Temporal Convolutional Network with Cwt Features for Accurate Schizophrenia Classification

Jananee J[1], Dr. F. Emerson Solomon[2]
[1]*Ph.D Research Scholar, Department of Biomedical Engineering, Bharath Institute of Higher Education and Research (BIHER), Chennai, India*
[2]*Professor, Department of Biomedical Engineering, Bharath Institute of Higher Education and Research (BIHER), Chennai, India*

***Abstract:** This research introduces a high-performance DL framework for predicting SZ(Schizophrenia) using EEG signals by seamlessly integrating comprehensive preprocessing, sophisticated feature extraction methods, and advanced temporal classification. Utilizing the openly accessible Kaggle dataset on mental attention states—comprising non-invasive EEG recordings—the study begins with data refinement through ICA, which effectively eliminates non-neural disturbances such as ocular movements and muscular noise. Subsequently, the cleaned EEG signals are subjected to feature extraction via three approaches: Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and CWT. Among these, CWT proves most effective, offering superior time-frequency resolution for analyzing the inherently non-stationary nature of EEG data. The features obtained are then processed by a TCN, chosen for its strong capability to capture long-term temporal patterns within the data. Empirical evaluations affirm that the integration of ICA-based noise reduction, CWT-driven feature extraction, and TCN classification yields the best predictive outcomes, achieving top-tier performance across accuracy, precision, and recall metrics. This approach significantly outperforms configurations involving FFT or STFT with TCN, underlining the effectiveness of combining multi-resolution signal analysis with temporal DL in enhancing the reliability of EEG-based SZ diagnosis.*

***Keywords:** EEG Signal Processing. Schizophrenia Prediction, Independent Component Analysis (ICA), Continuous Wavelet Transform (CWT), Temporal Convolutional Network (TCN), Feature Extraction, Deep Learning (DL), Brain Signal Classification, Time-Frequency Analysis, Signal Preprocessing*

1. INTRODUCTION

SZ is a debilitating neuropsychiatric condition that can shorten an individual's lifespan by as much as two decades. Characterized by disturbances in cognition, emotion, and perception, it remains one of the most severe chronic mental illnesses globally. Diagnosing SZ early is vital for timely and effective treatment, yet conventional diagnostic methods rely predominantly on subjective assessments, often resulting in delayed or inaccurate diagnoses.

EEG has emerged as a valuable, non-invasive modality for detecting brain disorders, offering real-time monitoring of cerebral electrical activity through electrodes placed on the scalp (Nivashini Nattudurai, 2023). Despite its potential, EEG signals are highly vulnerable to various artifacts, including eye blinks, muscle contractions, and ambient noise, which can obscure the neural signatures crucial for accurate analysis. To mitigate this, advanced preprocessing techniques like ICA are utilized to filter out these non-neural components and enhance the integrity of the EEG data.

Furthermore, because EEG signals are inherently non-stationary, sophisticated feature extraction techniques such as CWT are employed. CWT provides detailed time-frequency representations, preserving both temporal dynamics and frequency characteristics. These rich features are well-suited for input into DL models designed for sequence data.

This study presents a DL architecture tailored for predicting schizophrenia, combining ICA-driven artifact removal, CWT-based multi-resolution feature extraction, and classification using a TCN. The TCN is chosen for its proficiency in capturing long-range temporal dependencies, which are essential in EEG analysis. Using the Kaggle EEG Mental Attention State Detection dataset, experimental results indicate that the ICA-CWT-TCN pipeline outperforms other configurations, delivering superior results in accuracy, precision, and recall. The findings underscore the promise of integrating advanced signal processing with DL techniques for dependable, non-invasive mental health diagnostics.

2. RELATED WORKS

SZ is a severe psychiatric condition that severely impairs higher-order cognitive processes such as thinking and perception, drastically affecting an individual's quality of life. DL techniques offer a promising avenue for the automated detection of SZ by hierarchically learning patterns in raw signal data, eliminating the reliance on manual feature extraction required in conventional ML approaches. In a comprehensive review conducted by Manish Sharma et al. (2023), various DL architectures have been evaluated for their effectiveness in identifying schizophrenia. The study explores models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), AlexNet, and hybrid techniques. These models have been applied to data derived from EEG recordings as well as structural and functional magnetic resonance imaging (MRI), collected from both schizophrenia patients and healthy control groups across a range of public and proprietary datasets. The review provides in-depth insights into the datasets used, methodological frameworks employed, and performance outcomes of each DL model. It also critically examines the current limitations facing DL-based SZ diagnosis and outlines key areas for future research and development in this evolving field.

SZ is a chronic and debilitating mental illness for which no definitive cure currently exists. Its rising prevalence, coupled with symptom overlap with other psychiatric disorders like bipolar disorder, often leads to underdiagnosis or misrecognition in daily life. Consequently, early identification is essential to enable timely intervention or effective management of the condition.Traditional SZ detection approaches using machine learning typically involve manual steps such as feature extraction and selection before classification. In contrast, Amin Mashayekhi Shams et al. (2024) present a novel, end-to-end DL framework designed to automate SZ diagnosis from EEG signals. Their method incorporates two architectures: a 15-layer CNN and a 16-layer hybrid CNN–LSTM model. The CNN layers are employed to capture temporal signal characteristics, while the LSTM layers enhance the model's ability to learn sequential dependencies within the data. To further improve model robustness, a data augmentation strategy using Generative Adversarial Networks (GANs) is applied to expand the training dataset and enhance its diversity. Experimental evaluation on a large-scale EEG dataset demonstrates the strong diagnostic capabilities of the proposed models, achieving impressive classification accuracies. These findings highlight the promise of the proposed deep learning system as a reliable tool for distinguishing individuals with SZ from healthy controls, potentially advancing the development of automated diagnostic solutions for this complex disorder.

SZ is a neurological disorder that often emerges in adolescence or early adulthood. Prompt diagnosis and intervention can ease the burden on families and lower the broader societal costs associated with the illness. However, the absence of an objective evaluation standard makes accurate diagnosis particularly challenging. To enhance the performance of traditional classification techniques on MRI data, JinChi Zheng et al. (2021) introduce a novel method that combines functionalMRI analysis with CNN algorithms. Their approach involves extracting meaningful time-series signals from preprocessed fMRI data and conducting correlation analyses on specific regions of interest. Leveraging transfer learning and the VGG16 deep neural network, the study classifies functional connectivity patterns between individuals with SZ and healthy control subjects. Experimental findings reveal that this VGG16-based fMRI classification method achieves an accuracy of 84.3%. This not only contributes to improving the early detection of SZ but also effectively addresses challenges posed by limited sample sizes and the high dimensionality of neuroimaging data. Moreover, the approach enhances the generalizability of DL models within the psychiatric diagnosis.

Identifying children who may be predisposed to developing SZ is crucial for enabling early interventions that can reduce the likelihood of progression to full-blown psychosis. EEG recordings of brain activity, paired with DL techniques, provide a powerful foundation for this kind of early risk assessment. David Ahmedt-Aristizabal et al. (2021) introduce automated approaches that analyze raw EEG waveforms to distinguish children with an elevated risk of SZ from their typically developing peers. The study also investigates persistent abnormal neural features observed over approximately four years in children originally assessed between the ages of 9 and 12. EEG data were collected using a passive auditory oddball paradigm, capturing neural responses to auditory stimuli. The research presents a comprehensive comparison between two strategies: one utilizing traditional ML algorithms applied to manually engineered features—specifically event-related potential (ERP) components—and the other employing end-to-end DL models that directly process raw EEG inputs. Experimental findings demonstrate that recurrent deep convolutional neural networks (DCNNs) outperform classical ML methods in modeling temporal EEG sequences. Furthermore, the study identifies the most informative post-stimulus segments that contribute to classification, offering insight into the underlying neural signatures of vulnerability. This baseline identification framework not only enhances understanding of early neural markers in schizophrenia but also supports broader applications in psychiatric classification and developmental neuroscience. The results reinforce the value of DL in facilitating early detection and personalized mental health care.

Timely diagnosis of schizophrenia can significantly improve patients' chances of maintaining a stable and functional life. EEG signals, which reflect the brain's network connectivity, offer valuable insights for detecting neurological irregularities associated with SZ. Leveraging the capabilities of deep learning for automatic feature extraction and classification, Rinku Supakar et al. (2022) introduced a deep learning framework based on a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) units to analyze EEG data for schizophrenia detection.

The proposed architecture features a 100-dimensional LSTM layer followed by three fully connected (dense) layers. EEG recordings from 45 individuals diagnosed with SZ and 39 healthy control participants formed the dataset for this investigation. To enhance model efficiency, a dimensionality reduction technique was applied to extract the most informative features. The model was evaluated on both the full and reduced feature sets, achieving classification accuracies of 98% and 93.67%, respectively. To assess its robustness, the model was tested using individual and combined performance metrics. Its results were benchmarked against conventional ML algorithms, including Random Forest, Support Vector Machine (SVM), FURIA, and AdaBoost, where it consistently outperformed these traditional approaches, particularly when using the complete feature set. Furthermore, when compared to prior studies utilizing CNN or RNN architectures on the same dataset, the proposed model demonstrated either superior or comparable classification performance, highlighting its effectiveness in EEG-based SZ diagnosis.

3. PROPOSED MODEL

SZ is a debilitating psychiatric disorder marked by profound symptoms such as hallucinations and delusions, which severely disrupt an individual's ability to function in daily life. While MRI has been instrumental in advancing psychiatric research—thanks to its high-resolution imaging and minimal side effects—traditional statistical approaches still demand extensive manual feature engineering. Additionally, both conventional ML and earlier DL methods often falter when processing the high-dimensional nature of MRI data, posing significant limitations for progress in schizophrenia-related studies (Guibing Li et al., 2023).

To overcome these challenges, a comprehensive DL framework has been developed for predicting SZ based on EEG data. This system comprises three core stages: preprocessing, feature extraction, and classification. It utilizes the publicly available Kaggle EEG Mental Attention State Detection dataset, which includes brainwave recordings from individuals with SZ and healthy controls.

The diagnostic pipeline begins with preprocessing using ICA, which effectively removes artifacts such as muscle noise and eye blinks, thereby enhancing the clarity of the EEG signals. Once cleaned, the data proceeds to the feature extraction phase, where three signal processing methods—FFT, CWT, and STFT—are employed to derive meaningful time-frequency features from the EEG signals.

After extraction, the features are partitioned into training and testing sets. These are input into a TCN, which is designed to capture and learn temporal dependencies within the EEG sequences. The model is trained to detect patterns indicative of schizophrenia and is then validated on unseen data to assess its generalization capability.

Performance evaluation is carried out using key classification metrics, including accuracy, precision, and recall. The final system classifies EEG samples as either reflecting the presence of SZ or representing healthy brain activity. This framework exemplifies a robust and non-invasive approach to mental health diagnostics, showcasing the synergy of advanced EEG signal processing and DL to enhance the reliability of SZ detection.

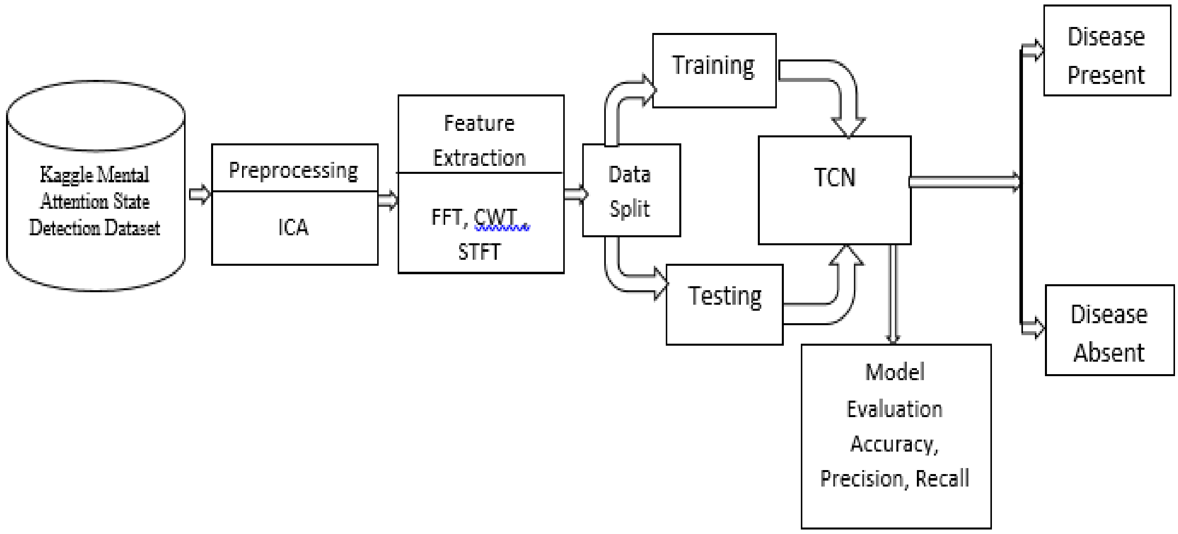

Figure 1: Workflow of EEG-Based Schizophrenia Prediction Using ICA, Feature Extraction, and TCN

3.1 Preprocessing Using ICA

Since raw EEG recordings are often contaminated with various forms of noise and physiological artifacts—such as eye movements, blinks, and muscle activity—preprocessing is a crucial step. One of the most effective methods for this is ICA, a statistical approach that decomposes the multichannel EEG signal into a set of independent, non-Gaussian source components. This decomposition enables the targeted removal of non-neural interferences without distorting essential neural signals. ICA proves particularly valuable in enhancing EEG data quality by isolating and eliminating artifacts like ocular or muscular activity and electrical line noise, ensuring the integrity of brain activity patterns remains intact for further analysis.

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

Where:

- X: observed EEG signals (mixed signals from electrodes)
- A: unknown mixing matrix
- S: independent source components (neural + artifact signals)

ICA plays a key role in EEG preprocessing by decomposing the recorded signals into statistically independent sources. Each EEG electrode captures a blended signal comprising both neural activity and various artifacts, such as eye blinks or muscle contractions. ICA works by computing a mathematical transformation that separates these mixed signals into their original, independent sources. Once isolated, components associated with artifacts are identified—typically through their recognizable patterns—and selectively removed. The EEG signal is then reconstructed using only the neural components, yielding a cleaner dataset that is better suited for subsequent analysis and classification tasks.

3.2 Feature Extraction

Following artifact removal, the clean EEG signals are passed through the feature extraction stage.FFT is an efficient algorithm to compute the DFT, which converts a signal from the time domain to the frequency domain. It shows which frequency components are present in the EEG signal and with what intensity.

$$X(k) = \sum_{n=0}^{N=1} x(n).\, e^{-j2\pi kn/N} - - - (2)$$

Where:

- $x(n)$: time-domain EEG signal
- $X(k)$: frequency-domain output at frequency index k
- N: total number of samples
- $e^{-j2\pi kn/N}$: complex exponential basis function (sinusoids)

3.2.1 STFT

The STFT is used to analyze how the frequency content of a signal changes over time, making it suitable for non-stationary signals like EEG.

$$STFT\{x(t)\}(t,f) = \int_{-\infty}^{+\infty} x(\tau).\,\mathrm{w}(\tau - \mathrm{t}).\, e^{-j2\pi f\tau} d\tau - - - (3)$$

Where:

- $x(t)$: input EEG signal
- $\mathrm{w}(\tau - \mathrm{t})$: window function centered at time t (e.g., Hamming or Hann window)
- f: frequency
- τ: time variable
- The result is a complex number representing amplitude and phase at timet and frequency f

3.2.2 CWT

The CWT breaks down signals into time–frequency representations, enabling the extraction of meaningful and discriminative features from non-stationary EEG data. Unlike traditional approaches such as FFT or STFT, CWT delivers a multi-resolution analysis that effectively captures both brief and sustained patterns—an essential capability for identifying neural irregularities linked to SZ. What sets CWT apart is its use of scalable and shiftable wavelets, as opposed to STFT's fixed window sizes, allowing it to adapt dynamically to different signal characteristics. This makes CWT particularly well-suited for analyzing the complex and time-varying nature of EEG signals.

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t).\psi * \left(\frac{t-b}{a}\right) dt - - - (4)$$

Where:

- x(t): the EEG signal
- ψ(t): the mother wavelet (e.g., Morlet, Mexican Hat)
- a: scale (inversely related to frequency)
- b: time shift (location of the wavelet in time)
- ψ∗: complex conjugate of the wavelet function
- $CWT_x(a,b)$: wavelet coefficient representing signal content at time b and scale a

3.3 Classification Using TCN

The features extracted from EEG signals are subsequently input into a TCN for classification. TCNs are specifically engineered to capture long-term dependencies within sequential data, making them highly appropriate for modeling time-series signals such as EEG. By analyzing how these features evolve, the TCN effectively distinguishes between individuals with schizophrenia and healthy controls.

Unlike recurrent models such as RNNs and LSTMs, TCNs rely on one-dimensional causal convolutional layers to process data. This architecture enables the network to learn long-range temporal relationships without relying on recursion, enhancing computational efficiency and stability. The combination of ICA-based artifact removal, CWT-driven multi-resolution feature extraction, and TCN-based classification creates a robust and high-performing framework. This end-to-end pipeline has shown exceptional results in terms of accuracy, precision, and recall, confirming its potential as a dependable approach for EEG-based SZ prediction.

$$y(t) = \sum_{k=0}^{k-1} w(k).x(t-d.k) - - - (5)$$

Where:

- y(t): output at time ttt
- x(t): input signal
- $w(k)$: convolutional filter weights of size K
- d: dilation factor
- $t - d.k$: ensures dilated spacing between inputs

Combining ICA-preprocessed EEG, CWT features, and TCN classification helps learn clean, high-resolution temporal patterns for accurate schizophrenia prediction.

4. RESULTS AND DISCUSSION

SZ is an intrinsic psychiatric disorder that often results in long-term disability, making early diagnosis and intervention critical for minimizing its adverse effects (Nadezhda Shanarova et al., 2024). Experimental findings affirm the efficacy of integrating robust preprocessing techniques, time–frequency feature extraction, and deep temporal modeling to predict schizophrenia using EEG data. Artifact removal played a pivotal role in improving signal clarity, enabling the model to learn more distinct and meaningful neural signatures from the recordings.

This enhancement translated into consistently strong performance across various classification metrics, demonstrating the model's generalizability and its ability to minimize misclassifications. The application of time–frequency analysis proved essential for revealing the non-stationary and dynamic features of brain activity, characteristics that are particularly relevant for distinguishing between individuals with schizophrenia and healthy controls. These enriched representations empowered the DL architecture to detect subtle signal deviations linked to cognitive dysfunction, thereby boosting both precision and recall. Overall, the findings underscore that when EEG signals are properly denoised and analyzed for their temporal structure, they offer valuable insights into the neural underpinnings of SZ and other cognitive disorders.

4.1 Performance Evaluation Metrics

4.1.1 Accuracy

Accuracy is a fundamental metric used to assess how well a classification model performs. It represents the ratio of correctly predicted outcomes—including both true positives and true negatives—to the total number of predictions generated by the model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\ \% - - - (6)$$

Where:

- TP: True Positives (correctly predicted schizophrenia cases)
- TN: True Negatives (correctly predicted control cases)
- FP: False Positives (control predicted as schizophrenia)
- FN: False Negatives (schizophrenia predicted as control)

4.1.2 Precision

Precision is an evaluation metric that quantifies the proportion of true positive predictions among all instances classified as positive by the model. It becomes especially critical in high-stakes applications, such as SZ diagnosis, where minimizing false positives is essential to avoid unnecessary concern or treatment.

$$Precision = \frac{TP}{TP + FP} \times 100\ \% - - - (7)$$

Where:

- TP: True Positives (correctly predicted SZ cases)
- FP: False Positives (healthy cases incorrectly predicted as SZ)

4.1.3 Recall

Recall—also known as Sensitivity or the True Positive Rate—is a performance metric that assesses a model's ability to correctly identify actual positive instances. In medical scenarios like SZ prediction, recall is particularly vital, as it indicates how successfully the model can detect individuals who genuinely have the disorder, helping to ensure that no true cases are overlooked.

$$Recall = \frac{TP}{TP + FN} \times 100\ \% - - - (8)$$

Where:

- TP: True Positives (correctly predicted SZ cases)
- FN: False Negatives (actual SZ cases missed by the model)

Table 1 provides a comparative evaluation of three DL frameworks designed for schizophrenia prediction using EEG signals. Each model employs ICA to eliminate artifacts and utilizes a TCN for the classification stage. The primary differentiating factor among these approaches lies in the feature extraction method used—namely, CWT, FFT, and STFT.

Table 1: Performance Comparison of ICA-Based EEG Classification with TCN

Methods	Accuracy (%)	Precision (%)	Recall (%)
ICA+CWT+TCN	91.20	92.10	90.70
ICA+FFT+TCN	87.30	85.40	83.80
ICA+STFT+TCN	86.50	85.80	83.20

The chart showcases a comparative performance analysis of three EEG-driven SZa prediction pipelines, all incorporating ICA for artifact removal and utilizing a TCN for classification. The main variation among these models lies in the feature extraction strategy employed (CWT, FFT, and STFT). The chart evaluates each method based on three key performance metrics: accuracy, precision, and recall.

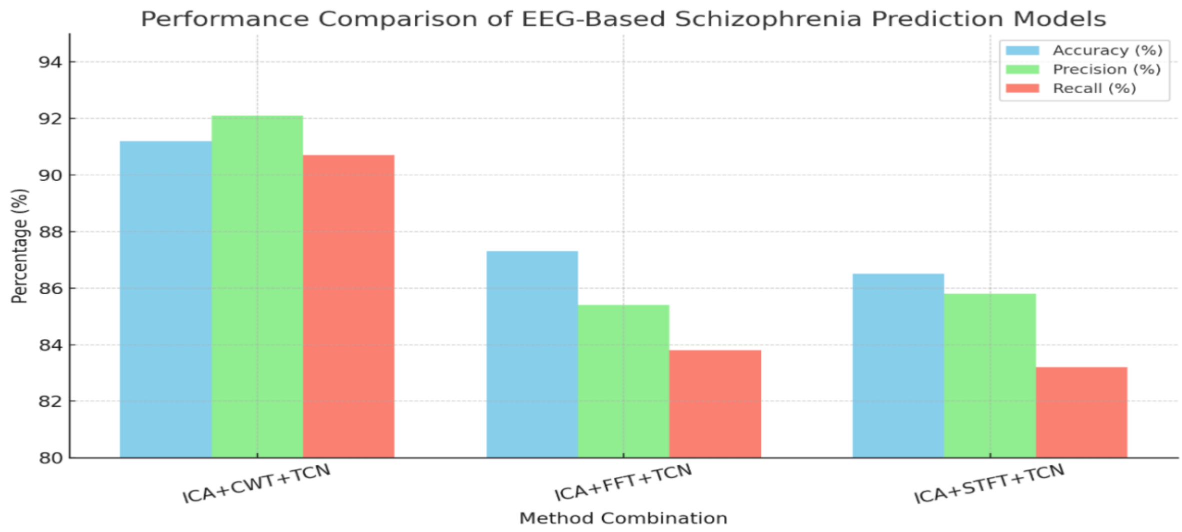

Figure 2: Performance Comparison of EEG-Based Schizophrenia Prediction Models Using ICA and TCN

This performance evaluation compares three EEG-based schizophrenia prediction frameworks, each combining ICA for signal preprocessing, a distinct feature extraction technique— CWT, FFT, or STFT—and a TCN for classification. The assessment is based on key classification metrics: accuracy, precision, and recall.

Among the three configurations, the ICA + CWT + TCN pipeline delivers the strongest performance. It achieves an accuracy of 91.20%, reflecting the highest proportion of correctly classified EEG samples. This setup also attains the best precision at 92.10%, indicating a low false-positive rate, and a recall of 90.70%, demonstrating its ability to effectively identify true schizophrenia cases. These results validate the advantage of CWT's multi-resolution time–frequency analysis, which enhances the discriminative quality of features used for deep learning.

The ICA + FFT + TCN configuration performs moderately well, with an accuracy of 87.30%, precision of 85.40%, and recall of 83.80%. While FFT offers solid frequency-domain analysis, its inability to capture time-localized information limits its effectiveness in modeling the transient EEG patterns associated with schizophrenia.

The ICA + STFT + TCN setup shows the lowest performance across all three metrics—accuracy of 86.50%, precision of 85.80%, and recall of 83.20%. Although STFT introduces time–frequency features, its fixed window resolution makes it less adaptable to the non-stationary characteristics of EEG signals compared to CWT.

Overall, these findings underscore the superiority of the ICA + CWT + TCN approach, which strikes the best balance between sensitivity and specificity, making it a powerful candidate for reliable EEG-based SZ prediction. This validated framework not only holds promise for real-world applications such as early diagnosis and ongoing patient monitoring, but also sets a strong foundation for future advancements in neuropsychiatric diagnostics, especially through the integration of multi-modal data and explainable AI models. The accompanying chart visually reinforces the importance of choosing an effective feature extraction method, with CWT emerging as the most impactful for capturing SZ-related EEG patterns.

5. CONCLUSION AND FUTURE WORK

This study presents an effective DL framework for SZ prediction. This study presents a comprehensive EEG-based approach for SZ detection by combining advanced preprocessing, feature extraction, and classification techniques. The pipeline begins with ICA to eliminate artifacts and enhance signal quality. Next, time–frequency feature extraction is performed to uncover informative neural patterns. A TCN is then applied to capture long-range temporal dependencies within the EEG data, enabling precise classification. Experimental results show that this integrated method yields excellent predictive performance, with high accuracy, precision, and recall. These outcomes emphasize the critical role of artifact-free preprocessing and rich temporal representations in accurately identifying cognitive disorders such as SZ through non-invasive techniques. Looking ahead, the proposed framework can be enhanced in several ways. Incorporating multi-modal data sources—such as functional MRI or genetic markers—alongside EEG could improve diagnostic accuracy and model robustness. The integration of explainable AI (XAI) would further aid clinical adoption by making model decisions more transparent and interpretable. Moreover, adapting the system for real-time analysis or mobile EEG devices would support on-the-spot diagnostics and continuous patient monitoring. Finally, validating the model on larger, more diverse datasets would help evaluate its generalizability and readiness for deployment in real-world clinical settings.

REFERENCE

[1] Manish Sharma, Ruchit Kumar Patel, Akshat Garg, Ru SanTan & U Rajendra Acharya (2023), “Automated detection of schizophrenia using deep learning: a review for the last decade”, Physiol Meas, 64(3). doi: 10.1088/1361-6579/acb24d.

[2] Amin Mashayekhi Shams & Sepideh Jabbari (2024), “A deep learning approach for diagnosis of schizophrenia disorder via data augmentation based on convolutional neural network and long short-term memory”, Biomed Eng Lett, (4):663–675. doi: 10.1007/s13534-024-00360-9

[3] JinChi Zheng, XiaoLan Wei, JinYi Wang, HuaSong Lin, HongRun Pan & YuQing Shi (2021),” Diagnosis of Schizophrenia Based on Deep Learning Using fMRI”, Comput Math Methods Med. 2021 Nov 9:2021:8437260. Doi: 10.1155/2021/8437260. eCollection 2021.

[4] David Ahmedt-Aristizabal, Tharindu Fernando, Simon Denman, Jonathan Edward Robinson, Sridha Sridharan, Patrick J Johnston, Kristin R Laurens& Clinton Fookes (2021), "Identification of Children at Risk of Schizophrenia via Deep Learning and EEG Responses", IEEE J Biomed Health Inform. (1):69-76. doi: 10.1109/JBHI.2020.2984238.

[5] Rinku Supakar, Parthasarathi Satvaya &, Prasun Chakrabarti (2022), “A deep learning based model using RNN-LSTM for the Detection of Schizophrenia from EEG data”, Comput Biol Med. 2022 Dec;151(Pt A):106225. doi:10.1016/j.compbiomed.2022.106225. Epub 2022 Oct 19.

[6] Nivashini Nattudurai (2023), “Classifying Schizophrenia Disorder through EEG Signal Analysis and Machine Learning," *2023 IEEE MIT Undergraduate Research Technology Conference (URTC)*, Cambridge, MA, USA, 2023, pp. 1-4, doi: 10.1109/URTC60662.2023.10535028.

[7] Guibing Li; Weidong Jin; Rude Lin; Ying Tan&Jiaqing Miao (2023), “A Classification and Pathology Study on Schizophrenia Based on Self-Attention Model," *2023 3rd International Symposium on Computer Technology and Information Science (ISCTIS)*, Chengdu, China, 2023, pp. 562-571, doi: 10.1109/ISCTIS58954.2023.10213043.

[8] Nadezhda Shanarova; Marina Pronina; Mikhail Lipkovich; Valery Ponomarev; Andreas Müller; Juri Kropotov (2024), “Classification of Schizophrenia Patients on the Basis of Latent Components of ERPs using a Machine Learning System," *2024 Sixth International Conference Neurotechnologies and Neurointerfaces (CNN)*, Kaliningrad, Russian Federation, 2024, pp. 198-201, doi: 10.1109/CNN63506.2024.10705876.

[9] Enkhmaa Luvsannyam , Molly S Jain , Maria Kezia Lourdes Pormento , Hira Siddiqui , Angela Ria A Balagtas , Bernard O Emuze & Teresa Poprawski (2022), “Neurobiology of Schizophrenia: A Comprehensive Review”, Cureus, . 2022 Apr 8;14(4):e23959. doi: 10.7759/cureus.23959

[10] Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. GBD 2017 Disease and Injury Incidence and Prevalence Collaborators. Lancet. 2018;392:1789–1858. doi: 10.1016/S0140-6736(18)32279-7

[11] Li K, Sweeney JA, Hu XP(2020), “Context-dependent dynamic functional connectivity alteration of lateral occipital cortex in schizophrenia. Schizophr Res. 2020;220:201–209.

[12] Mahmood T, El-Asrag ME, Poulter JA, et al. A recessively inherited risk locus on chromosome 13q22-31 conferring susceptibility to schizophrenia. Schizophr Bull. 2021;47(3):796–802