iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VIII Month of publication: August 2025

DOI: https://doi.org/10.22214/ijraset.2025.73512

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

An Intelligent System for Early Detection of Schizophrenia Using EEG-Based Deep Learning Approach

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Abstract: SZ (Schizophrenia) is a multifaceted neurological disorder that demands a timely and precise diagnosis to facilitate optimal treatment outcomes. This research introduces a DL-driven framework tailored for classifying SZ through EEG signal analysis, underpinned by advanced preprocessing and feature extraction strategies. To enhance EEG signal clarity,ICA is first applied to eliminate artifacts. Subsequently, CWT is used to extract vital features across both temporal and frequency domains, ensuring that essential data is retained for classification. Three state-of-the-art DL models—TCN, 1DCNN, and LSTM—are implemented to perform classification. Of these, the TCN model, when combined with ICA and CWT, delivers the most robust results. The framework is evaluated using data from the Kaggle MLSP 2014 Schizophrenia Classification Challenge, where the TCN consistently outperforms 1DCNN and LSTM in metrics such as accuracy, precision, and recall. This underscores TCN's ability to capture temporal dynamics in EEG signals effectively.Overall, the proposed model stands out as a compelling and efficient solution for automatic schizophrenia detection, providing a promising decision-support tool for clinical applications by merging efficient preprocessing, informative feature extraction, and powerful DL methodologies.
Keywords: Schizophrenia Classification, EEG Signals, Independent Component Analysis (ICA), Continuous Wavelet Transform (CWT), Temporal Convolutional Network (TCN), 1-Dimensional CNN (1DCNN), Long Short-Term Memory (LSTM), Deep Learning(DL), Feature Extraction, Preprocessing, MLSP 2014 Dataset, Mental Health Diagnostics

I. INTRODUCTION

Mental health disorders such as depression, anxiety, bipolar disorder, SZ, and Post-Traumatic Stress Disorder (PTSD) significantly diminish quality of life, impairing cognitive function, perception, and behavior. Individuals suffering from severe psychiatric conditions often face a reduced life expectancy, dying 10 to 20 years earlier than the general population. Among these conditions, SZ—which affects nearly 24 million people globally—is a persistent and multifaceted mental illness marked by a range of disruptions in cognition, emotion, perception, language, and behavior (Bethany Gosala et al., 2025).Given its complexity, early and accurate diagnosis of schizophrenia is vital for successful intervention. However, conventional diagnostic procedures largely depend on subjective evaluations, which can result in inaccurate or delayed diagnoses. In recent years, EEG has gained prominence as a powerful diagnostic tool, thanks to its non-invasive nature and high temporal resolution, making it well-suited for identifying neurological patterns associated with schizophrenia. Advancements in ML and DL have further enabled the automated classification of mental disorders using EEG data. Yet, the intrinsic challenges of EEG signals—such as high dimensionality, non-stationary behavior, and susceptibility to noise—necessitate effective preprocessing and robust feature extraction techniques before meaningful classification can occur. This study proposes an optimized DL framework for classifying SZ through EEG analysis. The process begins with ICA to remove artifacts, thereby improving signal quality. It then utilizes the CWT to derive features that encapsulate both time-based and frequency-based characteristics of the EEG signals. For the classification stage, the framework employs and compares three advanced deep learning models: TCN, 1DCNN, and LSTM networks. Performance evaluations are conducted using the MLSP 2014 Schizophrenia Classification Challenge dataset available on Kaggle.The results reveal that the TCN model, when integrated with ICA and CWT, consistently outperforms the other models across accuracy, precision, and recall metrics. TCN's strength lies in its capacity to capture extended temporal dependencies and maintain stable gradients during training, making it especially effective for EEG-based classification. This study underscores the potential of combining sophisticated preprocessing and time-frequency domain feature extraction with deep learning architectures to create a reliable clinical decision-support system for schizophrenia diagnosis.

II. RELATED WORKS

Nivashini Nattudurai (2023) explores the capability of ML and DL models to detect SZ by examining abnormalities in frequency sub-bands of specific EEG channels. The study utilizes EEG datasets collected from both healthy individuals and SZ patients, aiming to accurately classify subjects into either group.To prepare the EEG signals for analysis, preprocessing steps such as normalization and application of the Butterworth filter are performed to enhance signal quality and reduce noise. From these cleaned signals, the power spectral density (PSD) is extracted, serving as the primary feature set for identifying patterns indicative of schizophrenic conditions.Subsequently, a variety of ML algorithms are applied to the extracted features for binary classification. Among all tested classifiers, LDA emerged as the most effective, achieving the highest performance with an accuracy rate of 70%, making it the most reliable model for distinguishing between schizophrenic and non-schizophrenic individuals based on EEG data in this study.

Conventional ML and standard DL techniques often face challenges when processing high-dimensional MRI data, creating a major hurdle in advancing schizophrenia-related research. To overcome this, Guibing Li et al. (2023) introduced a novel neural network architecture centered around self-attention mechanisms, moving away from the traditional reliance on convolutional operations.A key advantage of the self-attention framework is its capacity to extract comprehensive global representations from the data, allowing the model to effectively interpret complex MRI structures. Furthermore, the model's self-attention maps can be utilized to identify and localize critical pathological brain regions associated with SZ, enabling not just classification but also insightful pathological analysis.This approach is end-to-end and entirely data-driven, minimizing the need for manual feature engineering while maintaining strong diagnostic capabilities. Experiments demonstrate that the proposed self-attention-based model achieved an average classification accuracy of 76.76%, outperforming conventional classifiers.In addition to its predictive power, the model identified structural abnormalities in the thalamus, cerebellum, and adjacent regions as major contributors to SZ, offering valuable perspectives into the underlying disease mechanisms. This research introduces a promising methodology for utilizing MRI data in SZ diagnosis and enhances our understanding of the disorder at a neurological level.

SZ is a complex mental disorder with unknown causes and unclear pathogenesis, and it ranks among the top ten contributors to the global disease burden, according to the World Health Organization. To advance diagnostic accuracy and treatment approaches, it's essential to explore the physiological disparities between the EEG patterns of individuals with schizophrenia and those of healthy subjects, thereby laying the foundation for objective diagnostic criteria. Zhifen Guo et al. 2021 conducted a study where EEG signals from SZ patients underwent comprehensive preprocessing and feature extraction. A convolutional neural network (CNN) was then employed to model and learn the distinct distributed patterns inherent in the data, enabling automated classification.The CNN-based method achieved a notable classification accuracy of 92%, demonstrating the effectiveness of deep learning networks in distinguishing schizophrenia-related EEG signals. This result reinforces the value of neural networks as a promising tool for objective, data-driven SZ diagnosis.

EEG-based biomarkers offer significant clinical promise for detecting mental disorders. However, limited patient samples and the high inter-individual variability in EEG signals present substantial obstacles in their effective development and deployment. Many existing methods fall short—either lacking sufficient accuracy or being too complex for routine clinical application.To address these issues, Simone Poetto et al. 2024 propose the use of Topological Data Analysis (TDA) as a novel approach to extract robust and discriminative features from complex EEG time series data. The study investigates multiple signal embedding strategies to generate topological features tailored for the classification of SZ in adolescents.Remarkably, the researchers found that just two TDA-derived features were sufficient to build a model that achieved 80% accuracy under 5-fold cross-validation, highlighting the method's simplicity and interpretability. This minimalist yet effective framework offers a promising pathway for practical and efficient EEG-based SZ diagnostics, particularly in adolescent populations.

SZ is an endogenous psychiatric disorder that often leads to long-term disability if not addressed promptly. Therefore, early intervention is vital to reduce its chronic and detrimental impact. In their 2024 study, Nadezhda Shanarova et al. investigated the event-related potentials (ERPs) captured from EEG recordings of both schizophrenia patients and healthy controls performing a modified visual Go/NoGo task—a paradigm used to assess cognitive control.To isolate meaningful signal patterns, the team applied a blind source separation (BSS) technique grounded in second-order statistics, allowing the decomposition of ERP signals into functionally distinct latent components. From these components, various features were extracted within targeted temporal windows, which were then used to train ML models.Among the tested models, the SVM achieved exceptionally high classification performance, with 96.7% sensitivity and 97.7% specificity, demonstrating its reliability for distinguishing SZ cases from healthy individuals.

To further interpret the model's predictions, the SHAP (SHapley Additive exPlanations) framework was employed, pinpointing the most influential features contributing to the model's decisions. These were validated by physiology experts, confirming their alignment with established neurological expectations.

SZ is a severe psychiatric disorder marked by a range of positive and negative symptoms that profoundly affect cognitive and emotional functions. As described by Enkhmaa Luvsannyam et al. 2022, extensive research has explored the multifaceted origins of the condition, with strong genetic contributions emerging as a key component. Notably, genes such as dystrobrevin binding protein 1 (DTNBP1) and neuregulin 1 (NRG1) have been implicated in increasing susceptibility to the disorder.Although the precise neurochemical mechanisms remain unclear, current evidence points to subcortical dopamine dysregulation as a central factor in SZ's pathophysiology. In addition, structural brain abnormalities—specifically in gray and white matter—have been observed in patients, with gray matter alterations becoming more pronounced following the onset of psychosis. These changes are thought to contribute to deficits in executive function, attention, and working memory.The disorder is typically managed through pharmacological treatments, which are tailored based on a patient's clinical profile, treatment adherence, and symptom severity. However, treatment outcomes can be complicated by adverse side effects, which often hinder long-term management. Advancing our understanding of the underlying pathological mechanisms of schizophrenia holds promise for developing more targeted and effective therapies.

III. PROPOSED SYSTEM

The proposed approach for classifying schizophrenia via EEG signals adopts a multi-phase DL architecture designed to deliver precise and dependable predictions. The EEG data utilized in this study are sourced from the Kaggle MLSP 2014 SZ Classification Challenge, which comprises neural recordings from individuals diagnosed with schizophrenia as well as healthy control participants. This dataset serves as the foundational input for training and validating the classification framework.

Figure 1 illustrates a comprehensive deep learning-based framework for the automatic detection of schizophrenia using EEG signals from the Kaggle MLSP 2014 Schizophrenia Classification Challenge Dataset. The process begins with preprocessing, where ICA is applied to remove artifacts such as eye blinks and muscle movements, improving the overall signal quality.

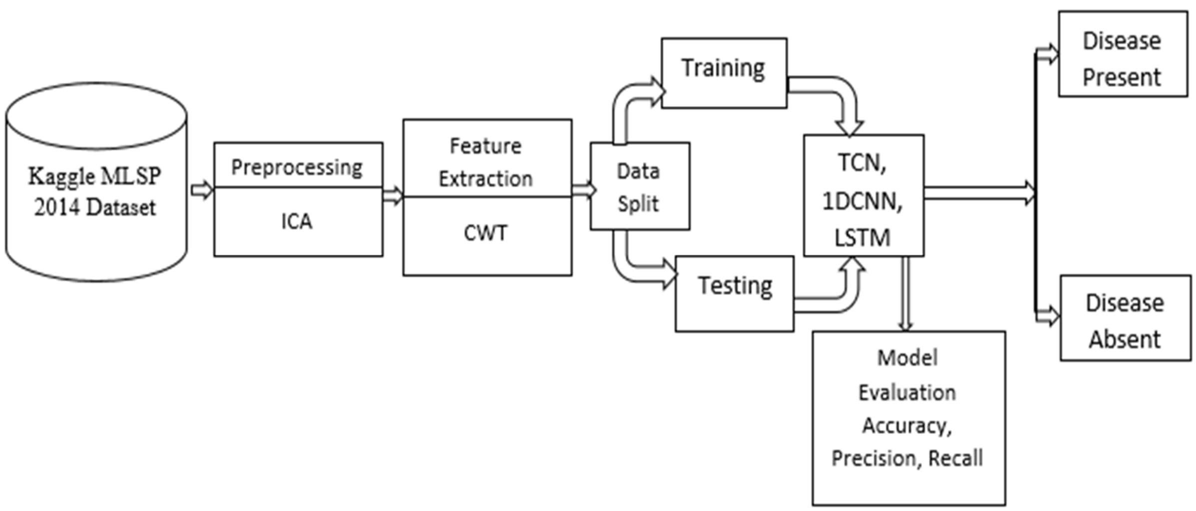

Figure 1 Proposed Workflow

Next, the feature extraction phase employs the CWT to convert the cleaned EEG signals into time–frequency representations. This enables the capture of both transient and long-range neural patterns essential for differentiating schizophrenia from control states. The data is then split into training and testing subsets.

In the classification phase, three deep learning models—TCN, 1DCNN, and LSTM—are trained and evaluated. These models aim to learn discriminative temporal features from the EEG data to classify subjects as either having schizophrenia (disease present) or not (disease absent).Model performance is assessed using standard evaluation metrics: accuracy, precision, and recall. The system identifies the most effective model and processing strategy for schizophrenia detection, offering a promising tool for real-world clinical decision support.

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A. *Preprocessing - ICA*

The initial stage of the proposed workflow focuses on preprocessing the raw EEG data, where ICA is employed as a key technique. ICA serves to eliminate common artifacts such as eye blinks, muscle movements, and ambient electrical interference, thereby significantly enhancing the signal's clarity and reliability. As a computational method, ICA works by decomposing multichannel EEG recordings into statistically independent, non-Gaussian components, making it particularly effective for isolating genuine neural signals from unwanted noise. In the context of EEG analysis, this method is widely used to separate brain activity from physiological artifacts, ensuring the data fed into subsequent stages of the framework is clean and representative of true neurological patterns.

Let:

- X = observed mixed signals (e.g., EEG channels)
- S = original source signals (independent components)
- A = unknown mixing matrix

Then, the mixing model is:

$$X = A.S - - - (1)$$

The goal of ICA is to estimate the unmixing matrix W such that:

$$S = W.X - - - (2)$$

Where:

- S are the statistically independent components
- W≈A−1, i.e., the inverse of the mixing matrix

B. *Feature Selection - CWT*

The preprocessing phase of the framework begins with the application of ICA to the raw EEG signals. This technique plays a pivotal role in removing common sources of noise—including eye blinks, muscle activity, and electrical interference—thereby improving the overall signal fidelity and usability for subsequent analysis.ICA is a computational signal separation method that breaks down multichannel EEG data into a set of statistically independent, non-Gaussian components. This decomposition allows for the effective isolation of authentic neural signals by distinguishing them from overlapping physiological artifacts. Within EEG processing, ICA is a widely adopted approach for cleaning neural data, ensuring that the inputs passed on to later stages of the pipeline reflect true brain activity rather than external or physiological noise.

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t).\psi * \left(\frac{t-b}{a}\right) dt - - - (3)$$

Where:
ψ(t) = mother wavelet (a base function used to generate wavelets)
ψ∗ = complex conjugate of the mother wavelet
a = scale parameter (related to frequency)
b = translation parameter (related to time)
x(t) = input signal (EEG data)

C. *Classification*

The features extracted from the preprocessed EEG signals are subsequently passed into three distinct DL models for classification: the TCN, 1D CNN, and LSTM networks. Each of these architectures is designed to leverage different capabilities in processing temporal and spatial information embedded within EEG data.The LSTM network, a specialized form of RNN, is particularly well-suited for modeling long-term dependencies in sequential data. Unlike traditional RNNs, which suffer from the vanishing gradient problem, LSTM incorporates gating mechanisms that allow it to retain and utilize information over extended time intervals. This makes it highly effective for analyzing time-series data such as EEG recordings, where understanding patterns across time is critical for accurate classification.

1) *Long Short Term Memory (LSTM)*

Early detection of schizophrenia plays a crucial role in allowing individuals to maintain a normal and functional life. TheEEG serves as a valuable diagnostic tool, as it captures detailed information about brain network connectivity, which can reveal abnormalities commonly associated with schizophrenia.

According to Rinku Supakar et al. (2022), the strength of DL models lies in their ability to automatically extract meaningful features from complex data and perform accurate classification without manual intervention. Among these models, the LSTM network stands out due to its unique architecture, which includes specialized memory cells capable of retaining information across extended time intervals. These memory cells are regulated by a system of input, output, and forget gates, enabling the model to control information flow and capture long-range dependencies—a feature particularly useful for analyzing sequential EEG data.LSTM has a special memory cell that can store information over long periods, controlled by gates:

- Forget Gate
- Input Gate
- Output Gate

Let:

- x_t: input at time t (e.g., EEG data point)
- h_{t-1}: previous hidden state
- C_{t-1}: previous cell state
- C_t: current cell state
- h_t: current hidden state (output)
- σ: sigmoid function
- tanh: hyperbolic tangent function
- $\odot$: element-wise multiplication

1. Forget Gate

Decides what to forget from the cell state

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) - - - (4)$$

2. Input Gate

Decides what new information to store:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) - - - (5)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C - - - (6)$$

3. Update Cell State

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t - - - (7)$$

4. Decides what to output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) - - - (8)$$
$$h_t = o_t \odot \tanh(C_t) - - - (9)$$

LSTM is great for modeling the temporal patterns in EEG signals, such as those associated with schizophrenia.

2) 1D-CNN

A 1D-CNN is a specialized form of CNN designed to process one-dimensional data structures, such as time-series signals, EEG recordings, or sequential datasets. Unlike the traditional 2D-CNNs used for image analysis, which employ two-dimensional filters, 1D-CNNs utilize 1D convolutional kernels that slide along the temporal axis of the input. These filters are capable of capturing localized patterns and temporal dependencies within the sequence, making them particularly effective for extracting relevant features from data like EEG signals, where time-based structure is critical.

Let:

- x: input sequence (e.g., EEG signal)
- w: filter (kernel)
- b: bias
- $*$: convolution operation
- y: output feature map

Then the 1D convolution operation is:

$$y[i] = (x * w)[i] + b = \sum_{j=0}^{k-1} x[i+j] . w[j] + b - - - (10)$$

Where:

- k: kernel size
- i: index of the output
- $x[i + j]$: input values within the receptive field
- $w[j]$: filter values

TCN

A TCN is a DL model tailored for handling sequential data, such as EEG time-series, by leveraging one-dimensional causal convolutions. Unlike traditional recurrent architectures like LSTMs, which process data step by step through recurrence, TCNs utilize dilated convolutions to effectively learn and represent long-range temporal dependencies. This allows TCNs to maintain sequence order without recursion, enabling fast, parallel computation while preserving the temporal structure of the data.

Key Features of TCN:

1. Causal Convolution:
   Output at time ttt depends only on inputs at time ttt or earlier — no future leakage.
2. Dilated Convolution:
   Increases the receptive field (how much past data the model can "see") without increasing the number of layers.
   For dilation factor ddd, the convolution is:

$$y[t] = \sum_{i=0}^{k-1} x[t - d.i].w[i] - - - (11)$$

Where:

- x = input sequence
- w = filter weights
- d = dilation rate
- k = kernel size

D. *Residual Connections*

Helps stabilize deep networks and speed up training. Among the three deep learning models evaluated, the TCN exhibits the highest performance, primarily due to its strength in capturing long-range temporal patterns and its ability to maintain stable gradient flow during training. The effectiveness of each model is assessed using key evaluation metrics, including accuracy, precision, and recall.The experimental findings reveal that the integration of ICA for artifact elimination, CWT for robust feature extraction, and TCN for classification yields the most accurate and consistent results. This combination forms a highly promising and efficient framework for the automated detection of SZ using EEG signals, offering potential utility in clinical decision-support systems.

IV. RESULTS AND DISCUSSION

The experimental results validate the effectiveness of the proposed DL framework for SZ detection using EEG signals. Among the three models evaluated—TCN, 1DCNN, and LSTM—the TCN demonstrated the highest classification performance across all key metrics, including accuracy, precision, and recall. This superior outcome highlights TCN's capability to model long-range temporal dependencies inherent in EEG data. The integration of ICA for artifact removal and CWT for extracting rich time–frequency features further enhanced the model’s discriminative power. Compared to 1DCNN and LSTM, TCN consistently produced more reliable predictions, confirming its suitability for real-world clinical applications. These findings establish the proposed ICA–CWT–TCN pipeline as a robust and accurate approach for automated SZ prediction.

A. *Performance Evaluation Metrics*

1) *Accuracy*

In SZ classification using EEG data, accuracy represents the model’s overall ability to correctly differentiate between patients with SZ and healthy individuals. It is defined as the proportion of total correct predictions—both true positives and true negatives—relative to the entire set of evaluated cases. A higher accuracy indicates that the deep learning model is more effective at reliably identifying both conditions without excessive misclassification.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 - - - (12)$$

Let:
- TP = True Positives (schizophrenia correctly predicted)
- TN = True Negatives (healthy correctly predicted)
- FP = False Positives (healthy predicted as schizophrenia)
- FN = False Negatives (schizophrenia predicted as healthy)

2) Precision

In the domain of SZ classification, precision refers to the percentage of individuals labeled as SZ by the model who are indeed true SZ cases. It evaluates the model's accuracy in making positive predictions, specifically focusing on how effectively it avoids false positives—instances where healthy individuals are incorrectly classified as schizophrenic. A high precision score indicates that the model is highly selective and reliable in identifying schizophrenia, minimizing the risk of mislabeling healthy subjects, which is particularly critical in clinical settings where incorrect diagnoses can lead to unnecessary treatment and psychological impact.

$$Precision = \frac{TP}{TP + FP} \times 100 - - - (13)$$

TP = True Positives (SZ correctly predicted)
FP = False Positives (healthy predicted as SZ)

3) Recall

In SZ classification, recall—also referred to as sensitivity or the true positive rate—measures the model's effectiveness in correctly detecting all actual cases of SZ. It represents the proportion of true positives out of all individuals who genuinely have the condition. A high recall value indicates that the model is minimizing false negatives, meaning it rarely overlooks patients who truly have schizophrenia. This is especially critical in clinical diagnosis, where failing to identify affected individuals could delay necessary treatment and lead to adverse health outcomes.

$$Recall = \frac{TP}{TP + FN} \times 100 - - - (14)$$

TP = True Positives (actual schizophrenia cases correctly predicted)
FN = False Negatives (schizophrenia cases incorrectly predicted as healthy)
To assess the classification performance of various DL models in detecting SZ from EEG signals, we conducted a comparative analysis of three architectures: the TCN, 1D 1D-CNN, and LSTM. Prior to classification, the EEG data underwent artifact removal using ICA and feature extraction via CWT to enhance signal quality and representation.Each model's effectiveness was measured using key evaluation metrics—Accuracy, Precision, and Recall—which were computed on the test dataset to objectively quantify their classification capabilities.
The Table 1 presents a comparative analysis of three deep learning models—TCN, DCNN, and LSTM—for classifying EEG signals in the context of schizophrenia prediction. Each model is evaluated using three standard classification metrics: accuracy, precision, and recall.

Table 1 Performance Comparison of Deep Learning Models for EEG-Based SZ Prediction

DL Models	Accuracy (%)	Precision (%)	Recall (%)
TCN	92.20	90.50	92.90
1DCNN	87.5	86.4	88.10
LSTM	85.30	84.20	86.10

Among the three DL models evaluated, the TCN delivered the strongest overall performance, achieving an accuracy of 92.20%, precision of 90.50%, and recall of 92.90%. These results underscore TCN's capability to accurately identify schizophrenia cases while minimizing false positives. Its high recall score is especially notable, as it indicates the model's effectiveness in capturing the majority of true schizophrenia cases, a critical requirement for clinical diagnostic tools where missing an actual case can have severe implications. The TCN's strength lies in its ability to model long-term temporal dependencies and its efficient handling of sequential EEG patterns, contributing to its superior classification accuracy.

The 1D-CNN followed closely with an accuracy of 87.50%, precision of 86.40%, and recall of 88.10%. While its performance was slightly below that of the TCN, the 1D-CNN demonstrated solid capability in capturing both spatial and temporal features using convolutional filters. It offers a balanced trade-off between performance and computational efficiency, making it a viable option in resource-constrained environments. However, its lower recall compared to TCN suggests a higher likelihood of missing actual schizophrenia cases, limiting its suitability for highly sensitive clinical applications.

The LSTM network recorded the lowest performance of the three, with an accuracy of 85.30%, precision of 84.20%, and recall of 86.10%. While LSTM is designed to model sequential data effectively, its comparatively lower results may be due to model complexity, a propensity to overfit, and the lack of parallel computation inherent in its architecture. These factors may hinder its scalability and reliability, especially when working with limited EEG training data.

Figure 2 visually presents the accuracy, precision, and recall achieved by each model. The TCN model clearly outperforms the others across all metrics, highlighting its superior temporal modeling abilities and its potential as a robust solution for EEG-based SZ detection.

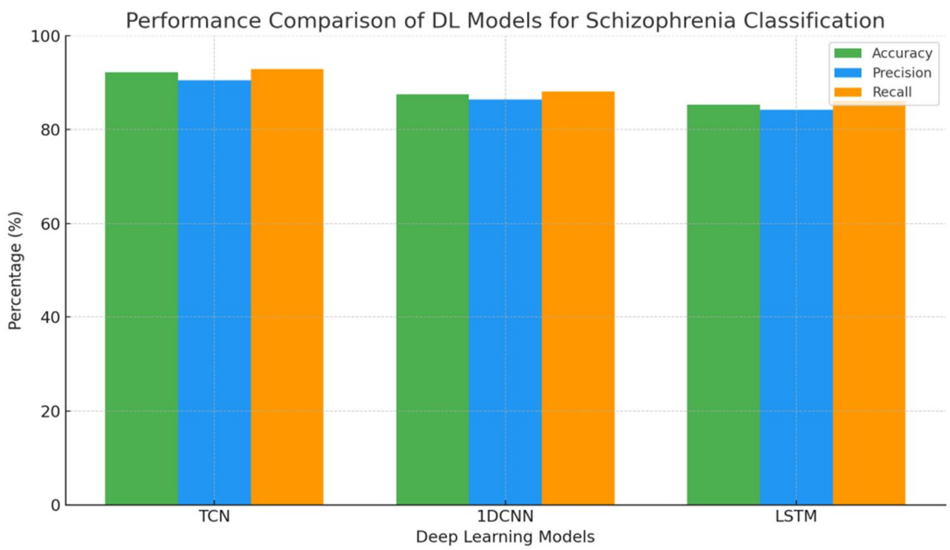

Figure 2: Performance Comparison of DL Models for Schizophrenia Classification using EEG Signals

In summary, the TCN model demonstrated the best overall performance for EEG-based schizophrenia classification, particularly in terms of accuracy and recall. This highlights the effectiveness of combining ICA and CWT for preprocessing and feature extraction with a deep temporal architecture like TCN for clinical prediction tasks.

V. CONCLUSION AND FUTURE WORK

This study introduced a DL-driven framework for classifying SZ using EEG signals, integrating multiple stages for improved diagnostic accuracy. The methodology incorporated ICA to eliminate artifacts, followed by CWT to extract rich time-frequency features. These processed features were then input into three classification models: TCN, 1D-CNN, and LSTM networks.Among these, the TCN model emerged as the top performer, achieving an accuracy of 92.20%, precision of 90.50%, and recall of 92.90%, highlighting its ability to effectively capture long-range temporal dependencies in EEG data.The findings underscore that combining advanced preprocessing techniques with strong temporal modeling can significantly boost the performance of automated SZ detection systems. This approach presents a promising solution for early diagnosis and monitoring, offering potential value in clinical decision-support environments.For future research, the framework could be further enhanced by incorporating multi-channel spatial feature fusion, attention mechanisms, or transformer-based architectures to improve both model interpretability and predictive accuracy. Additionally, evaluating the system on larger and more heterogeneous clinical datasets would help improve its generalizability. Another important direction is the real-time integration of this framework with EEG acquisition systems to enable practical deployment in clinical settings.

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