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Deep learning model-based Schizophrenia disease detection by analyzing brain EEG signal

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***Abstract*—A mental illness called schizophrenia (ScZ) is characterized by abnormalities in the social, behavioral, perceptual, cognitive, and other domains of life. ScZ is traditionally diagnosed by an experienced psychiatrist conducting patient interviews, which is a laborious, subjective, and biased procedure. Researchers have recently demonstrated that the diagnostic accuracy of ScZ may be improved by integrating the deep learning (DL) model into the detection process. EEG signals offer more thorough insights into the underlying neural mechanisms and brain biomarkers of ScZ than other modalities like computed tomography (CT) scan or functional magnetic resonance imaging (fMRI). The use of EEG signals as an efficient biomarker is still being studied, despite the fact that deep learning models demonstrate encouraging results in identifying ScZ. For automatic ScZ detection using only EEG signals, a thorough evaluation of Extended 1-Dimensional Convolutional Neural Network (Ex-1DCNN) models and Recurrent Neural Network (RNN) deep learning models have been developed. The EEG signals are preprocessed by ICA (Independent Component Analysis) to remove artifacts and noises. These results show that the RNN model outperforms the Ex-1DCNN in terms of test loss, F1 score, and accuracy (86.44% vs 64.78%), making it a better option for ScZ classification.**

***Index Terms*—EEG, Deep Learning, Independent Component Analysis (ICA), Schizophrenia.**

I. Introduction

A dangerous mental illness that alters thoughts, feelings, and behavior is schizophrenia. A combination of delusions, hallucinations, and disordered thought patterns and actions could be the outcome. When someone has a hallucination, they see or hear things that other people aren't witnessing. Firm ideas about untrue things are a sign of delusions. Schizophrenia patients may appear to lose all sense of reality, which can make day-to-day living extremely difficult [1]. Electroencephalogram (EEG) has emerged as a powerful tool for studying the electrical activity and functional changes in the brain associated with Schizophrenia diseases. EEG can help identify alterations in the brain's electrical activities that occur in the early stages of the disease. Machine learning (deep learning) techniques, applied to EEG data, offer the potential to enhance the accuracy and efficiency of Schizophrenia disease diagnosis and classification. Using EEG data for schizophrenia classification is facilitated with early detection and intervention, large-scale data analysis, and reduced diagnosis. EEG (electroencephalogram) records electrical activity in the brain, capturing real-time neural dynamics. This can reveal abnormalities in brain function that are often associated with schizophrenia, such as altered brain wave patterns. Machine learning (deep learning) models can analyze these complex EEG signals to identify biomarkers of schizophrenia, potentially leading to earlier and more accurate diagnoses. This approach could also help in understanding the underlying mechanisms of the disorder, paving the way for better treatments. The application of artificial intelligence (AI) techniques, especially machine learning (ML) and deep learning (DL) has shown promising results for automated schizophrenia detection. Traditional ML models like support vector machines (SVM) and random forests have been utilized to predict schizophrenia using neuroimaging data such as magnetic resonance imaging (MRI). However, these models often require substantial feature engineering and preprocessing, limiting their practical use [2]. In contrast, DL models such as convolutional neural networks (CNNs) have been effective in directly learning patterns from raw EEG and MRI data, significantly improving diagnostic accuracy. Recent advancements highlight hybrid CNN-recurrent neural networks (RNNs) and transfer learning as effective approaches to handle limited annotated datasets, while combining sensor-level and source-level EEG data further enhances diagnostic capability [3]. Multi-modal approaches that integrate both EEG and MRI data offer better robustness and performance. Shen et al. (2023) demonstrated how 3D CNNs can leverage dynamic functional connectivity from EEG data to identify schizophrenia with high precision [3]. However, Sharma et al. (2023) emphasize that these models must balance complexity with interpretability for clinical settings [4]. Key challenges in deploying these models in practice are Ensuring transparency and addressing concerns related to data privacy and bias [5].

II. Materials and Methods

A. EEG Dataset Description

The dataset comprised 14 paranoid schizophrenia patients with 7 males (Age: 27.9 ± 3.3 Y) and 7 females (Age: 28.3 ± 4.1 Y), and 14 healthy controls with 7 males (Age: 26.8 ± 2.9 Y) and 7 female (Age: 28.7 ± 3.4 Y). The patients met the International Classification of Diseases ICD–10 criteria for paranoid schizophrenia (category F20.0). The control group

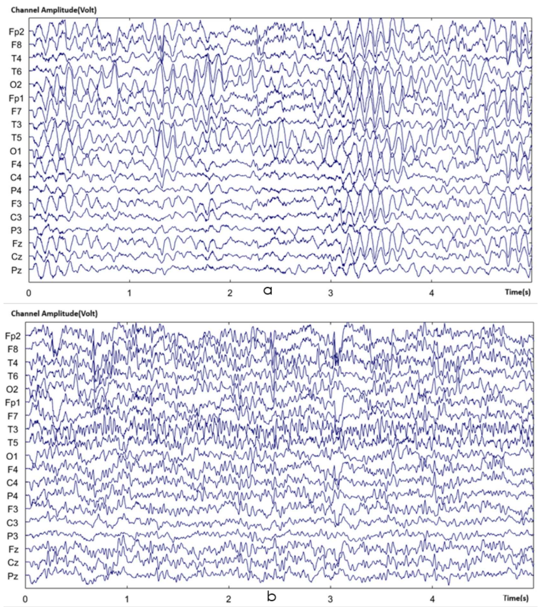

Fig. 1. (a) Healthy Control, (b) Schizophrenia Patient.

was matched in gender and age to the 14 patients completing the study [6]. All subjects were placed in an eyes-closed resting state condition, and their EEG data was captured for 15 minutes. The conventional 10–20 EEG montage with 19 EEG channels—Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2 was used to collect the data at a sampling frequency of 250 Hz. FCz was the location of the reference electrode. EEG signals of a healthy control and a schizophrenia patient are illustrated in Fig. 1.

B. Proposed Methodology

The analytical pipeline of the proposed work for diagnosing Schizophrenia patients employing multichannel EEG signals is shown in Fig. 2. It encompasses six key steps: (i) Preprocessing EEG signals, (ii) Epoching the Signals, (iii) data standardization, (iv) training an Extended 1DCNN (Ex-1DCNN) model (v) training an RNN model, (vi) 10-fold cross-validation testing, and (vii) A comparison between Two model performance also done for better accuracy.

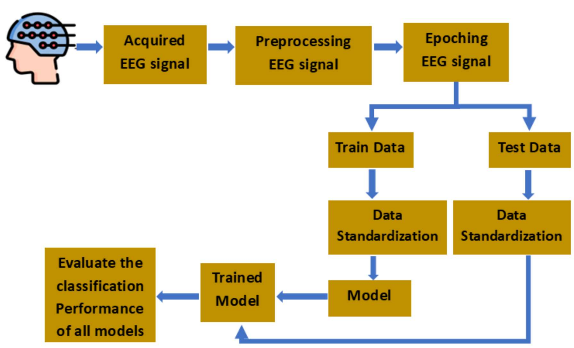

Fig. 2. Analytical pipeline of the proposed work.

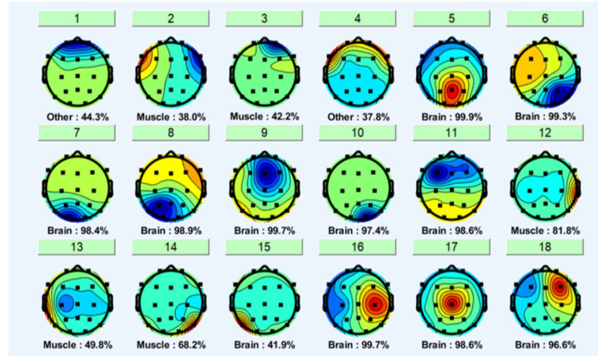

Fig. 3. ICA Components after decomposition.

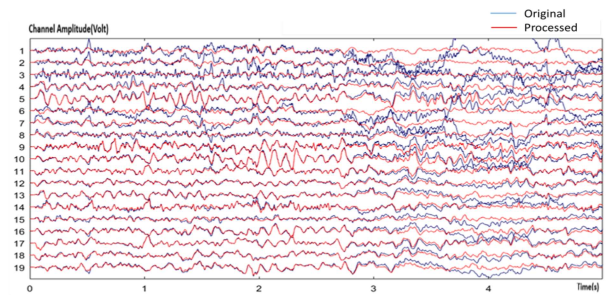

Fig. 4. 19-Channel EEG Signal before and after ICA components removal.

C. Preprocessing EEG Signals

Preprocessing EEG Signals can be contaminated with different artifacts and noises during the acquisition. The artifacts can be from both biological and non-biological sources. Artifacts of biological sources include eye blinks, cardiac activity, movements, and muscular activities, and non-biological sources can be attributed to channel noise and power line noise. For artifacts of non-biological origins, such as power line noise, we employ a 45 Hz notch filter for noise suppression purposes. Biological artifacts can account for the vast majority of artifacts in EEG signals [7]. To ensure that our preprocessed signal accurately represents sole brainwave activity, preventing erroneous analysis, we employ the independent component analysis (ICA) algorithm [8] on EEG data to remove biological artifacts. The ICA algorithm assumes that the EEG signal is a mixture of independent components and distinguishes them as either neurological or artifact components that are suppressed. The process is performed using the MATLAB function EEGLAB as follows:

- Load the Dataset: Load EEG dataset into EEGLAB1
- Preprocess the Data: Reject bad channels and artifacts
- Decompose data by ICA: In EEGLAB ICA decomposition is performed.
- Inspect ICA Components: Visualize and inspect the ICA components to identify and remove artifacts. ICA Components after decomposition are illustrated in Fig. 3.
- Back Project Data: Subtract the identified artifact components from the original data.

A comparative illustration of the EEG signal before and after ICA components removal is shown in Fig. 4.

D. Epoching EEG Signals

Epoching the time series data in 5 s epochs with a one-second overlap between successive epochs.

E. Spliting EEG Signals

After obtaining the preprocessed data, we need to divide the data set into training, testing, and validation sections. In this experiment, we use 80 percent of the data for training and 20 percent for testing and validation. Each section contains schizophrenia and healthy control classes.

F. Extended 1D Convolutional Neural Network (Ex-1DCNN) Architecture

A typical CNN model consists of convolution, pooling, and fully connected layers [9]. Fig. 5(a) illustrates the extended 1DCNN (Ex-1DCNN) architecture that we propose in this study, which comprises 5 1D convolution layers (Filter size=5), Batch normalization layer, 5 pooling layers (Activation LeakyReLU), 2 Dropout layers (0.5) and 1 fully connected layer (Activation= Sigmoid). Unlike the conventional method of employing only max pooling, we combined 2 Maxpooling, 2 Averagepooling, and 1 Global Average pooling layer in the pooling layers. The development of an extended 1DCNN (Ex-1DCNN) architecture resulted from this change [10].

This extended 1DCNN model is designed for binary classification tasks, employing several layers to achieve effective feature extraction and classification. It starts with a Conv1D layer that applies convolution using 5 filters with a kernel size of 3 and strides of 1. Batch normalization follows to stabilize and accelerate training, along with a LeakyReLU activation function to introduce nonlinearity. A MaxPooling1D layer reduces the spatial dimension of the data. The sequence repeats with another Conv1D layer, LeakyReLU activation, and MaxPooling1D layer. Dropout layers, with a 50 percent dropout rate, are interspersed to prevent overfitting. Additional Conv1D layers and average pooling layers further process the data, with GlobalAveragePooling1D ultimately reducing each feature map to a single value. Finally, a Dense layer with a sigmoid activation function provides the binary classification output. The model is compiled with the Adam optimizer and binary cross-entropy loss function, emphasizing accuracy as a performance metric. This structure efficiently captures and processes one-dimensional data for classification tasks.

G. Recurrent Neural Network (RNN) Architecture

In this study, Fig. 5(b) illustrates the RNN architecture with LSTM layers is designed for binary classification tasks, specifically capturing temporal dependencies in input data. An LSTM layer with 128 units is the first layer in the model. using the ReLU activation function and configured to return sequences, allowing for deeper stacking of LSTM layers. This is followed by a Batch Normalization layer to stabilize and speed up training, and a LeakyReLU activation

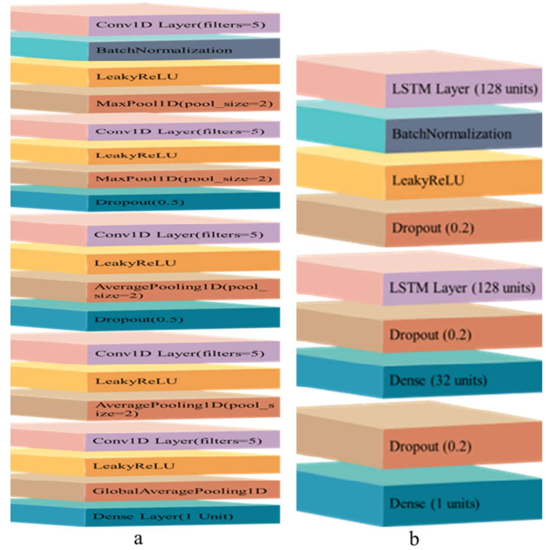

Fig. 5. Model architecture (a) Ex-1DCNN (b) RNN.

function prevents dead neurons by allowing a small gradient even when inactive. A Dropout layer then randomly sets 20 percent of the input units to zero to prevent overfitting and improve generalization. The sequence includes another LSTM layer with 128 units and a ReLU activation, followed by another Dropout layer. The subsequent Dense layer has 32 units with ReLU activation, followed by Dropout. Finally, a Dense layer with a single unit and sigmoid activation outputs the final prediction for binary classification. With accuracy as a performance parameter, the model is assembled using the binary cross-entropy loss function and the Adam optimizer. This architecture, a combination of LSTM layers and regularization techniques, is robust for capturing complex patterns in sequential data while mitigating overfitting. [11].

H. Evaluation of the Models

Upon completing model training for both models, we conducted comprehensive evaluations by testing them on separate test datasets, thus identifying the best-performing model. The result of the experiment is given in the performance Table I. The confusion matrices and the Receiver Operating Characteristic (ROC) curves of the Ex-1DCNN and RNN models are shown in Fig. 6 and Fig. 7, respectively.

III. Discussion

The results presented in Table I represent the performance of the Extended 1-Dimensional Convolutional Neural Network (Ex-1DCNN) model as well as the performance of the Recurrent Neural Network (RNN) model for classifying Schizophrenia Disease using Electroencephalogram (EEG) data. The reported metrics include accuracy, precision, test loss, and F1 score, which provide a comprehensive view of the model's capabilities and limitations. For the RNN model architecture, the accuracy is 86.44%, while for the Ex-1DCNNN model architecture, the accuracy is 64.78%. All other parameters

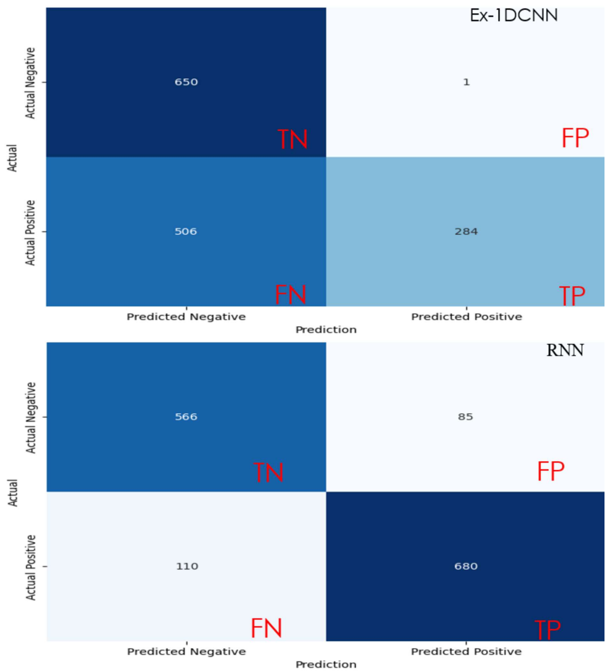

Fig. 6. Confusion Matrix for Ex-1DCNN and RNN models.

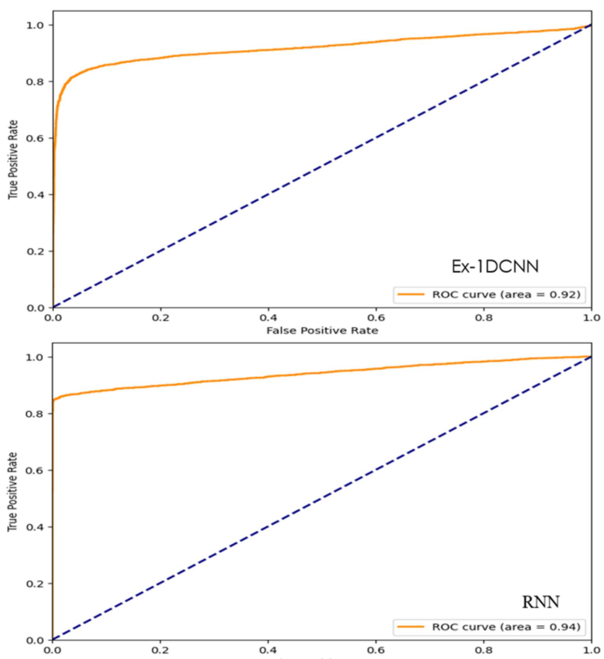

Fig. 7. ROC curves for Ex-1DCNN and RNN models.

(Test Loss, F1 score, Confusion Matrix, AUC of ROC curve) are also better for the RNN model than Ex-1DCNN except precision. Therefore, for this experiment, the RNN model is preferable for classifying schizophrenia.

IV. Conclusion

In this work, our objective was to creat a deep learning model for the classification of Schizophrenia (Scz) by analyzing the raw EEG dataset (EDF = European Data Formate). We used a total of 28 brain EEG data. Our approach involved utilizing an Extended 1-Dimensional Convolutional Neural Network (Ex-1DCNN) and a Recurrent Neural Network (RNN) for the classification of Schizophrenia and Healthy control. In addition, we have compared the performances of these two deep learning models to find which model may contribute better to detecting Schizophrenia diseases. In this experiment, the higher accuracy was obtained from the RNN model. The performance of the Ex-1DCNN model is low compared to the performance of the RNN model. Hence, the RNN model architecture can be used as a reliable method for the automated detection of Schizophrenia diseases.

In essence, This study advances the continuous investigation of novel techniques for automated and early schizophrenia detection, ultimately striving to make a positive impact on the lives of individuals with Schizophrenia by enabling more timely interventions and personalized treatment strategies.

TABLE I
Result of different models and performance parameters

Models	Accuracy (%)	Test Loss	Precision	F1 score
RNN	86.44	0.326	0.89	0.874
Ex-1DCNN	64.78	0.938	0.99	0.527

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