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Research Article

A Hybrid Cnn-Lstm-Based Rnn Model for Classification of Schizophrenia

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ABSTRACT

Schizophrenia is a mental health condition that affects the behavior and thought process of a person. With proper treatment, such as medication and therapy, many people with this medical condition are able to manage their symptoms and live meaningful lives. Thus, there is a need for early diagnosis of schizophrenia. However, due to the wide range of symptoms displayed by different schizophrenic patients, accurately identifying schizophrenia can proof challenging. Different conventional methods to try to classify schizophrenia are applied in many instances. Nevertheless, all aspects of the condition could not be sufficiently addressed by any of the conventional classification techniques. Researchers are currently testing the application of deep learning approaches for improved schizophrenia categorization. In this study, we present a novel hybrid RNN model that uses both CNN and LSTM technology for use in the classification of schizophrenia. The twelve layered model was developed using a total of 28 samples as input data. The dataset consisted of EEG signal recordings from 14 healthy controls and 14 schizophrenic patients. After training and testing, an accuracy of 79.35% was recorded by the model. This model has the potential to enable early detection of schizophrenia thereby leading to more optimized treatment and management methods. The study describes a new twelve-layered CNN-LSTM hybrid framework for identifying schizophrenia employing EEG signals. Trained on data from 14 patients and 14 healthy controls, the framework obtained 79.35% accuracy, highlighting deep learning's promise for early success in schizophrenia detection.

1. INTRODUCTION

Schizophrenia is a complex mental health condition that affects how a person feels, behaves, thinks and perceives reality [1]. Common symptoms include slurred speech, hallucinations, loss of motivation or emotional expression, and delusions [2]. Today, treatment typically involves a combination of medication and therapy, although the success of these approaches often depends on the severity of the condition and how well the individual responds to care [3]. The evolution of technology and machine learning, has seen many researchers experiment utilize deep learning techniques for better

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classification of diseases such as [4] schizophrenia [5]. These researchers aim to develop models capable of precisely categorizing people who suffer from schizophrenia based on diagnostic criteria, while utilizing EEG waves as input data [6]. The electroencephalogram (EEG) is a neuroimaging technique used to monitor brain activities or waves. Since EEG signal recordings depict the electrical activity of the brain over a given period of time, the readings obtained from these recordings are naturally sequential. As a result, researchers frequently employ the use of EEG to detect brain issues and extensively study brain illnesses [7]. Our study presents a novel hybrid RNN model for the classification of schizophrenia. The combination of CNN-LSTM and RNN models provide various advantages in schizophrenia classification, including the capacity to handle sequential data, extract spatial features, capture long-term dependencies, and enable multimodal fusion.

2. RELATED STUDIES

Researchers have created several models for the classification of schizophrenia in recent years utilizing sophisticated deep learning algorithms. In 2019, a group of researchers. introduced a model to be used in distinguishing between healthy controls and individuals with schizophrenia. The model created spatial maps from fMRI data using both independent component analysis and convolutional neural networks. Following subject level classification, an average accuracy of 91.32% and 98.75% were attained based on majority vote [8].To interpret EEG readings taken from the brain, Shu et al. developed an eleven-layer convolutional neural network model. Both healthy and schizophrenic patients' brain impulses were gathered and used as experiment input data. During subject based testing, the model achieved an accuracy of 81.26% and 98.07% during non-subject based testing [9].

Kanghan and his team developed a classification algorithm that could classify healthy controls and schizophrenia using outcome visualization and a 3D CNN. When trained on task-based functional magnetic resonance imaging data, the model outperformed similar 3D CNN and support vector machine models, recording classification accuracy levels of 84.15-84.43% [11]. Manohar Latha and Ganesan Kavitha, proposed a method for identifying anatomical anomalies in the brain linked to schizophrenia. This was achieved through the use of deep belief networks to analyze segmented magnetic resonance images of the brain's ventricle [12].

Carlos Alberto presented a categorization model that utilizes EEG signals to distinguish between healthy individuals and patients that had been diagnosed with schizophrenia. The system utilized the Pearson correlation coefficient to create a means of characterizing the connections among the channels. A reduced matrix from the EEG data recordings was used as input data to train the neural network. The suggested categorization model recorded an accuracy of 90% when categorizing [13]. Shuai Wang and his fellow researchers suggested a method of evaluating resting-state fMRI scans of healthy and schizophrenia patients using regional homogeneity [14]. Support vector machines and receiver operating characteristic curves and were employed to assess the impact of aberrant regional homogeneity in distinguishing between healthy individuals and people who are schizophrenic. Overall, the model attained 90.14% accuracy, 91.89% specificity, and 88.24% sensitivity [14] .

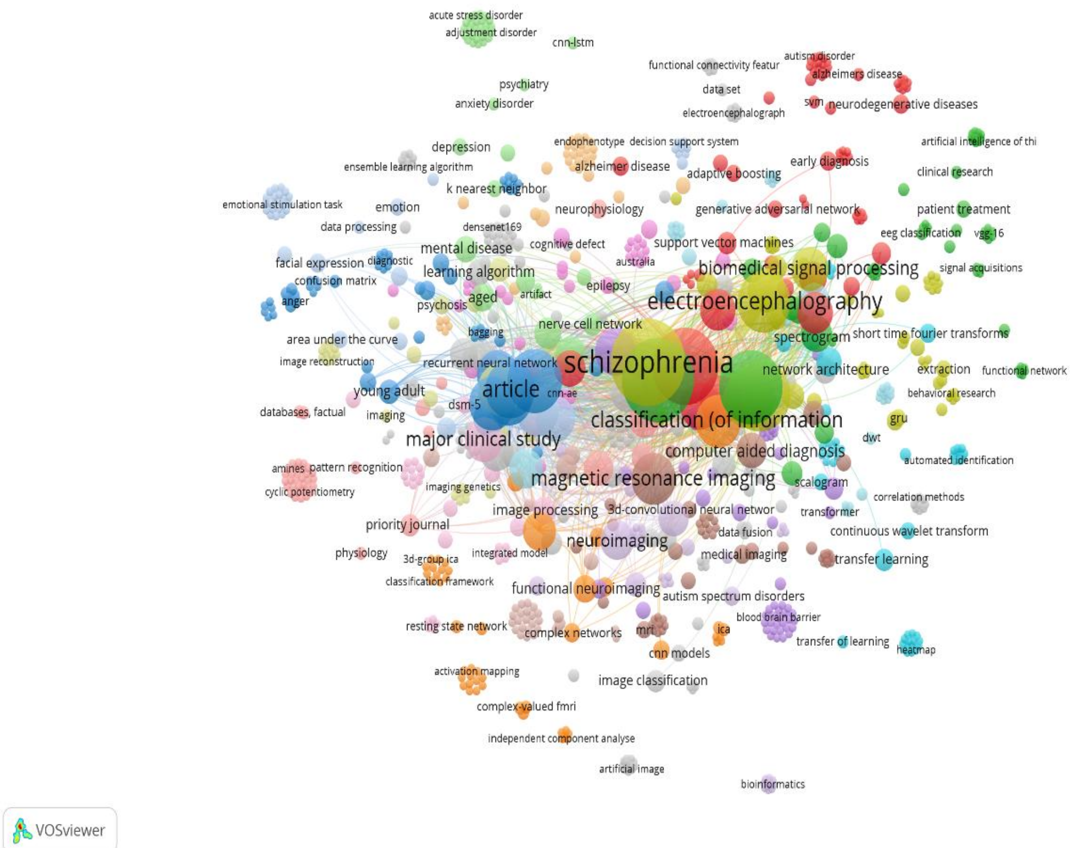

Figure 1: Bibliometric report [10]

The use of a hybrid system to identify schizophrenia in EEG signals was first proposed by Afshin et al in 2021. The system used implemented a rectified linear unit activation function integrated with L2 and z-score normalization. The Afshins model produced findings that were superior to those of the vast majority of previous studies in this field with an accuracy rate of 99.25% [15]. Jia Fu et al. underlined the need to develop an unbiased and accurate approach for identifying negative symptoms of schizophrenia. Jia and his team of researchers were some of the first researchers to explore the use of deep learning algorithms to identify point-point schizophrenia speech. They created a sch-net neural network to analyze schizophrenia speech. The model was able to correctly interpret the speech from the schizophrenia speech data set with an accuracy of 97.68% [16]. In 2021, a team of researchers performed an experiment with a goal to classify the functional relationship between healthy controls and patients with schizophrenia. Correlational analysis was performed on focus areas using preprocessed fMRI data that have been integrated with the transfer learning and VGG16 net methods. The method achieved an accuracy of up to 84.3% [17] . To improve classification accuracy, Jung-Jin Yang and Dong-Woo Ko proposed the use of deep learning algorithms to examine input data set that contain time series images that are EEG based. The study's findings suggested that using EEG based gramian angular field and CNN models could improve the effectiveness and accuracy of identifying a number of mental disorders, including schizophrenia [18]. By integrating Transformer, GridMask and Node2vec together Gan et al. created a high precision computer aided system capable of diagnosing schizophrenia. The experiment proved that using node2vec to convert a brain network formed from fMRI data into low dimensional dense vectors makes it easy for deep learning models to learn from brain network signals. After training and testing, the system recorded a classification accuracy of 97.78% [19]. Despite these promising results, the majority of the reviewed studies only used one deep learning architecture rather than merging several models for potentially better performance.

This paper presents an RNN model that uses both CNN and LSTM technology. By combining CNN and LSTM layers in an RNN architecture we aim to develop a novel model that will have higher resistance to input noise and better feature extraction abilities. Our goal is to create an advanced system with fewer parameters and better understanding of spatial and temporal patterns. This model has the potential to enable early detection of schizophrenia thereby leading to more optimized treatment and management methods.

3. METHODS AND MATERIALS

3.1 Research Methodology.

This work employs deep learning to classify schizophrenia based on EEG signal data. The experimental architecture is divided into several critical phases: data gathering, preprocessing, feature extraction, model construction, training, assessment, and result generation, similar to [20]. EEG signals were obtained from 14 schizophrenia patients and 14 healthy controls. The raw signals were preprocessed, which included filtering, resampling, and noise reduction, to enhance signal quality and eliminate artefacts. The correct characteristics were subsequently extracted in order to detect meaningful trends in the EEG data. An integrated deep learning framework was created by combining Convolutional Neural Networks (CNN) for geometric feature extraction with Long Short-Term Memory (LSTM) networks for temporally sequence training. The data that had been preprocessed and feature extracted was used to train the twelve-layered CNN-LSTM algorithm. Following training, the model's performance was tested using evaluation metrics to determine how well it differentiated between schizophrenia and non-schizophrenic patients. Figure 2 summarizes the complete workflow.

3.2 Execution Frameworks

The analysis was performed through a powerful computing platform to ensure accurate EEG analysis and deep learning approach training. Python 3.0 was chosen as the main programming language because of its versatility and significant compatibility with machine learning packages similarly to [21], [22], [23]. The studies were carried out on a 64-bit Windows 10 Pro operating system powered by an 11th Gen Intel® Core processor, 64 GB of RAM, and 1 TB of storage space, which provided sufficient processing capacity to handle EEG data and model complexity[24].

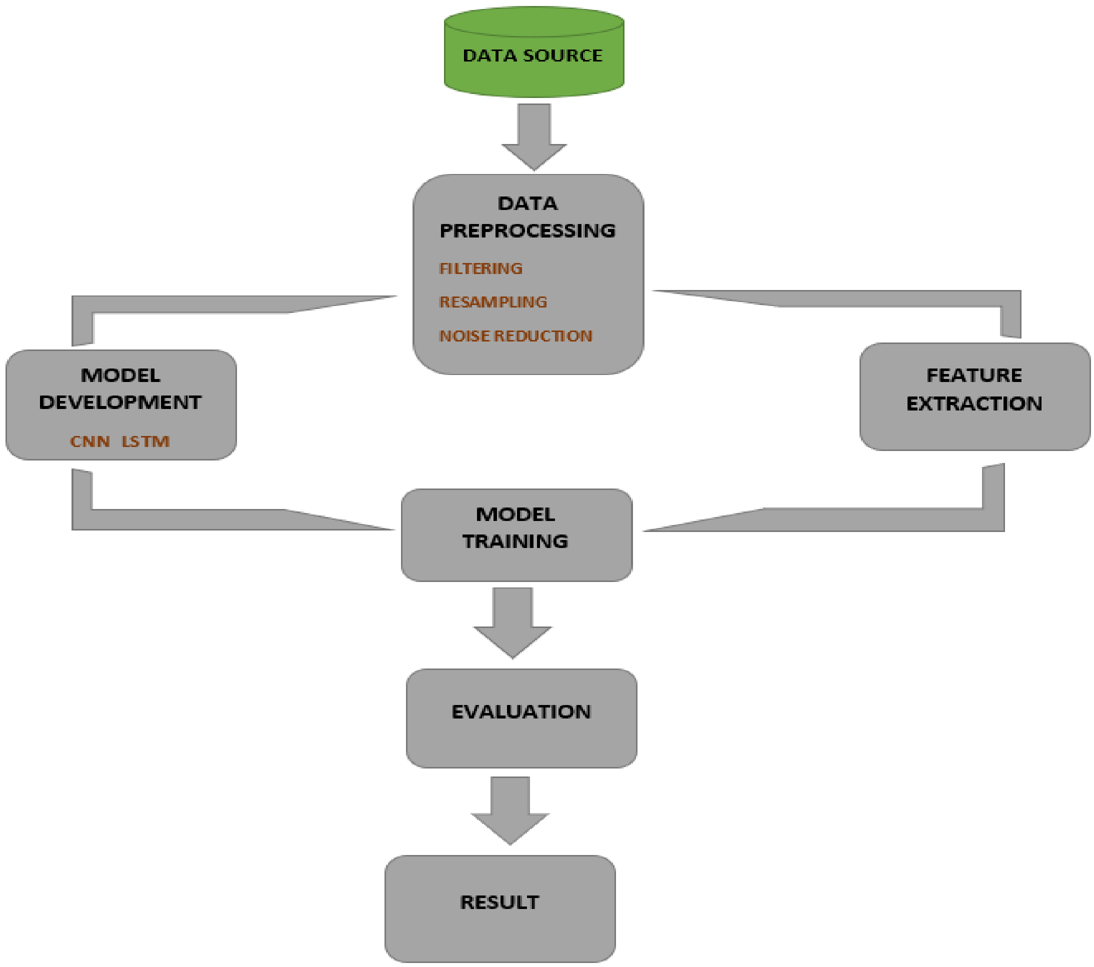

Figure 2: Experimental Framework

Table 1: Frameworks and settings

Frameworks	**Settings**
Programming language	Python 3.0
Operating system	64bit operating system x 64-based processor
Windows	Windows 10 pro
Random Access Memory (RAM)	64.0GB
Libraries	TensorFlow, Keras, Numpy, Matplotlib
Storage space	1 TB x1
Processor	11^{th} Gen Intel ® core

3.3 Data Collection:

The EEG dataset was acquired from a public database from the Polish Academy of Sciences http://repod.icm.edu.pl/dataset.xhtml?persistentId=doi%3A10.18150%2Frepod.0107441&utm_sourc

e=chatgpt.com. The dataset called "dataverse_files" was downloaded and used for the purpose of this research. The data was collected from a research Department in Polish Academy of Sciences Zakład[25]. The data consists of time series data reflecting electrical activity recorded from reference electrode implanted on the scalp. Recordings were captured using 19 EEG channels with a sampling rate of 250 hertz. A total of 28 samples were used as the input data, 14 of which were obtained from healthy individuals and 14 from patients with schizophrenia. The data were downloaded as .edf files, which are simple to read and manipulate using standard data analysis tools. The dataverse_files dataset is a well-liked option for training schizophrenia classification models and is frequently utilized in the research community.

3.4 Data Preprocessing:

An organized deep learning Data pre-processing approach was utilized, similar to the studies [26]. Following data collection, a "read_data" function was written to read the dataset EEG data from a specified file, after which it was preprocessed to eliminate any redundant or irrelevant data. Preprocessing techniques such as filtering, resampling and noise reduction were utilized to improve the signal quality. Lastly using feature extraction methods, the raw EEG data was transformed into meaningful representations that could be inputted into the hybrid CNN_LSTM based RNN model.

3.5 Feature Extraction

In the feature extraction, the end-to-end learning strategy was adopted, based on [20]. In other words, the CNN layers were tasked with spatial feature extraction, while the LSTM layers learned the temporal dependencies within the EEG.

3.6 Model Development:

The model was developed using python under the google collab environment, key libraries such as mne, numpy, pandas, matplotlib, pyplot etc [27]. which were needed for evaluation were imported. We utilized the tensorflow keras API design the architecture of the model incorporating five CNN Conv1D layers, six LSTM layers, and a dense output layer.

Table 2: Model Architecture

Types of layers	**Configuration**
Input	2D EEG epochs (19 channels X time points)
Output	Dense layer with 1 unit and sigmoid activation
CNN Block	5X ConV1D + ReLu +MaxPooling 1D
Drop out	0.5 after each LSTM to reduce overfitting
LSTM Block	6X LSTM layers with 64 units

Using the convolutional filters of its CNN layers, the model identified significant patterns across several EEG channels while extracting spatial features of the data. Over time, the LSTM layers examined these spatial features and recorded any temporal dependencies in the EEG data series. At the model's output layer, a sigmoid activation function was applied this enabled the model to perform binary classification. Maxpooling1D layers and 'ReLU' activation were used to regularize the model, while Dropout layers were used to prevent overfitting as shown in Table 2.

3.7 Model Training and Evaluation:

During training, binary cross entropy loss function was used to measure how well the model's predictions matched the actual labels, providing feedback to improve learning. The Adam optimizer was employed to efficiently update the model's weights during training, helping the model learn faster and more accurately.

Table 3: Training Parameters

Training Parameters	**Values**
Hardware	Intel i7 CPU, 64GB RAM, 1 TB SSD
Framework	Tensor Flow +Keras
Validation split	20%
Epochs	20
Batch size	120

Following this, the data into validation and training sets using a GroupKFold technique which enabled the model to accomplish group-wise separation. Standard scaling was applied to the data using scikit-learn "StandardScaler". The model was trained using 120 batches over 20 epochs as shown in table 3. Following this, the model was evaluated using a set of data for validation. For each fold of the cross-validation procedure, the model's accuracy was calculated and saved in the "accuracy" list. The mean accuracy was determined by averaging the accuracy values acquired from each fold. The model's overall accuracy was reported as the mean accuracy across all folds.

4. RESULTS AND DISCUSSION

The CNN_LSTM based RNN model classified healthy control and schizophrenic patients brain recordings with a 79.35 % accuracy rate. From our results, the model performance is very good and thus, we say the generated CNN-LSTM based RNN model will be useful to physicians as a diagnostic tool for detecting early stages of schizophrenia as shown in Table 4.

Table 4: Performance metrics

Metric	**Score %**
Accuracy	79.35
Recall	80.50
Precision	77.80
F1-score	79.10
AUC-ROC	0.85

4.1 Comparative Result

Numerous research studies were conducted using deep learning models to identify different medical conditions. Therefore, there are different results obtained based on the approaches utilized.

Table 5: Table of Comparison

Study	Year	Model	Sample size	Accuracy
Our study	**2025**	**CNN+LSTM(RNN)**	**28(14Sz, 14 Hc)**	**79.35**
Shu *et al*	2019	CNN +LSTM (RNN)	28 (14sz, 14 Hc)	79.35
Dong-woo Ko and Junng-jin Yang	2022	CNN	56	91
Gan A *et al*	2019	GridMask	60	97.78
Afshin Shoeibi *et al*	2021	CNN-LSTM	67	99.25

Despite our model exhibiting a lower accuracy (79.35%) compared to other recent research, it is predictable given the small sample size (n = 28) and dependence solely on raw EEG data with no augmentation or multimodal inclusion. Deep learning models typically require huge datasets to generalize successfully, and in our case, the absence of further signal improvements or sophisticated architectures limited peak performance.

5. CONCLUSION

We proposed the use of a hybrid CNN-LSTM based RNN model which is in this paper as a method for classification of schizophrenia. One advantage of using this hybrid model is its ability to extract sample features and capture temporal dependencies and long-term relationships in the timeseries data. The model is trained using EEG brain signal recordings obtained from [13].After training, testing, and performance evaluation, the hybrid RNN model classified healthy control and schizophrenic patients brain recordings with a 79.35% accuracy rate. From the outcomes of this study, it is evident that the hybrid RNN model could be an effective tool that can be used to diagnosis and classify schizophrenia. It is recommended for use to future researchers. To enhance the model's accuracy, future researchers should consider training the model using a larger sample size.

Although the accuracy of the model is not as high as that of numerous recent researches, this is mostly because of the limited sample size and lack of multimodal input or data augmentation approaches. However, the study effectively demonstrates how CNN-LSTM algorithms can learn both temporal and spatial EEG data using a single pipeline. A non-invasive, scalable, and computationally economical diagnostic tool, the suggested method is especially well-suited for clinical settings with limited resources when access to sophisticated imaging technology or sizable datasets is restricted.

Future improvements to this framework could include adding multimodal variables (such as behavioral, imaging, or speech data), implementing data augmentation approaches, and expanding and diversifying the dataset. All things considered, this study adds to the expanding field of neuropsychiatric diagnostics by laying a solid foundation for AI-assisted early identification of schizophrenia using EEG.

Author Contribution

- Conceptualization, Data curation: T. R. Mangai
- Formal analysis, Validation: B. B. Duwa
- Writing - original draft:, Writing - review editing: D. U. Ozsahin

Conflicts of Interest

The author declares no conflicts of interest.

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Data Availability Statement

The dataset used in this study is publicly available [25].

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