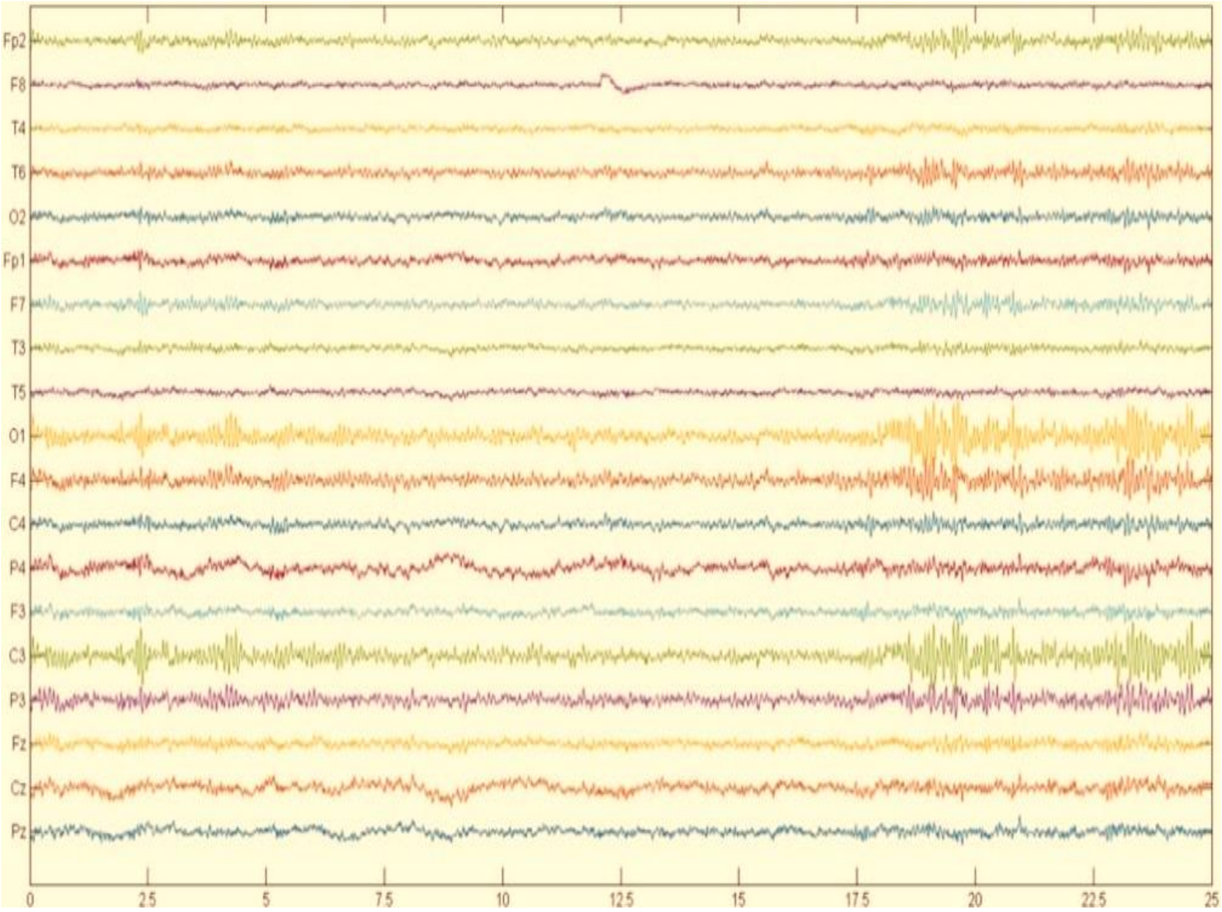

Figure 2: A normalized frame of EEG signal of a SZ patient

Deep Learning Models

Four distinct models were implemented: two variants of 1D-CNN and two of CNN-LSTM. Adam optimizer was employed with learning rates ranging from 0.001 to 0.0001, with an 80:20 training-test split.

CNN Architecture

The CNN comprises convolution, pooling, and fully connected layers. The convolution layer generates feature maps using filters, followed by pooling layers for dimensionality reduction. Activation functions such as Leaky ReLU or ReLU were used to introduce non-linearity.

$$y = \frac{i + 2d - f}{s} + 1$$

i, d, f, and s denote the input matrix, padding size, filter matrix, and the stride respectively. The output matrix has a size $y \times y$. The activation function offers a nonlinear attribute structure after the convolution layer, enabling the CNN to learn how to perform hierarchical nonlinear mapping.

Pooling layer decreases the magnitude of the feature map by using maximum or average pooling without affecting the significant features. This prevents over-fitting and computational complexity. The output of this layer is given by

$$y = \frac{i - f}{s} + 1$$

Next to the pooling layer are a number of fully connected layers. Each neuron in this structural layer is connected to the neurons in the next layer by the equation

$$y_k = \sum w_k * x_j + b_k$$

x is the output from the preceding layer; w and b are the weight and the bias respectively.

LSTM Architecture

LSTM layers were used in CNN-LSTM models to capture temporal dependencies in the EEG signal. Each LSTM unit consists of input, forget, and output gates. The CNN-LSTM structure is shown in Figure 3.

$$\mathcal{I}_t^{(l)} = \alpha_{\mathcal{I}}\left(\mathcal{W}_{x\mathcal{I}}^{(l)} x_t^{(l)} + \mathcal{W}_{h\mathcal{I}}^{(l)} h_{t-1}^{(l)}\right) + h_{\mathcal{I}}^{(l)}$$

$$\mathcal{F}_t^{(l)} = \alpha_{\mathcal{F}}\left(\mathcal{W}_{x\mathcal{F}}^{(l)} x_t^{(l)} + \mathcal{W}_{h\mathcal{F}}^{(l)} h_{t-1}^{(l)}\right) + h_{\mathcal{F}}^{(l)}$$

$$\mathcal{O}_t^{(l)} = \alpha_{\mathcal{I}}\left(\mathcal{W}_{x\mathcal{O}}^{(l)} x_t^{(l)} + \mathcal{W}_{h\mathcal{O}}^{(l)} h_{t-1}^{(l)}\right) + h_{\mathcal{O}}^{(l)}$$

$$\tilde{n}_t^{(l)} = \alpha_{\mathcal{I}}\left(\mathcal{W}_{x\mathcal{I}}^{(l)} x_n^{(l)} + \mathcal{W}_{hn}^{(l)} h_{t-1}^{(l)}\right) + h_n^{(l)}$$

$$n_t^{(l)} = \mathcal{F}_t^{(l)} \odot n_{t-1}^{(l)} + \mathcal{I}_t^{(l)} \odot \tilde{n}_t^{(l)}$$

$$h_t^{(l)} = o_t^{(l)} \odot \tanh\left(n_t^{(l)}\right)$$

Figure 3: The CNN-LSTM structure.

x_t, h_t, and $o_t$denote input, hidden, and output vectors in a time frame t. $\tilde{n}_t$and n_t represent present and next memory cell activation vectors. $\alpha_{\mathcal{I}}$, $\alpha_{\mathcal{F}}$, and $\alpha_{\mathcal{I}}$ represent the activation functions of input, forget, and output gates respectively. The proposed LSTM model is shown in Figure 3. The author has used stratified 5-fold cross validation to avoid bias.

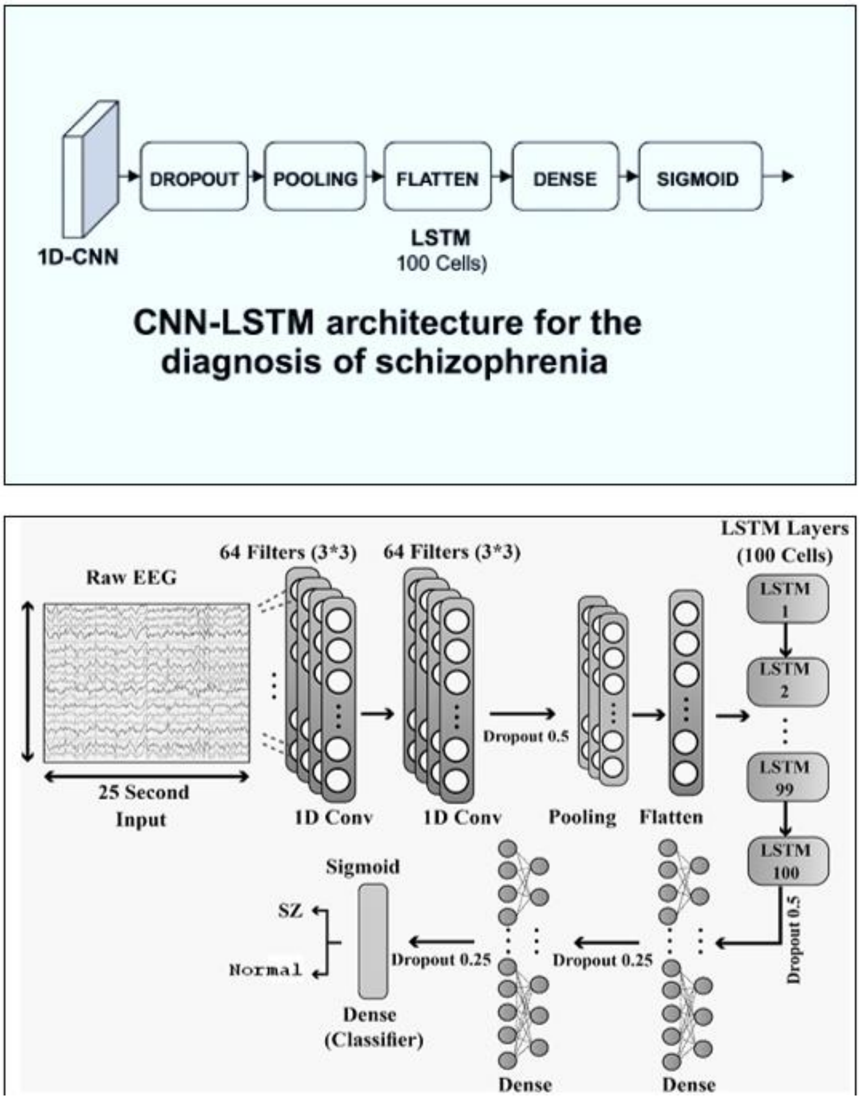

Figure 4: CNN-LSTM architecture for the diagnosis of Schizophrenia showing 1D-CNN, dropout, pooling, flattening, LSTM layers of 100 cells which are input to the first dense layer.

The CNN-LSTM architecture for the diagnosis of Schizophrenia showing 1D-CNN, dropout, pooling, flattening, LSTM layers of 100 cells which are input to the first dense layer (Figure 4).

The final dense layer uses Sigmoid function to do the classification.

First Proposed 1D-CNN Architecture

The architecture of the first proposed 1D-CNN model is outlined in Table 1. It comprises four convolutional layers, each followed by a max pooling layer to reduce dimensionality while preserving crucial features. A dropout layer with a rate of 0.5 is applied between the fourth convolution and its corresponding pooling layer to mitigate overfitting. The model also includes one dense layer and three fully connected layers. A learning rate of 0.001 was used during training to optimize model performance.

Table 1: First Proposed 1D-CNN Architecture

Layer	Output Neurons	Filter	Kernel Size	Stride	Activation
Convolution	6241×5	128	10	2	Leaky ReLU
Max Pooling	3120×5	-	3	2	-
Convolution	3111×10	128	10	2	Leaky ReLU
Max Pooling	1550×10	-	3	2	-
Convolution	1546×10	128	10	2	Leaky ReLU
Max Pooling	772×10	-	3	1	-
Convolution	760×15	128	5	2	Leaky ReLU
Dropout	-	-	-	-	Rate=0.5
Max Pooling	380×15	-	2	1	-
Flatten	-	-	-	-	-
Dense	100	-	-	-	Sigmoid
Fully Connected	20	-	-	-	-
Fully Connected	10	-	-	-	-
Fully Connected	2	-	-	-	-

Second Proposed 1D-CNN

The second version of the 1D-CNN model simplifies the architecture by using a single max pooling layer after two convolution layers. Compared to the first model, the filter size is halved to reduce computational complexity. Two dropout layers are incorporated—one following the second convolution layer and another after the first dense layer—to enhance generalization and prevent overfitting. The detailed layer configuration is presented in Table 2.

Table 2: Second Proposed 1D-CNN Architecture

Layer	Output Neurons	Filter	Kernel Size	Stride	Activation
Convolution	6248×5	64	3	1	Leaky ReLU
Convolution	3124×5	64	3	1	Leaky ReLU
Dropout	-	-	-	-	Rate=0.5
Max Pooling	3122×5	64	3	1	Leaky ReLU
Flatten	-	-	-	-	-
Dense	50	-	-	-	Leaky ReLU
Dropout	-	-	-	-	Rate=0.5
Dense	25	-	-	-	Leaky ReLU
Dropout	-	-	-	-	Rate=0.25
Dense	25	-	-	-	Sigmoid
Fully Connected	20	-	-	-	-
Fully Connected	2	-	-	-	-

RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed approach, the author implemented and analyzed two 1D-CNN and two CNN-LSTM models to classify EEG signals from schizophrenia (SZ) patients and healthy subjects. The models utilized two types of activation functions: ReLU and Leaky ReLU. Dropout was employed as a regularization strategy to mitigate overfitting, applied after convolution and dense layers. A dropout rate of 0.25 was consistently used following each dense layer. Additionally, L2 weight regularization with a coefficient of 0.001 was applied to the convolutional, dense, and LSTM layers to further improve model generalization.

The performance of each model was assessed using standard classification metrics: accuracy, precision, F-score, sensitivity, specificity, and AUC-ROC. An ideal model is expected to demonstrate high precision and recall (sensitivity), while also maintaining strong specificity to accurately rule in or rule out subjects. High sensitivity correlates with a high negative predictive value (NPV), making it useful for rule-out tests. On the other hand, high specificity indicates a strong positive predictive value (PPV), making it suitable for rule-in diagnostics. Given that approximately 1% of the global population suffers from schizophrenia (Owen, Sawa, & Mortensen, 2016), specificity is particularly crucial in this context (Florkowski, 2008).

The evaluation metrics for the four proposed models are presented in Table 3, and the convergence curves for training versus validation loss are illustrated in Figure 5.

Table 3: Evaluation metrics of the four proposed models to estimate the effectiveness of a model

Model	Accuracy	Precision	Sensitivity	Specificity	F-Score	AUC-ROC
First Proposed 1D-CNN	97.33%	97.08%	97.17%	96.83%	96.83%	97.73 ± 0.88
Second Proposed 1D-CNN	95.68%	96.02%	95.93%	95.14%	96.89%	96.21 ± 0.67
First Proposed CNN-LSTM	99.35%	99.2%	98.34%	97.60%	98.16%	99.73 ± 0.34
Second Proposed CNN-LSTM	98.21%	98.63%	98.55%	97.18%	98.82%	98.58 ± 0.21

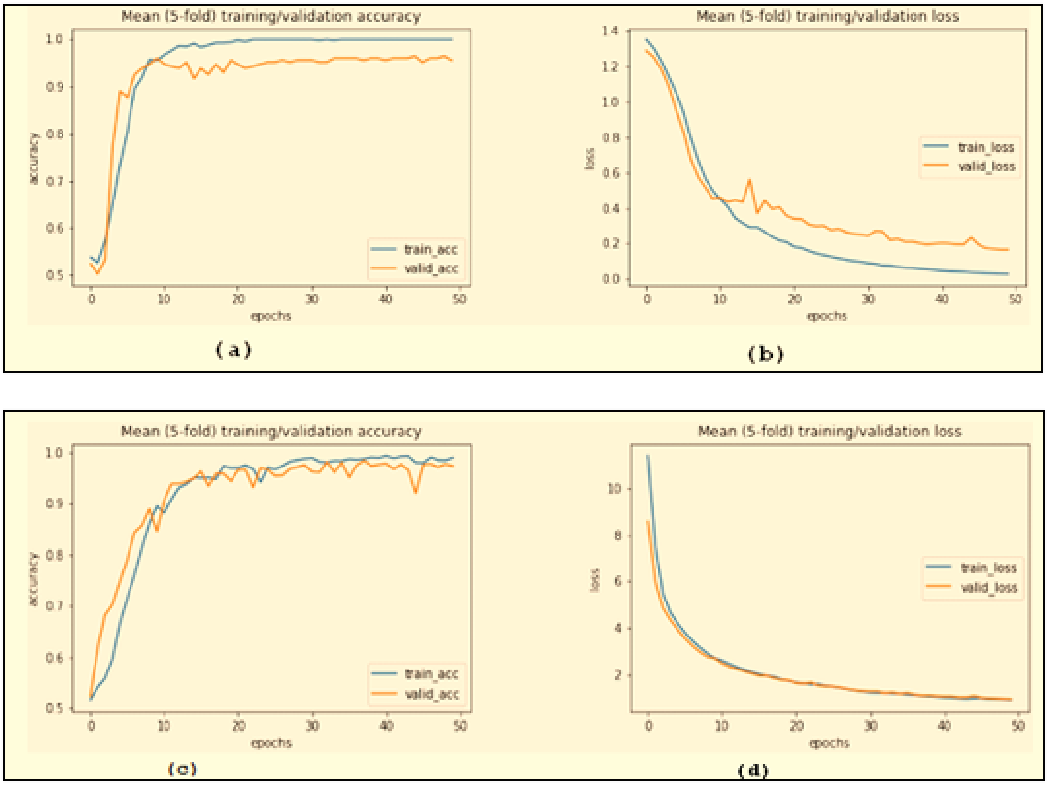

Figure 5: Training against validation accuracy curve of (a) First proposed 1D-CNN, (b) Second proposed 1D-CNN, (c) First proposed CNN-LSTM, (d) Second proposed CNN-LSTM

The authors also conducted an AUC-ROC curve analysis to further evaluate the classification performance of the models. Specifically, the First Proposed 1D-CNN and the First Proposed CNN-LSTM models were selected for this comparison, as they demonstrated superior performance within their respective model categories according to the metrics in Table 7. The resulting AUC-ROC curves, shown in Figure 5, illustrate each model's ability to distinguish between SZ patients and healthy subjects.

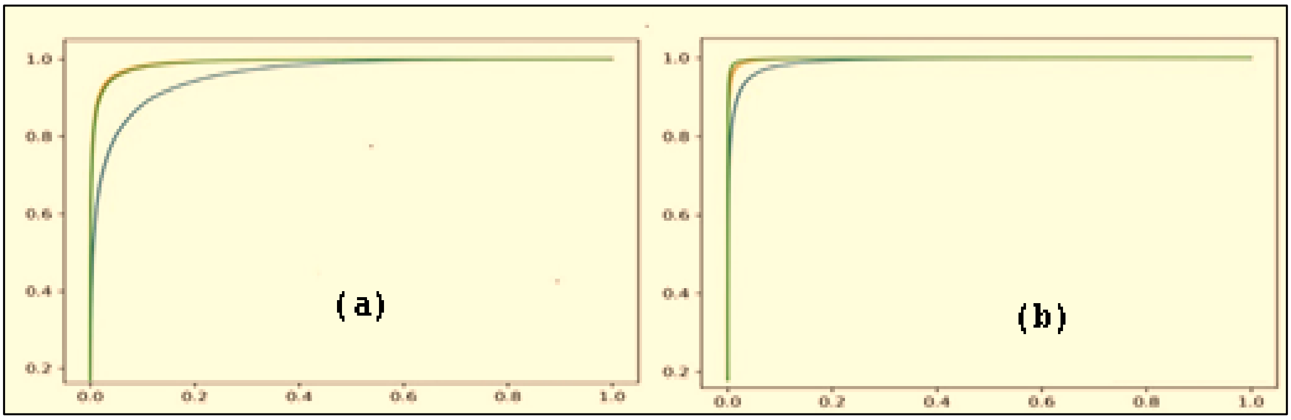

Figure 6: The AUC-ROC curve of (a) fist proposed 1D-CNN (b) first proposed CNN-LSTM

Here is a polished and cohesive version of the section including the AUC-ROC analysis and a rewritten comparison table with a concluding discussion:

AUC-ROC Analysis
To further assess the discriminative power of the models, AUC-ROC (Area Under the Receiver Operating Characteristic curve) analysis was performed. The First Proposed 1D-CNN and First Proposed CNN-LSTM models were selected for this evaluation, as they demonstrated the highest performance within their respective categories. The AUC-ROC curves, shown in Figure 5, depict how effectively each model distinguishes between schizophrenia patients and healthy individuals. A higher AUC value indicates better model capability in differentiating between the two classes.

Comparison with Other Works
To contextualize the performance of the proposed models, a comparative analysis was conducted against similar studies from recent literature. The results are presented in Table 8, which includes details on the number of subjects, classification methods, and achieved accuracy for each study. As seen below, the proposed CNN-LSTM model achieves a notably high accuracy of 99.35%, outperforming most existing methods despite the use of a relatively small dataset.

Table 4: Comparative analysis of related studies on schizophrenia detection from EEG

Author	Number of Subjects	Classification Method	Accuracy
Jahmunah *et al*. (2019)	SZ:14, Healthy:14	SVM-RBF	92.90%
Shalbaf *et al*. (2020)	SZ:14, Healthy:14	SVM	98.60%
Prabhakar *et al*. (2020)	SZ:14, Healthy:14	AdaBoost	98.77%
Supakar *et al*. (2022)	SZ:45, Healthy:39	RNN-LSTM	98.60%
Oh *et al*. (2019)	SZ:14, Healthy:14	CNN	89.59%
Chu *et al*. (2017)	SZ:40, Healthy:40	CNN	99.20%
Aristizabal *et al*. (2020)	SZ:65, Healthy:40/45/57	CNN+LSTM	72.54%
Sun *et al*. (2021)	SZ:54, Healthy:55	CNN-LSTM	99.22%
Phang *et al*. (2019)	SZ:45, Healthy:39	MDC-CNN	93.06%
Naira and Alamo (2019)	SZ:45, Healthy:39	CNN	90.00%
Sharma *et al*. (2021)	SZ:21, Healthy:24	CNN-LSTM	99.10%
Singh *et al*. (2021)	SZ:45, Healthy:39	CNN-LSTM	98.56%
Current Work	SZ:14, Healthy:14	CNN-LSTM	99.35%

Summary and Limitations

The outstanding performance of the proposed 12-layer CNN-LSTM architecture demonstrates its robustness in classifying EEG signals even with limited training data. The model achieves exceptional precision, sensitivity, and specificity, surpassing several existing approaches.

Advantages of the proposed system:

- Effective with small datasets.
- High classification accuracy.
- Robust architecture combining CNN and LSTM capabilities.

Limitations:

- Dataset size limits generalizability.
- Cannot assess the severity or onset stage of schizophrenia.
- Larger, more diverse datasets are required for broader clinical applicability.

CONCLUSION

Schizophrenia is a complex mental disorder that significantly disrupts brain function, often leading to severe cognitive and emotional impairments. Among various screening methods, electroencephalography (EEG) has emerged as a non-invasive, cost-effective tool capable of capturing functional brain abnormalities associated with schizophrenia. However, interpreting EEG signals remains a challenging task due to their high dimensionality and temporal complexity.

To address this, recent advancements in artificial intelligence—particularly deep learning—have shown great promise in automating the diagnosis process. In this study, the authors proposed and evaluated several deep learning frameworks, including two 1D-CNN models and two CNN-LSTM hybrid architectures, for distinguishing schizophrenia patients from healthy individuals based on EEG data.

Experimental results, supported by rigorous statistical evaluation metrics, demonstrated that all proposed models performed effectively. Notably, the 12-layer CNN-LSTM model achieved the highest accuracy of 99.35%, confirming its superiority in learning discriminative features from EEG signals. These outcomes highlight the potential of deep learning techniques in enhancing early diagnosis and clinical decision-making in schizophrenia.

Looking ahead, the authors intend to expand their research using larger and more diverse datasets encompassing subjects of various age groups and different stages of the disorder. The goal is to develop more generalized and robust models capable of early detection and severity classification of schizophrenia, further contributing to personalized and timely treatment strategies.

CONFLICTS OF INTEREST

Authors have no conflict of interests.

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