NASE
Natural Sciences and Engineering Bulletin
May 2025, 2(1)
Received: 18/10/2024
Accepted: 27/02/2025

RESEARCH ARTICLE http://dergipark.gov.tr/nase

FFT-based CNN Classification for Schizophrenia Detection in EEG Recordings

Zekeriya EDAHIL[1*], Sema KOÇ KAYHAN[2]

Keywords
CNN,
EEG,
Schizophrenia,
FFT,
Classification

Abstract – Machine learning enhances computer-aided medical diagnosis by enabling accurate and swift decision-making. This study proposes a method for detecting schizophrenia (SZ) using electroencephalography, which measures brain electrical activity to diagnose neurological disorders. Schizophrenia is characterized by complex neural patterns, challenging to identify with traditional methods. This research employs deep learning algorithms to analyze EEG signals for schizophrenia detection, aiming to improve classification accuracy. The methodology involves preprocessing Electroencephalography (EEG) time series to extract spectral power features using Fast Fourier Transformation (FFT), which transforms time-domain signals into the frequency domain, revealing brain oscillatory activity. These features are converted into RGB images representing brain activity's spatial information. A convolutional neural network (CNN) is then used to classify these images. The proposed method achieved an average accuracy of 95.97% with FFT, indicating that FFT-based features are highly effective for classification in this context. The results underscore the importance of data representation when using CNN models for EEG signal analysis.

1. Introduction

EEG is a non-invasive diagnostic tool that records brain electrical activity through electrodes placed on the scalp (Figure 1). EEG captures continuous time-series data generated by synaptic currents, reflecting brain communication networks. The method relies on detecting voltage differences between electrodes and visualizing these patterns to assess brain function.

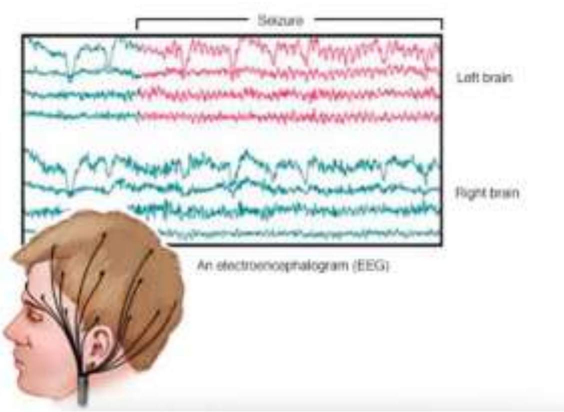
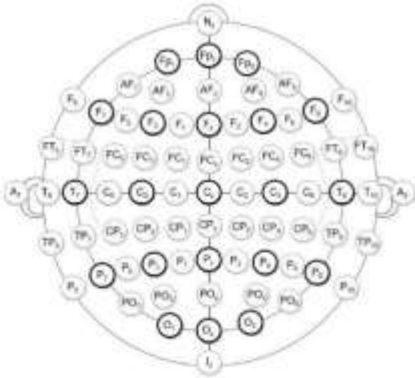


Figure 1. Electroencephalogram (EEG) brain activity

The standardized International 10–20 system ensures consistent electrode placement for data collection during EEG studies (Figure 2). This system correlates electrode positions with specific brain regions like the frontal, temporal, and occipital lobes, ensuring reliability in clinical and research applications (Oostenveld and Praamstra, 2001).

[1] * **Corresponding Author.** Gaziantep University, Graduate School of Natural and Applied Sciences, Department of Electrical and Electronics Engineering, Division of Computer Science, Türkiye. E-mail: zekeriyaedahil@gmail.com OrcID: 0009-0002-2297-5100
[2] Gaziantep University, Faculty of Engineering, Department of Electrical and Electronics Engineering, Division of Computer Science, Türkiye. E-mail: skoc@gantep.edu.tr OrcID: 0000-0002-8129-7672
Citation: Edahil, Z., and Koç Kayhan, S. (2025). FFT-based CNN classification for schizophrenia detection in EEG recordings. *Natural Sciences and Engineering Bulletin*, 2(1), 10-25.



(a)

Figure 2. The 10-20 electrode placement system

EEG plays a vital role in the early detection of brain disorders due to its exceptional temporal resolution, surpassing techniques like fMRI in capturing rapid changes in brain activity. Its non-invasive approach, cost-effectiveness, and ability to track electrical patterns in real-time make it especially valuable for identifying abnormalities associated with conditions such as schizophrenia. Although imaging methods like MRI and CT provide detailed spatial data, they lack EEG's capability to continuously monitor brain activity, which is crucial for diagnosing a wide range of neurological disorders across different levels of consciousness (Niedermeyer and Lopez de Silva, 2005).

EEG offers high temporal resolution, making it ideal for capturing dynamic brain activity in real-time, which is particularly valuable for studying cognitive processes and diagnosing neurological disorders. Its cost-effectiveness and non-invasive nature make it accessible for clinical and research applications, especially in psychiatric conditions like schizophrenia. However, EEG has limitations, including low spatial resolution compared to techniques like fMRI and susceptibility to noise and artifacts, requiring rigorous preprocessing. Despite these challenges, EEG remains a powerful tool for understanding brain dynamics and developing diagnostic frameworks (Kwon and Carpenter., 2007).

SZ is a serious neuropsychiatric disorder characterized by disruptions in thought, emotion, and behavior, leading to psychosis, cognitive deficits, and impaired social functioning. Affecting approximately 24 million people globally, or 0.32% of the population, it typically emerges in late adolescence or early adulthood, with a higher incidence in males. Patients with schizophrenia face a 2-3 times higher mortality rate than that of healthy individuals due to preventable physical conditions like cardiovascular and metabolic diseases (Harrison et al., 2001). The disorder's widespread personal, social, and economic impact underscores the need for effective strategies to mitigate its challenges.

Schizophrenia presents a range of symptoms, disrupting both cognitive and perceptual functions. It includes positive symptoms like hallucinations and delusions, and negative symptoms such as emotional flatness and social withdrawal. Disorganized thoughts, impaired memory, and difficulty with attention are also typical. While some patients experience periods of remission, others face a decline in functioning, emphasizing the importance of early diagnosis and intervention. Common symptoms include disorganized thought processes, social withdrawal, cognitive impairments, and challenges in self-assessment (Harrison et al., 2001).

Schizophrenia is a complex neuropsychiatric disorder characterized by positive symptoms like hallucinations and delusions, and negative symptoms such as emotional withdrawal and cognitive impairments (Figure 3). Diagnosis primarily relies on clinical evaluations of symptoms, which can be subjective and prone to bias, highlighting the need for objective tools like EEG. Early intervention is critical, as addressing the disorder during its initial stages can significantly improve long-term outcomes and reduce residual disabilities (Harm et al., 2013).

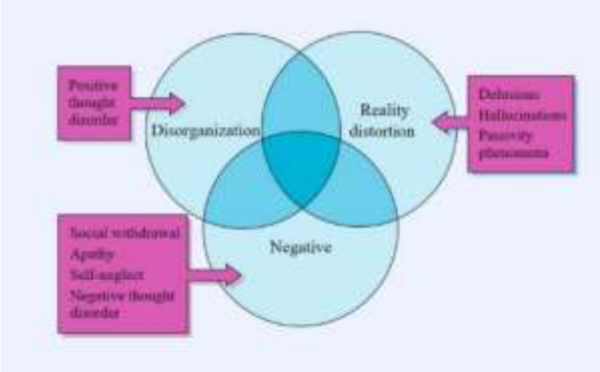


Figure 3. Syndromes of schizophrenia

The treatment of schizophrenia requires a comprehensive approach that combines medication to address neurochemical imbalances with additional therapies aimed at enhancing psychosocial skills. Despite available treatments, there are notable gaps in mental healthcare provision, especially in community settings. Institutional care often falls short in meeting the holistic needs of individuals with schizophrenia, highlighting the need for a shift towards community-based mental health services. Such services should integrate primary care, community mental health centers, housing and employment support, and outreach initiatives for in-home care. Active participation from patients, their families, and communities is essential in promoting recovery-focused care, where individuals are encouraged to take an active role in their treatment (World Health Organization, 2023).

The World Health Organization asserts that schizophrenia is manageable but acknowledges the heavy burden of prolonged treatment on healthcare systems and families. Early diagnosis and intervention play a crucial role in improving outcomes, as addressing schizophrenia at its onset can significantly reduce long-term impairments. Preventive early intervention strategies focus on engaging individuals during their first episode of psychosis, which is vital for slowing disease progression and mitigating residual disabilities. Effective early-stage interventions should include public education, streamlined referral processes from primary care, and efforts to combat stigma and discrimination, which often delay access to care (World Health Organization, 2023).

Managing schizophrenia goes beyond clinical care, requiring sustained support from mental health services, families, and communities. A holistic treatment strategy involving assisted living, employment opportunities, and supported housing is essential not only for improving the quality of life for those affected but also for fostering societal integration and reducing dependency on caregivers. This multidimensional approach emphasizes the need for a treatment plan that addresses both the medical and socio-economic challenges faced by individuals with schizophrenia (Jaeschke et al., 2021).

In the medical field, disease diagnosis generally relies on laboratory tests, biomarkers, and imaging techniques. However, for psychiatric disorders, the diagnostic process is primarily based on patient interviews, observed symptoms, and behavioral indicators (Savio et al., 2010). Traditionally, diagnosing schizophrenia has depended heavily on qualitative assessments like psychiatric history, current symptoms, and behavioral evaluations. However, these methods can be subjective, imprecise, and susceptible to bias, making the diagnostic process time-consuming and potentially unreliable. This has driven interest in more objective tools, such as neuroimaging and EEG, to enhance diagnostic accuracy for schizophrenia.

This study introduces a novel approach for schizophrenia detection using EEG signals, leveraging FFT for feature extraction and CNNs for classification. Spectral power features extracted via FFT are transformed into RGB images, preserving spatial representations of brain activity. These images are then classified using a CNN to achieve high diagnostic accuracy. The proposed method demonstrates a significant improvement in schizophrenia detection, achieving an average accuracy of 95.97%, and highlights the critical role of effective data representation in enhancing CNN-based EEG signal analysis.

2. Literature Review

Between 1993 and 2018, 184 studies were published, with 37 specifically focused on schizophrenia (Table 1). Among these studies, EEG recordings with eyes closed were prevalent, constituting 92% of the cases. The average

age of participants was 31 years, with females representing 33% of the sample. The median number of participants was 63, with a control group included in 54% of the studies. This body of research highlights common practices and methodologies in analyzing EEG signals in schizophrenia research (Newson and Thiagarajan, 2019).

Table 1. Overview of 184 Studies on Various Disorders (1993-2018) Highlighting 37 Schizophrenia Studies with Predominantly Eyes-Closed EEG Recordings

	No. of studies	Median N	% Controls	Average age (years)	% Females	% Eyes closed
ADHD (children)	56	76	45	11	25	75
ADHD (adults)	14	55.5	50	33	43	54
Schizophrenia	37	63	54	31	33	92
ASD/Autism	16	56	52	8.5	21	33
Depression	18	55	44	39	57	86
OCD	10	61.5	49	32	56	100
PTSD	13	74	50	40	37	67
Addiction	16	45	49	33	30	88
Panic disorder	4	79	44	35	69	50
Bipolar disorder	6	99.5	55	30	55	50
Anxiety	3	50	50	31	76	50

Deep learning distinguishes itself from traditional machine learning (ML) by eliminating the necessity for manual feature engineering, as models autonomously develop optimal features during the learning process. Unlike traditional ML, which involves multiple preliminary steps, deep learning integrates learning and classification into a single progression. This approach allows for adaptability to various data types through techniques like transfer learning.

While basic neural networks can approximate underlying truths, the inclusion of additional hidden layers refines models, enhancing accuracy. Despite its computational intensity and the need for large datasets, deep learning's challenges are sometimes alleviated by transfer learning, where pre-trained models on large datasets are adapted to classify new, limited data. This adaptability makes deep learning increasingly significant in medical and healthcare applications, including mental health and neuroimaging (Sharma et al., 2023).

The dynamic and transient nature of EEG signals necessitates sophisticated feature extraction methods for effective analysis. Machine learning techniques, including algorithms like Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Adaptive Boosting (AdaBoost), must be paired with robust feature extraction practices. However, extracting nonlinear features from these signals, whether in the time or frequency domain, is intricate and labor-intensive. Such complexity renders conventional machine learning strategies less viable for processing extensive data from EEG signals for the timely identification of schizophrenia in patients (Upadhyay et al., 2015).

In the pursuit of utilizing EEG signals for schizophrenia diagnosis, various machine learning approaches have been adopted to distinguish between affected individuals and healthy controls. Techniques ranging from k-means clustering for grouping similar data points to spectral analysis for identifying characteristic signal patterns have been instrumental. Investigations into the alpha and gamma frequency bands offer insights into the disorder's pathophysiology and treatment response (Chen Z et al., 2019).

In the current landscape, deep learning (DL) strategies are increasingly preferred over conventional ML methods. DL models efficiently process large EEG datasets, making them suitable for real-time applications in clinical settings, including portable devices and hospital environments. Key deep learning models in this domain include CNNs, recurrent neural networks (RNNs), long short-term memory networks (LSTM), gated recurrent units (GRU), and autoencoder architectures (Figure 4).

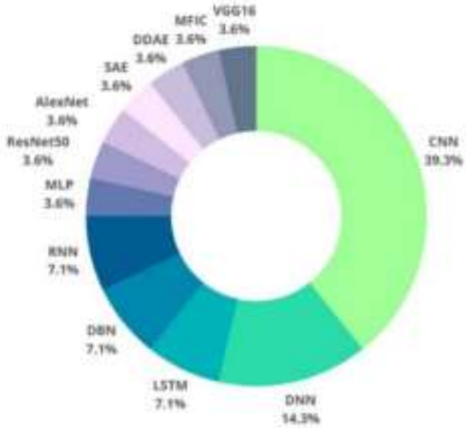


Figure 4. Different deep learning methods that are used by schizophrenia detection studies between (2016-2022)

Deep learning diverges from traditional ML by eliminating the need for manual feature engineering, with models instead developing optimal features autonomously through the learning process. This unified approach encompasses learning and classification in a singular progression, in contrast to the multiple preliminary steps required by traditional ML. Deep learning models can also adapt to a variety of data types through transfer learning. While simple neural networks can approximate underlying truths, incorporating additional hidden layers fine-tunes the models, enhancing precision. However, deep learning's computational demands are considerable, and it often necessitates substantial datasets for training, which can be scarce. This challenge is sometimes mitigated through transfer learning, leveraging models pre-trained on large datasets to categorize new, limited data. Hence, deep learning's versatility enables the automatic extraction of features across numerous applications, marking its rising significance in medical and healthcare domains, including mental health disorders and neuroimaging (Sharma et al., 2023).

The integration of machine learning in neuroimaging presents the opportunity to analyze complex neurological functions and decipher the pathophysiology of disorders like schizophrenia. Traditional ML, coupled with advanced feature extraction, has paved the way for analyzing the complexities of EEG signals. Recently, deep learning algorithms have demonstrated their superiority in medical imaging and signal processing, often outperforming established ML methods (Min et al., 2017). While deep learning models can excel with large datasets, they remain less explored in neuroimaging due to the typically smaller sample sizes. However, studies employing Deep Belief Networks (DBN) and CNNs have shown promising results in extracting meaningful information from EEG data, even with moderate dataset sizes (Plis et al., 2014). These studies suggest the potential advantages of deep learning in neuroimaging despite the absence of vast datasets (Figure 5). Yet, there is a need for models that can preserve the intricate spatial, temporal, and frequency structures inherent in EEG data, an area not fully explored in previous research.

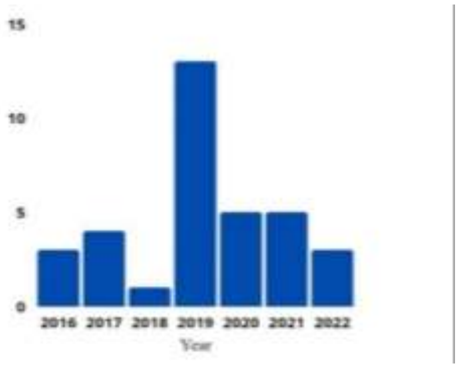


Figure 5. Annual distribution of 34 (25 involving DL, 9 involving combined DL and ML) EEG studies utilizing DL & ML for schizophrenia detection (Sharma et al., 2023).

Several studies using the NNCI dataset (45 schizophrenia cases, 39 healthy controls) have demonstrated the effectiveness of deep learning models for schizophrenia diagnosis (Table 2). A CNN model with a Softmax classifier achieved 90% accuracy, while a CNN-LSTM hybrid model reached 98.56% accuracy using a Sigmoid classifier. Another approach utilizing DBN with a Softmax classifier reported 95% accuracy. These results highlight the effectiveness of the NNCI dataset in supporting the development of high-performing deep learning models for schizophrenia diagnosis.

Table 2. Comparison of other works in diagnosis of schizophrenia that used NNCI dataset

Work	Dataset	Methodology	Classifier	% Accuracy
"Classification of people who suffer schizophrenia and healthy people by EEG signals using deep learning" (Naira and Alamo, 2019)	NNCI	CNN	Softmax	90.00
"Classification of EEG-based effective brain connectivity in schizophrenia using deep neural networks" (Phang et al., 2019)		DBN	Softmax	93.06
"Spectral features based convolutional neural network for accurate and prompt identification of schizophrenic patients" (Singh et al., 2021)		CNN-LSTM	Sigmoid	94.08

3. Materials and Methods

3.1. Data collection and preprocessing

The study utilized EEG recordings from 84 adolescents (mean age 12.3 years), divided into two groups: healthy individuals (n=39) and those exhibiting schizophrenia symptoms (n=45). The data, hosted by the Laboratory for Neurophysiology and Neuro-Computer Interfaces (NNCI) at Lomonosov Moscow State University, consists of one-minute EEG recordings captured across 16 channels at a sampling rate of 128 Hz, following the traditional 10/20 electrode placement system (Figure 6) (Gorbachevskaya and Borisov, 2019). The recordings, free from psychoactive medication influence, were taken during a resting state with eyes closed. Diagnoses were confirmed using ICD-10 criteria at the Research Center for Psychological Disorders of the Russian Academy of Medical Sciences. This dataset, meticulously compiled and prepared by Prof. N.N. Gorbachevskaya and Borisov, supports the exploration of EEG patterns for schizophrenia diagnosis in adolescents, aiding in mental health research (Bonita et al., 2014).

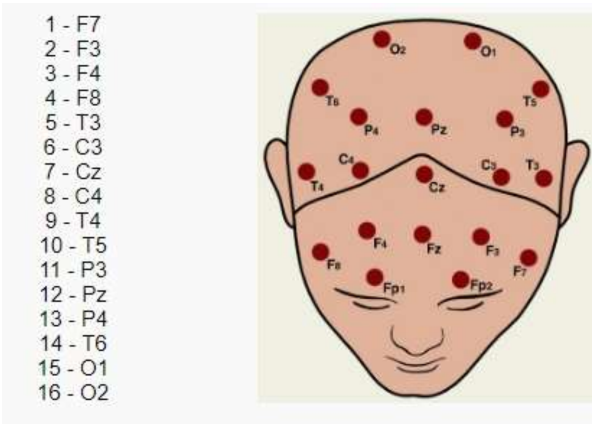


Figure 6. The topographical positions of the 16 channels

Data preprocessing in EEG analysis is a vital process that prepares raw EEG signals for in-depth examination, ensuring the data is clean and reliable for further analysis. The process begins by importing raw EEG data into specialized software tools like MATLAB's EEGLab, Brainstorm, FieldTrip, or MNE-Python, which also incorporate EEG electrode placement information. Preprocessing addresses the susceptibility of EEG signals to various forms of noise and artifacts, crucially improving the signal-to-noise ratio and accurately reflecting brain activity, which is foundational for extracting meaningful insights from EEG recordings (Figure 7).

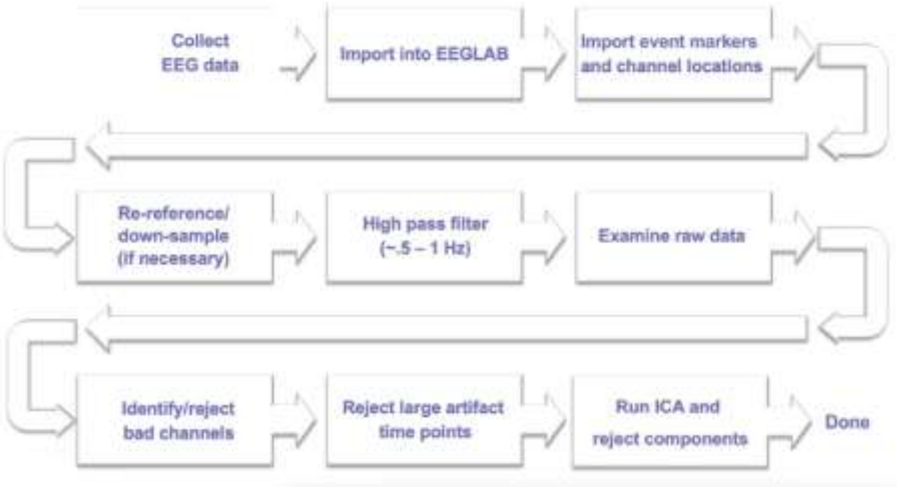


Figure 7. Pre-Processing pipeline in EEGlab (Delorme, 2019)

3.1.1. Filtering and artifact rejection

Filtering and artifact rejection are essential steps in EEG data preprocessing that significantly improve signal quality. A Band-Pass Filter, specifically a second-order Infinite Impulse Response (IIR) Butterworth filter, is applied to allow frequencies between 0.1 Hz and 64 Hz while attenuating those outside this range (Figure 8). Additionally, artifacts—unwanted signals not originating from cerebral activity—are manually identified and removed from each recording. This combination of filtering and artifact rejection minimizes external interference, producing cleaner EEG data that more accurately represents brain function.

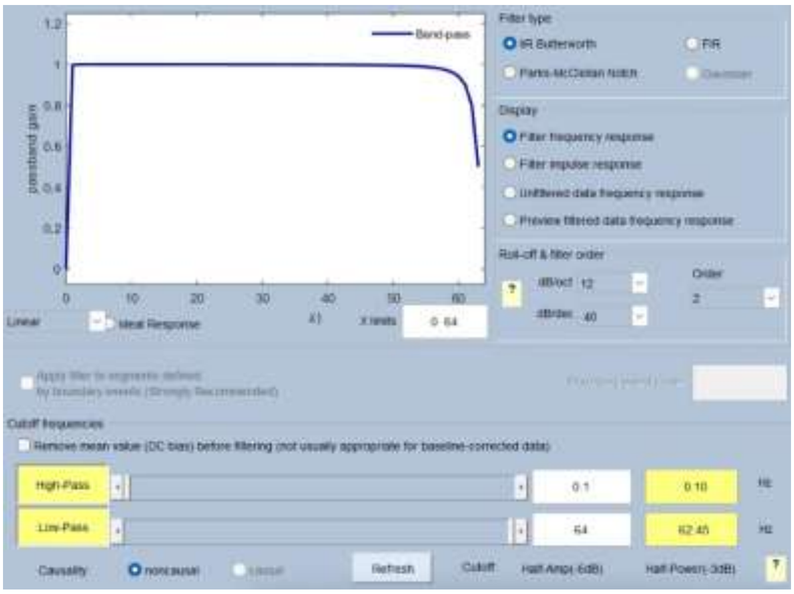


Figure 8. Infinite impulse response (IIR) butterworth filter of the 2nd order

3.1.2. Noise removal and signal enhancement

Noise removal and signal enhancement involve advanced techniques to clarify the recorded EEG signals. Independent Component Analysis (ICA) is a key computational method used to separate multivariate signals into independent components, allowing for the identification and exclusion of noise or artifacts. ICA is particularly useful for signals with a low signal-to-noise ratio, ensuring that the true neurological signals are not obscured. By enhancing the signal quality, ICA plays a critical role in preparing EEG data for detailed analysis (Ganesh and Kumar, 2011).

The integration of Bandpass Filters and ICA in EEG preprocessing exemplifies a strategic approach to refining and analyzing neurological signals. The Butterworth filter, known for its flat frequency response and sharp cutoffs, maintains the integrity of the desired frequencies while eliminating interference. In conjunction with ICA, which removes non-brain components based on their statistical independence, this synergy ensures that EEG signals are thoroughly prepared for accurate and insightful analysis, enhancing the reliability and depth of neurological studies (Kingphai and Moshfeghi, 2021).

3.2. Features extraction

FFT is a powerful algorithm for converting time-domain EEG signals into the frequency domain, helping to reveal relationships between frequencies and amplitudes. It computes the power spectrum, segmenting EEG data into major frequency bands—theta, alpha, beta and integrates spatial measurements from electrodes, producing a multidimensional feature vector essential for understanding brain functions and diagnosing disorders like schizophrenia (Sun et al., 2021).

FFT is preferred over the Discrete Fourier Transform (DFT) due to its computational efficiency, especially when processing large EEG datasets. The algorithm categorizes data into even and odd elements, using a recursive strategy to optimize DFT calculations. This decomposition allows for swift processing of EEG signals, a key feature of the FFT's utility in frequency-domain analysis.

The FFT method involves breaking a sequence of N data points (where N is a power of two) into smaller, recursive calculations, using the 'butterfly' operation to efficiently compute the DFT, as detailed in Equations 1 to 4 (Sun et al., 2021). This process highlights FFT's role in processing multidimensional EEG data, combining spatial, frequency, and temporal domains for comprehensive signal analysis.

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi i}{N} nk} \quad (1)$$

$$X(k) = \sum_{n=0}^{N/2-1} x(2n) W_N^{nk} + \sum_{n=0}^{N/2-1} x(2n+1) W_N^{\left(n+\frac{N}{2}\right)k} \quad (2)$$

$$X(2r) = \sum_{n=0}^{N/2-1} g(n) W_{N/2}^{nr} \quad (3)$$

$$X(2r+1) = \sum_{n=0}^{N/2-1} h(n) W_{N/2}^{nr} \quad (4)$$

3.3. Azimuthal equidistant projection

The Azimuthal Equidistant Projection (AEP) offers a novel method for representing 3D EEG data on a 2D surface, minimizing distortion while preserving data integrity, particularly useful in EEG analysis (Wu and Yao, 2007). This technique involves converting EEG spatial data into geographical coordinates, and then projecting them onto a flat plane using AEP (Figure 9). Electrode positions are first translated into longitude and latitude and then mapped with the AEP formula (Equation 5), where λ, ϕ, and R represents longitude, latitude, and the sphere's radius, respectively.

$$x = R\cos(\lambda)\cos(\phi) \; ; \; y = R\sin(\lambda)\cos(\phi) \quad (5)$$

The method ensures that distances from a central point are accurately preserved, effectively capturing the spatial and temporal dimensions of EEG data on a single visual plane. While this approach maintains spatial relationships vital for EEG interpretation, it primarily preserves accuracy near the central point, with potential distortions in peripheral regions (Bashivan et al., 2016). AEP's strength lies in its capacity to present complex EEG data dynamically, offering an effective visualization of brain activity.

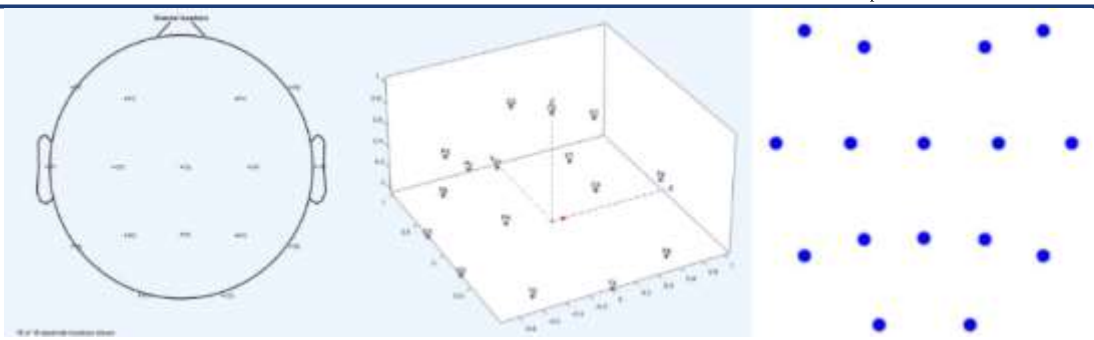


Figure 9. 2D Representation of 16 EEG electrodes placements based on the concept of the AEP

3.4. Transforming features into RGB images

The transformation of EEG signals into RGB images involves capturing the spatial, spectral, and temporal complexities of the data. Traditional methods that form vectors from electrode measurements fail to preserve these intricate structures, leading to the development of a two-dimensional imaging strategy. This approach not only maintains the spatial distribution of the EEG but also encodes spectral information through different color channels.

Using azimuthal equidistant projection, 3D electrode locations are mapped onto a 2D plane. This technique ensures that distances from a central point on the spherical model of the head are accurately reflected on the plane, although relative distances between electrode pairs may shift. The projection yields a spatial distribution of cortical activity, which is then interpolated onto a 32x32 grid using the Clough-Tocher scheme (Alfeld, 1984), optimizing the balance between signal resolution and computational efficiency.

Each frequency band produces a topographical map, and these maps are combined to create a tri-channel (RGB) image (Figure 10). This image, rich in spatial and spectral detail, is fed into a deep convolutional neural network for advanced analysis.

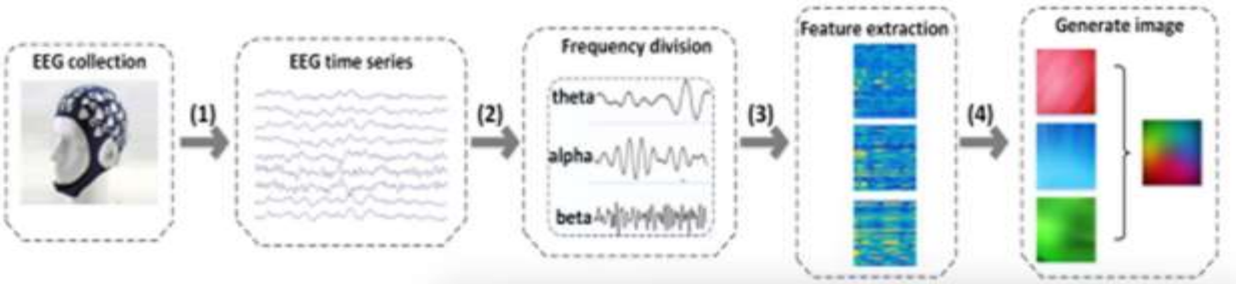


Figure 10. Image construction algorithm

3.5. CNN model architecture

CNN is highly effective in extracting relevant features from visual data by using specialized convolutional filters to identify patterns. The CNN architecture consists of three key layers: the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layer applies filters (or kernels) to the input data, generating feature maps that capture significant data patterns. The pooling layer, particularly max pooling, reduces the dimensionality of these feature maps by selecting the maximum values, simplifying the data while retaining essential information.

Finally, the fully connected layer classifies the input into categories, such as healthy or pathological states, based on a trained dataset. The network's architecture includes an input layer followed by convolutional, pooling, and fully connected layers. Each pixel of the input image is processed through convolution, forming a feature map, and non-linearities are managed using ReLU layers. CNNs excel at extracting spatial features, such as color and edges, but struggle with time-series data, such as EEG signals, which include crucial temporal dynamics (Sharma, G. and Joshi, A, 2021).

Two CNN models were utilized in this study to classify EEG data represented as RGB images. Both models were designed to capture spectral and temporal features through convolutional and pooling layers. Model A, with a simpler architecture, processed the input images using fewer layers, while Model B incorporated additional convolution and pooling layers for more complex feature extraction. In both models, dense layers were employed for classification, with regularization techniques such as dropout, early stopping, data augmentation, and 5-fold cross-validation applied to prevent overfitting. These models were used to analyze and classify EEG data into healthy or schizophrenia states based on the extracted features (Tables 3 and 4).

Table 3. Model A summary

Layer (type)	Output Shape	Parameters
input_layer (InputLayer)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 256, 256, 32)	896
conv2d_1 (Conv2D)	(None, 256, 256, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 32)	0
flatten (Flatten)	(None, 131072)	0
dense (Dense)	(None, 512)	67,109,376
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 1)	257
Total Parameters:	201,753,317	
Trainable Parameters:	67,251,105	
Optimizer Parameters:	134,502,212	

Table 4. Model B summary

Layer (type)	Output Shape	Parameters
input_layer (InputLayer)	(None, 256, 256, 3)	0
conv2d_2 (Conv2D)	(None, 256, 256, 32)	896
conv2d_3 (Conv2D)	(None, 256, 256, 32)	9,248
max_pooling2d_2 (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_4 (Conv2D)	(None, 128, 128, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 64, 64, 64)	0
flatten_1 (Flatten)	(None, 262144)	0
dense_3 (Dense)	(None, 512)	134,218,240
dropout_2 (Dropout)	(None, 512)	0
dense_4 (Dense)	(None, 256)	131,328
dropout_3 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 1)	257
Total Parameters:	403,135,397	
Trainable Parameters:	134,378,465	
Optimizer Parameters:	268,756,932	

3.6. Implementation and training

The implementation of the current study was performed on a system with an AMD Ryzen 7 7730U CPU, 16 GB RAM, AMD Radeon Vega 8 GPU, and Windows 10 OS. MATLAB was used for EEG data tasks such as loading, filtering, sampling, and visualization, while Google Colab was employed for training, validating, and classifying the RGB images using deep neural networks (DNNs). Multiple Python libraries, including Keras and TensorFlow, were utilized. The model's performance was assessed based on accuracy, precision, recall, F1 score, ROC AUC, and convergence speed.

Deep learning parameters like filter dimensions, output channel quantity, and network depth were optimized through experimental trials. Weight adjustments during training were guided by back-propagation, and performance was enhanced using batch normalization and dropout techniques. The Adam optimizer with an initial learning rate of 0.0001 was employed, and the model was trained for 50 epochs with a batch size of 32. Binary cross entropy served as the loss function. The final approximate ratios for training, validation, and testing in this K-Fold cross-validation setup are Training: 72%, Validation: 8%, and Testing: 20%. This is achieved by dividing the data into 5 folds for K-fold cross-validation. Within each fold, 90% of the training data is used for actual training, and 10% is used for validation.

The network architecture included stacked convolutional layers with small 3×3 receptive fields, each using ReLU activation and one-pixel padding to maintain spatial resolution. Max-pooling layers with 2×2 windows followed the convolutional layers, gradually expanding the receptive field. The number of kernels doubled as the network deepened.

The dataset consisted of 12264 non-overlapping epochs from 84 patients (both healthy and schizophrenia), with each epoch converted into 256x256 RGB images using FFT. Data augmentation was performed by adding Gaussian noise (0.1 of σ), generating a total of 24528 RGB images (Figure 11).

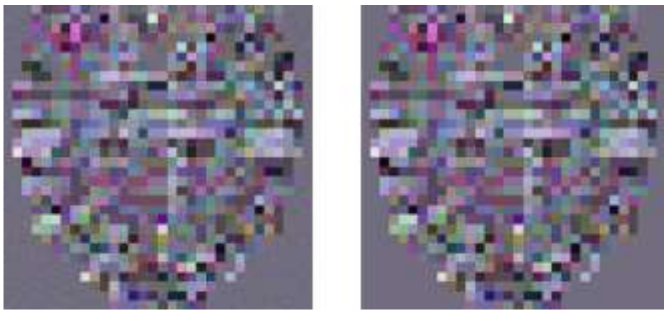


Figure 11. Augmented RGB image for FFT features (left), generated RGB image for FFT features (right)

4. Results

Power Spectral Density (PSD) was applied for FFT feature extraction on the EEG data, comparing the mean PSD values across three frequency bands (α, β, and θ) for healthy controls (HC) and SZ patients (Figure 12).

Model B achieved the best performance in terms of accuracy, precision, recall, F1 score, ROC AUC, and implementation time for FFT analysis, with the following metrics: Accuracy: 95.97%, Precision: 95.71%, Recall: 96.73%, F1: 96.22%, and ROC AUC: 95.91%. The detailed results are illustrated in Figures 13 to 16.

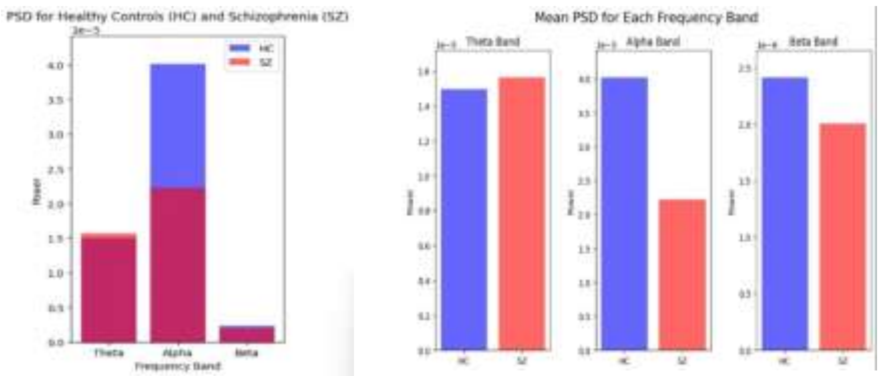


Figure 12. Comparison of PSD values for α, β and θ bands for HC and SZ (left), mean PSD values for each frequency band (right)

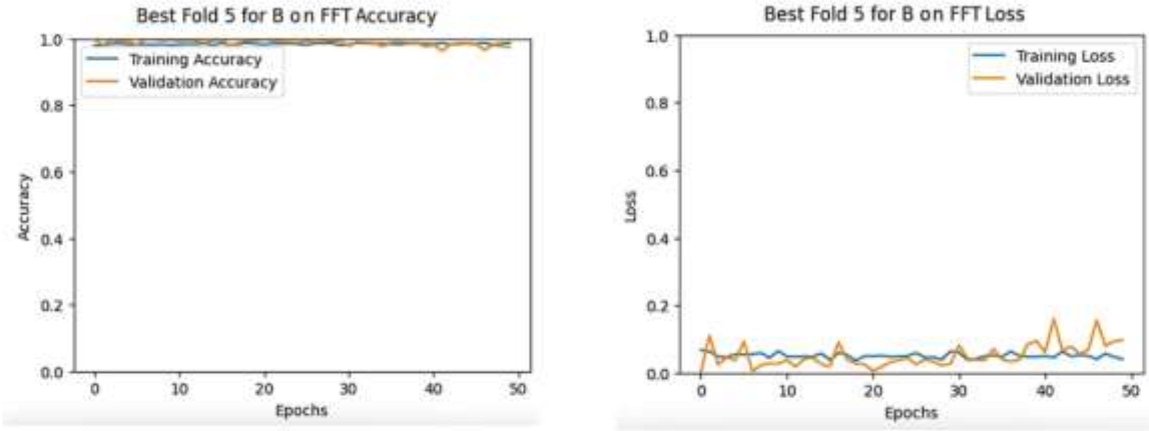


Figure 13 Training and validation accuracies for B model on FFT (left), training and validation losses for B model on FFT (right)

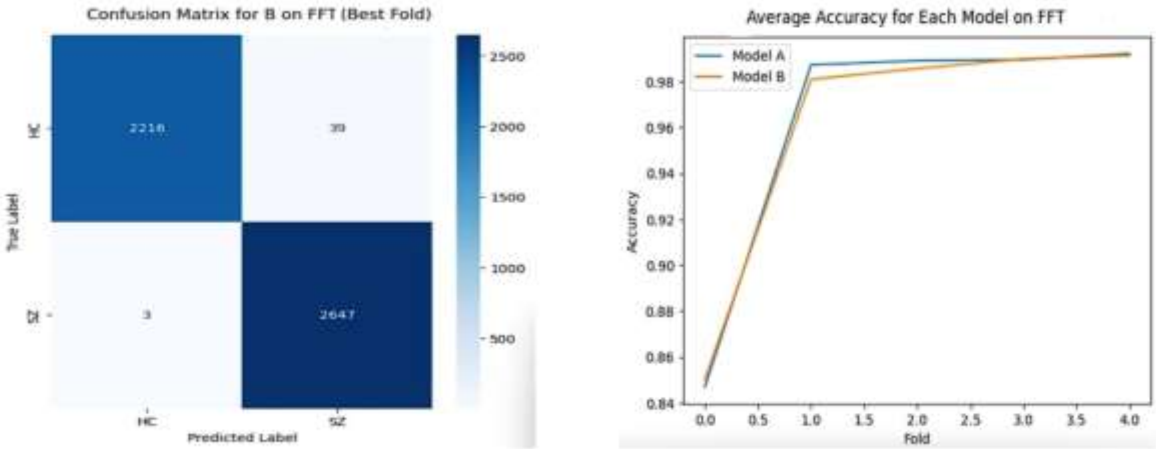


Figure 14. Model B confusion matrix on FFT (left), average accuracy for both models on FFT (right)

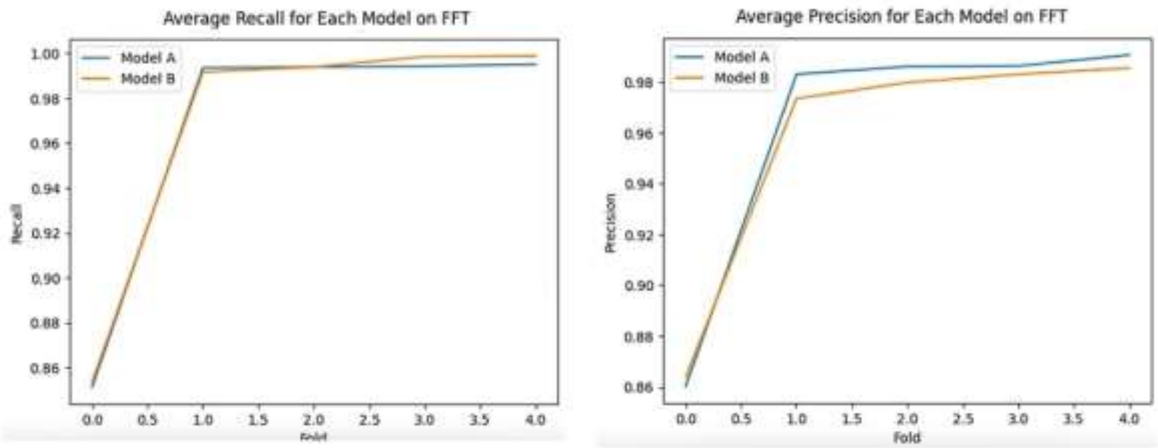


Figure 15. Average recall for both models on FFT (left), average precision for both models on FFT (right)

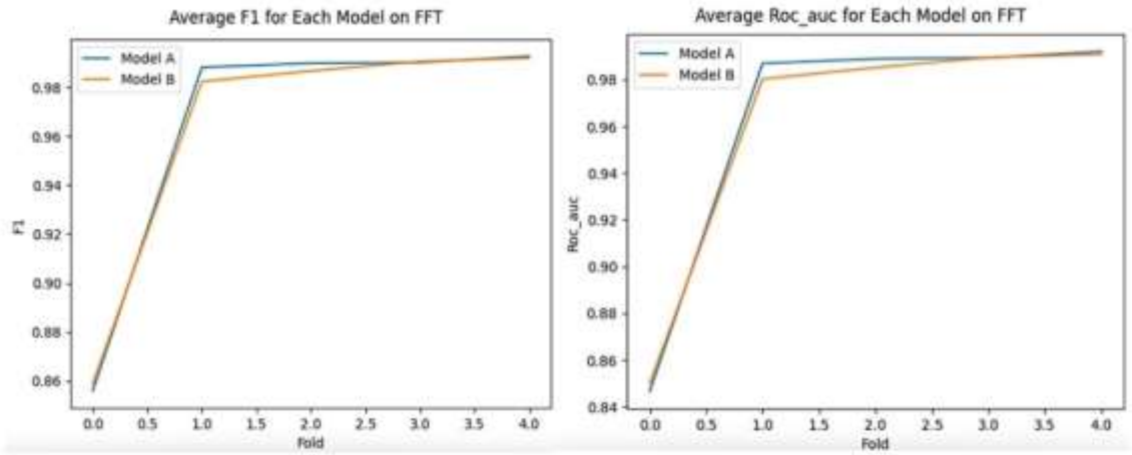


Figure 16. Average F1 for both models on FFT (left), average ROC AUC for both models on FFT (right)

5. Discussion

The findings of the current study highlight significant differences in the PSD of alpha, beta, and theta frequency bands between HC and SZ patients. These results are in agreement with previous studies, particularly the findings by (Murphy and Öngür, 2019), (Koshiyama et al., 2021) and others, which have documented abnormalities in the PSD and phase dynamics of alpha and theta oscillations in individuals with schizophrenia.

The results indicate a pronounced difference in the alpha band PSD, with healthy controls exhibiting significantly higher alpha power compared to schizophrenia patients. This aligns with the established literature, which reports a lower peak frequency and decreased alpha power in schizophrenia, particularly in regions such as the temporal and cingulate cortices. The study by Murphy and Öngür (2019) describes this phenomenon as "alpha slowing," where the peak frequency of alpha oscillations shifts leftward. This abnormality, widely distributed across multiple brain regions in schizophrenia patients, has been linked to disrupted neural synchrony and impaired cognitive functions.

In the current study, the reduced alpha PSD in schizophrenia patients could reflect a similar pathological mechanism, pointing to widespread cortical dysregulation. The robust nature of this finding warrants further exploration, as alpha oscillations are critical for various neural processes, including attention, memory, and sensory integration. The comparison with healthy controls further underscores the significance of alpha abnormalities as a biomarker for schizophrenia.

The consistent reduction in alpha PSD and the subtle differences in beta and theta PSD highlight the importance of frequency-specific analyses in understanding schizophrenia pathology. The widespread and robust alpha slowing observed in both the current and previous studies underscores its potential as a biomarker for schizophrenia. Future research could focus on regional-specific analyses to explore the spatial distribution of these abnormalities further. Moreover, integrating phase dynamics and functional connectivity analyses with PSD measures could provide a more comprehensive understanding of neural oscillatory disruptions in schizophrenia. Such approaches could pave the way for novel therapeutic targets and interventions aimed at restoring normal oscillatory dynamics in affected individuals.

The proposed CNN-Sigmoid model demonstrated superior performance compared to prior studies utilizing the same EEG dataset for schizophrenia classification. Achieving an accuracy of 95.97%, it surpassed the CNN model by Naira and Alamo (2019) with 90% accuracy, the DBN model by Phang et al. (2019) with 93.06%, and the CNN-LSTM model by Singh et al. (2021) with 94.08%. Sensitivity, a critical metric in medical diagnostics, was notably higher (96.73%) in the proposed model compared to the CNN-LSTM (92.70%). Additionally, the model achieved a ROC AUC of 95.91%, providing a robust measure of classification ability, which previous studies did not report. The precision (95.71%) and F1 score (96.22%) also outperformed Singh et al.'s model, indicating balanced and reliable predictions (Table 5).

Table 5. Comparison with other DL models' performances that used the same NNCI dataset

Work	Model	Classifier	% Accuracy	% Sensitivity	% ROC AUC	% Precision	% F1 Score
(Naira and Alamo, 2019)	CNN	Softmax	90.00	90.00	NA	NA	NA
(Phang et al., 2019)	DBN	Softmax	93.06	95.00	NA	NA	NA
(Singh et al., 2021)	CNN-LSTM	Sigmoid	94.08	92.70	NA	NA	93.62
The Proposed Method	CNN	Sigmoid	95.97	96.73	95.91	95.71	96.22

The improvements can be attributed to the model's architecture and feature extraction techniques, which effectively capture EEG data's spatiotemporal complexity. However, the reliance on deep learning methods poses challenges, such as computational demands and susceptibility to overfitting, particularly with limited dataset sizes. While regularization techniques were applied, further validation on larger, diverse datasets is needed.

Compared to other studies, the proposed model demonstrates higher predictive accuracy and sensitivity while addressing issues such as noise in EEG data. Despite these strengths, challenges related to class imbalance and generalizability persist, aligning with broader challenges in biomedical deep learning. Future efforts should focus on integrating techniques like transfer learning and explainability to enhance clinical applicability and reliability.

6. Conclusion

This study aimed to improve SZ diagnosis using EEG data and deep learning models, focusing on classification accuracy by extracting spectral power features via FFT and analyzing them with CNNs.

The proposed CNN model achieved an accuracy of 95.97%, outperforming previous studies that used the same dataset. Notably, it exceeded the 90% accuracy reported by Naira and Alamo (2019) with a CNN model, the 93.06% accuracy achieved by Phang et al. (2019) using a DBN, and the 94.08% accuracy obtained by Singh et al. (2021) with a CNN-LSTM model. This highlights the effectiveness of the proposed approach in improving classification performance for EEG-based schizophrenia detection.

Despite these advancements, limitations such as class imbalance, overconfidence in predictions, and high computational demands remain challenges. The reliance on a limited dataset further emphasizes the need for more comprehensive data collection in future research.

Future work should focus on alternative data representation, enhanced data augmentation, and larger, more balanced datasets. Addressing the underperformance of certain FFT-based models could further refine EEG-based diagnostic tools for schizophrenia and other neurological disorders.

Ethics Permissions

This paper does not require ethics committee approval.

Conflict of Interest

The authors declare that there is no conflict of interest for this paper.

Author Contribution

Sema Koç Kayhan identified the research problem, suggested methodological approach, and reviewed the manuscript. Zekeriya Edahil developed the software, tested the results and wrote the manuscript.

References

Alfeld, P. (1984). A trivariate Clough-Tocher scheme for tetrahedral data. *Computer Aided Geometric Design*, 1(2), 169–181.

Bashivan, P., Rish, I., Yeasin, M., and Codella, N. (2016). *Learning representations from EEG with deep recurrent-convolutional neural networks,* published as a conference paper at ICLR

Bonita, J. D., Ambolode, L. C. C., Rosenberg, B. M., Cellucci, C. J., Watanabe, T. A. A., and Rapp, P. E. (2014). Time domain measures of inter-channel EEG correlations: a comparison of linear, nonparametric and nonlinear measures. *Cogn Neurodyn*, 8, 1–15.

Chen, Z., Zhao, Y., Jin, C., & Zhao, W. (2019). A Review on EEG Based Emotion Classification. https://doi.org/10.1109/iaeac47372.2019.8997704

Delorme, A. (2019). EEG preprocessing in EEGLAB [PDF]. Swartz Center for Computational Neuroscience. https://sccn.ucsd.edu/githubwiki/files/eeglab2019_aspet_artifact_and_ica.pdf

Ganesh, R. N., and Kumar, D. K. (2011). An overview of independent component analysis and its applications. *Informatica*, 35(1).

Gorbachevskaya, N. and Borisov, S. (2019). EEG of healthy adolescents and adolescents with symptoms of schizophrenia (Database). http://brain.bio.msu.ru/eeg_schizophrenia.htm, 2019. (Accessed date: 7 January 2025).

Harm, M., Hope, M., and Household, A. (2013). Diagnostic and Statistical Manual of Mental Disorders. *American Psychiatric Association*. (5th ed. pp. 87-90).

Harrison, G., Hopper, K., Craig, T., Laska, E., Siegel, C., and Wanderling, J. (2001). Recovery from psychotic illness: A 15-and 25-year international follow-up study. *The British Journal of Psychiatry*, 178, 506-517.

Jaeschke, K., Hanna, F., Ali, S., Chowdhary, N., Dua, T., and Charlson, F. (2021). Global estimates of service coverage for severe mental disorders: Findings from the WHO Mental Health Atlas 2017. *Global Mental Health*, 8, e27.

Kingphai, K., and Moshfeghi, Y. (2021). On EEG Preprocessing Role in Deep Learning Effectiveness for Mental Workload Classification. 10.1007/978-3-030-91408-0_6.

Koshiyama, D., Miyakoshi, M., Tanaka-Koshiyama, K., Joshi, Y. B., Sprock, J., Braff, D. L., and Light, G. A. (2021). Abnormal phase discontinuity of alpha- and theta-frequency oscillations in schizophrenia. *Schizophrenia Research*, *231*, 73–81. https://doi.org/10.1016/j.schres.2021.03.007

Kwon, J. S., and Carpenter, C. J. (2007). Electroencephalography in schizophrenia. *Schizophrenia Bulletin*, 33(2), 253-265.

Min, S., Lee, B., and Yoon, S. (2017). Deep learning in bioinformatics. *Briefings in Bioinformatics*, 18, 851–869

Murphy, M., and Öngür, D. (2019). Decreased peak alpha frequency and impaired visual evoked potentials in first episode psychosis. *NeuroImage. Clinical*, *22*, 101693. https://doi.org/10.1016/j.nicl.2019.101693

Naira, C. A. T., and Alamo, C. J. L. D. (2019). Classification of People who Suffer Schizophrenia and Healthy People by EEG Signals using Deep Learning. *International Journal of Advanced Computer Science and Applications(IJACSA)*, 10(10). http://dx.doi.org/10.14569/IJACSA.2019.0101067

Newson, J. J., and Thiagarajan, T. C. (2019). EEG frequency bands in psychiatric disorders: A review of resting state studies. *Frontiers in Human Neuroscience*, 12, 521. https://doi.org/10.3389/fnhum.2018.00521

Niedermeyer, E., and Lopes da Silva, F. H. (2005). *Electroencephalography: Basic principles, clinical applications, and related fields* (6th ed., pp. 123-145, 200-210). Lippincott Williams & Wilkins.

Oostenveld, R., and Praamstra, P. (2001). The five percent electrode system for high-resolution EEG and ERP measurements. *Clinical Neurophysiology*, 112(4), 713–719.

Phang, C. R., Ting, C. M., Samdin S. B., and Ombao, H. (2019). *Classification of EEG-based Effective Brain Connectivity in Schizophrenia using Deep Neural Networks.* 9th International IEEE/EMBS Conference on Neural Engineering (NER), San Francisco, CA, USA. pp. 401-406, doi: 10.1109/NER.2019.8717087.

Plis, S. M., Hjelm, D. R., Salakhutdinov, R., Allen, E. A., Bockholt, H. J., Long, J. D., Johnson, H. J., Paulsen, J. S., Turner, J. A., and Calhoun, V. D. (2014). Deep learning for neuroimaging: a validation study. *Frontiers in Neuroscience*, 8(August):1–11. ISSN 1662-453X. https://doi.org/10.3389/fnins.2014.00229

Savio, A., Charpentier, J., Termenon, M., Shinn, A. K., and Graña, M. (2010). Neural classifiers for schizophrenia diagnostic support on diffusion imaging data. *Neural Network World*, 20, 935–949.

Sharma, G., and Joshi, A. (2021). *Novel EEG based Schizophrenia Detection with IoMT Framework for Smart Healthcare*. cornell university. https://doi.org/10.48550/arxiv.2111.11298

Sharma, M., Patel, R.K., Garg, A., SanTan, R., and Rajendra Acharya, U. (2023). Automated detection of schizophrenia using deep learning: A review for the last decade. *Physiological Measurements*, 44(03TR01). https://doi.org/10.1088/1361-6579/acb24d

Singh, K., Singh, S., and Malhotra, J. (2021). Spectral features based convolutional neural network for accurate and prompt identification of schizophrenic patients. Proceedings of the Institution of Mechanical Engineers, Part H: *Journal of Engineering in*

Medicine, 235(2), 167-184. doi:10.1177/0954411920966937

Sun, J., Cao, R., Zhou, M., Hussain, W., Wang, B., Xue, J., and Xiang, J. (2021). A hybrid deep neural network for classification of schizophrenia using EEG data. *Scientific Reports*, 11, 4706. https://doi.org/10.1038/s41598-021-83350-6

Upadhyay, R., Manglick, A., Reddy. D. K., Padhy, P. K., and Kankar, P. K. (2015). Channel optimization and nonlinear feature extraction for electroencephalogram signals classification. *Computers and Electrical Engineering*, 45, 222–234

World Health Organization. (2023). Schizophrenia. [Fact sheet]. World Health Organization. September 1. https://www.who.int/news-room/fact-sheets/detail/schizophrenia

Wu, D., and Yao, D. (2007). The azimuth projection for the display of 3-D EEG data. *Computers in Biology and Medicine*, 37(12), 1821-1826. https://doi.org/10.1016/j.compbiomed.2007.06.006