Advancing Early Schizophrenia Detection Through the Integration of EEG Based Neuroimaging Preprocessing Techniques and Hybrid Deep Learning Models

Abstract

Mental illnesses represent a critical global health challenge, affecting nearly one in five individuals and encompassing conditions such as major depressive disorder, bipolar disorder, autism spectrum disorder, and schizophrenia. Among these, schizophrenia is one of the most debilitating, characterized by persistent disturbances in thought, perception, and behavior, leading to significant functional impairment, reduced quality of life, and increased risk of premature mortality. Despite its prevalence and impact, current diagnostic approaches remain limited. Conventional methods relying on clinical interviews and behavioral observations are subjective, prone to inter-clinician variability, and often fail to detect prodromal stages. Neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) have provided valuable insights but are costly, resource-intensive, and unsuitable for large-scale deployment. Electroencephalography (EEG), by contrast, offers a non-invasive, cost-effective, and temporally precise modality capable of capturing subtle neural oscillatory abnormalities associated with schizophrenia. However, existing EEG-based studies often face challenges including small and imbalanced datasets, computationally complex models, reliance on handcrafted features, and limited interpretability. To address these gaps, the proposed research will develop a novel hybrid deep learning framework that leverages EEG signals for the early and accurate detection of schizophrenia. The framework will incorporate rigorous preprocessing, overlapping segmentation, and data augmentation to enhance dataset robustness, while explainable artificial intelligence (AI) techniques will ensure interpretability and clinical trust. By advancing an intelligent, scalable, and resource-efficient diagnostic system, this research will contribute to reducing diagnostic subjectivity, enabling earlier intervention, and ultimately improving patient outcomes while alleviating healthcare burdens.

Keywords: *Mental illnesses, neuropsychiatric disorders, schizophrenia, EEG signals, artificial intelligence*

1. Introduction

Mental illnesses represent one of the most pressing challenges to global health, significantly influencing individuals, families, and societies at large [1]. These conditions arise from a combination of genetic predispositions, neurobiological alterations, and environmental factors.

According to the widely accepted definition, a mental disorder is characterized by clinically significant disturbances in cognition, emotional regulation, or behavior that cause marked distress or impairment in social, occupational, or other areas of functioning. The scale of this issue is enormous. Data from the National Alliance on Mental Illness (NAMI) highlights that nearly one in five adults experience some form of mental illness in their lifetime, underscoring the need for continuous research and innovation in prevention, diagnosis, and treatment [2]. Mental health disorders are not only associated with suffering but also place a significant financial and healthcare burden on systems worldwide.

Among the vast spectrum of mental illnesses, certain conditions such as major depressive disorder, bipolar disorder, autism spectrum disorder, and schizophrenia are widely regarded as the most disabling and costly [3]. These conditions often manifest early in life, affecting development across emotional, cognitive, and social domains, which exacerbates their long-term impact. One of the most concerning aspects of mental illness is the decreased life expectancy of affected individuals. This reduction in lifespan is attributed not only to medical complications but also to increased risks of self-harm and suicide. Therefore, mental health must be approached comprehensively, incorporating early detection, prevention strategies, and accessible, interdisciplinary treatment plans to mitigate the burden on patients and healthcare systems alike.

Schizophrenia, in particular, is one of the most debilitating neuropsychiatric disorders [4]. It is a chronic and severe condition characterized by profound disturbances in thought, perception, emotion, and behavior. Patients with schizophrenia often live with persistent psychosis, presenting symptoms such as delusions, hallucinations, disorganized thought patterns, speech abnormalities, and erratic behaviors. These symptoms distort an individual's perception of reality, hinder social interaction, and impair daily functioning. In addition to psychotic features, schizophrenia often involves negative symptoms such as reduced motivation, diminished emotional expression, and difficulty forming or sustaining social connections. Cognitive deficits, including problems with attention, working memory, and executive function, further complicate the condition, making it a multifaceted disorder with a wide range of presentations.

Epidemiological studies highlight the global burden of schizophrenia. According to the World Health Organization (WHO), approximately 24 million people worldwide live with this disorder, which accounts for roughly 1% of the global population [5]. The incidence of schizophrenia ranges between 8 and 60 individuals per 100,000 each year, with variations linked to genetic predisposition, geographical region, and socioeconomic factors. Men are typically diagnosed in their late teens to early twenties, while women often develop symptoms in their late twenties or early thirties. Childhood-onset cases are rare, whereas diagnoses after the age of 45 are uncommon. Notably, individuals with schizophrenia face a significantly increased risk of premature mortality compared to the general population, largely due to comorbid physical health issues such as cardiovascular disease, diabetes, and metabolic syndrome. Limited access to physical healthcare, under-diagnosis of medical problems, and lifestyle risk factors such as poor diet, sedentary behavior, and substance use further compound these vulnerabilities.

The complexity of schizophrenia extends to its underlying causes. Historically, schizophrenia was viewed primarily as a psychiatric condition with a strong psychological basis. However, advances in neuroimaging, neuropathology, and genetics have revealed its biological underpinnings. Structural abnormalities in the brain, such as reductions in gray matter volume in regions like the hippocampus, amygdala, caudate, and thalamus, have been consistently observed in patients with schizophrenia. Enlargement of the ventricles and alterations in cortical thickness and connectivity further point to widespread neurodevelopmental disruptions. These brain changes often precede the manifestation of clinical symptoms, suggesting that schizophrenia is a progressive neuropsychiatric disorder with a neurodevelopmental origin that unfolds later in life [6]. Despite this progress, the disorder remains poorly understood, with genetic, environmental, and neurobiological factors interacting in complex ways.

Traditional methods for diagnosing schizophrenia have primarily relied on clinical interviews, behavioral observations, and standardized criteria outlined in diagnostic manuals such as the DSM-5 [7]. While useful, these methods remain subjective, often leading to variability in diagnosis and delayed recognition of early or prodromal stages. In addition, neuroimaging techniques like functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) have been explored to understand the structural and functional brain abnormalities associated with schizophrenia. Although these tools provide valuable insights, they are costly, require specialized expertise, and are not easily accessible in routine clinical practice, particularly in resource-limited settings.

Electroencephalography (EEG), by contrast, has proven to be a more practical and effective tool [8]. It records brain activity with high temporal resolution, is portable, cost-efficient, and non-invasive, making it especially suitable for large-scale screenings and early diagnostic applications. EEG has demonstrated the ability to capture subtle neural dysfunctions linked to schizophrenia, offering an objective complement to traditional psychiatric evaluations. Recent advancements in artificial intelligence have further strengthened the potential of EEG-based diagnostics [9]. Deep learning and machine learning models can detect intricate patterns in EEG signals that may not be visible to human experts, thereby enhancing diagnostic precision and reliability. These systems enable automated analysis, reduce dependence on manual feature extraction, and offer scalable solutions that address the limitations of conventional methods.

Despite growing interest in AI-driven EEG analysis, existing approaches often suffer from challenges such as limited dataset size, lack of generalizability across populations, and difficulties in model interpretability. Furthermore, many studies rely on complex architectures requiring substantial computational resources, which hinders their translation into clinical practice. These gaps highlight the need for a lightweight yet robust hybrid framework capable of achieving high diagnostic accuracy while remaining computationally efficient and clinically practical. The proposed study will address these gaps by integrating advanced novel hybrid deep learning strategies with EEG analysis, thereby contributing to the development of scalable, interpretable, and clinically applicable tools for schizophrenia diagnosis

2. Literature Review

Espino-Salinas *et al*. [10] presented a CNN-based approach for detecting depression and schizophrenia using motor activity data from the Depresjon and Psykose datasets. Motor signals were transformed into images and classified using a 2D-CNN architecture trained via 3-fold cross-validation. The model achieved an overall accuracy of 84% on blind testing, with high F1-scores across schizophrenia, depression, and control classes. Notable findings revealed lower motor activity in depression and heightened activity in schizophrenia, highlighting CNNs' capacity to capture subtle behavioral patterns. Compared to traditional models like Random Forest, CNNs outperformed in accuracy and required no manual feature extraction. However, the study faced limitations such as class imbalance, affecting recall in depression classification, and challenges in generalizing results to broader populations. Despite this, the use of full-day motor activity recordings and image-based deep learning proved effective for non-invasive mental disorder diagnosis.

Jalan *et al*. [11] proposed a deep learning framework for schizophrenia detection using EEG data from the MV Lomonosov Moscow State University dataset, which included recordings from adolescents with schizophrenia and healthy controls. EEG signals were transformed into two-dimensional Markov Transition Field images to preserve temporal dynamics, followed by deep feature extraction using a pre-trained VGG-16 model. These features were evaluated through two pipelines: a Support Vector Machine and a deep learning approach combining an autoencoder with a neural network. SHAP analysis added interpretability to the model's decision-making process. The study demonstrated strong discriminative performance in classifying schizophrenia. However, limitations included the model's focus on binary classification, restricting its use in detecting other psychiatric conditions, reliance on a single, limited dataset, high computational demands, and the black-box nature of deep learning models, which could impact interpretability and clinical adoption despite explainability tools like SHAP.

Sukemi *et al*. [12] explored the application of modified deep learning models for classifying EEG signals to assist in schizophrenia diagnosis. The study utilized a dataset comprising EEG recordings from 14 individuals diagnosed with paranoid schizophrenia and 14 healthy controls. Several CNN architectures including LeNet-5, AlexNet, VGG-16, and ResNet-18 were adapted to process 1D EEG data by replacing 2D layers with 1D counterparts. Additionally, hybrid models combining CNN with LSTM and GRU were implemented to capture both spatial and temporal dynamics. These architectures underwent training using cross-validation and were evaluated using accuracy and F1 scores. The findings demonstrated strong classification capabilities across all models, particularly those integrating recurrent layers. While the study showcased promising results in automated EEG-based diagnosis, the limited sample size posed a challenge to generalizability. Further, adaptation complexity in architecture tuning restricts broader applicability across different EEG datasets.

Sarwer *et al*. [13] investigated automated diagnosis of Alzheimer's disease and schizophrenia using EEG functional connectivity data from public databases containing patient and control recordings. EEG signals were preprocessed through filtering, artifact removal, and segmentation before extracting connectivity metrics such as coherence and phase locking value across delta, theta, alpha, beta, and gamma bands. A hybrid deep learning framework combining convolutional neural networks and long short-term memory networks was employed to capture both spatial and temporal patterns. The model achieved high accuracy with 94% for Alzheimer's disease and 91% for schizophrenia, supported by strong ROC curve results. Findings revealed reduced theta and alpha connectivity in Alzheimer's disease and abnormal beta and gamma hyper synchronization in schizophrenia.

Paraschiv et al. [14] proposed a deep learning-based framework for detecting schizophrenia-related abnormalities using an openly available EEG dataset consisting of 49 schizophrenia patients and 32 healthy controls. Event-related potentials from nine key electrode sites were analyzed using transfer entropy to capture the directional flow of information between brain regions. These TE matrices were used as input for a hybrid model combining convolutional neural networks and Bidirectional Long Short-Term Memory networks. The study identified disrupted connectivity patterns, particularly in the frontal and central brain regions, which are critical for cognitive processing. Validation using Muse 2 EEG headband data supported the potential for real-time, portable mental health monitoring. The model was integrated into the NeuroPredict platform, enabling continuous tracking of neural activity. Limitations included the small sample size, dependence on preprocessed data, and technical constraints in deploying real-time TE analysis for clinical applications.

Shams and Jabbari [15] proposed a deep learning-based framework combining a 15-layer CNN and a 16-layer CNN-LSTM for diagnosing schizophrenia using EEG signals from adolescents. The dataset, collected from the Laboratory for Neurophysiology at Lomonosov Moscow State University, included recordings from 45 patients and 39 healthy controls. The study applied wavelet-based denoising, Z-score normalization, and DCGAN-based data augmentation to address data scarcity. CNN layers extracted temporal features, while LSTM layers captured sequential dependencies directly from raw EEG. The model showed strong diagnostic capability. However, limitations included the small and imbalanced dataset, lack of multiclass classification to differentiate between similar disorders, low interpretability of deep models, and the need for extensive hyperparameter tuning. Additionally, training relied on high computational power, raising concerns about hardware accessibility and reproducibility.

Bhadra *et al*. [16] introduced five deep learning frameworks for schizophrenia identification using EEG signals from the Repository for Open Data, which included recordings from 19 electrodes collected in a resting state. The study employed Discrete Wavelet Transform (DWT) and Multivariate Empirical Mode Decomposition (MEMD) to extract entropy-based complexity features. These features were transformed into 2D matrices and classified using both pretrained CNNs and custom neural networks. The study also explored multiview feature fusion through concatenation, PCA, and Canonical Correlation Analysis (CCA), and evaluated performance using different optimizers and activation functions. Feedforward Neural Networks (FFNN) were used for 1D feature representations. The CCA-based fusion model demonstrated superior performance with minimal computational complexity. Despite the promising outcomes, limitations included the use of a geographically restricted dataset and reliance solely on entropy features.

Shivaprasad *et al*. [17] utilized the Schizophrenia and Digital-Palmar Dermatoglyphics dataset, which included 176 participants comprising 69 diagnosed cases and 107 controls. The dataset contained 50 attributes, with 15 categorical and 35 numerical values. Preprocessing steps involved encoding, normalization, and data balancing to ensure quality and consistency. Feature selection was performed using Pearson's correlation and Mutual Information, identifying attributes such as age range, sex, and palmar ridge patterns as significant. Multiple machine learning models, including Logistic Regression, Ridge, and SVM, alongside deep learning approaches, were employed for classification. Explainable AI methods such as LIME, SHAP, ELI5, Anchor, and QLattice enhanced interpretability, highlighting age range and triradii as key predictors. Results indicated reliable classification performance. The study concluded that dataset size limitations introduced overfitting risks, and larger data samples would have improved model generalizability and robustness.

Saadatinia and Armin [18] proposed a deep learning approach for the automatic diagnosis of schizophrenia using EEG brain recordings. The study utilized two datasets, one with 16 channels from 84 adolescents and another with 19 channels from 28 subjects, both processed into spectrograms through short time Fourier transform. A custom convolutional neural network inspired by VGGNet architectures was applied for initial classification, followed by data augmentation using variational autoencoder and Wasserstein GAN with gradient penalty. The VAE augmented dataset achieved higher accuracy, outperforming baseline models and showing faster convergence compared to the non-augmented dataset. The Local Interpretable Model Agnostic Explanations algorithm was employed to identify key spectrogram features influencing diagnosis, enhancing model transparency. Findings demonstrated that generative data augmentation significantly improved classification accuracy, although WGAN required extensive computational resources and longer training times, marking a key limitation of the approach.

Sunil *et al*. [19] investigated the early detection of schizophrenia using the UCLA Consortium for Neuropsychiatric Phenomics LA5c dataset, which included 50 schizophrenic and 122 control subjects. Resting-state fMRI data underwent extensive preprocessing, including realignment, normalization, smoothing, and filtering, followed by parcellation into 164 brain regions. Graph theory, machine learning, and graph neural network methods were employed, including Random Forest, XGBoost, SVM, and a deep graph convolutional neural network. The DGCNN achieved an accuracy of 0.82, sensitivity of 0.84, and specificity of 0.94. Biomarker identification methods, including ROI local feature selection and spectral clustering, revealed key regions such as the supramarginal gyrus, inferior and superior temporal gyri, superior parietal lobule, and planum temporale. Interpretability techniques such as SHAP values and GNNExplainer highlighted crucial graph features. The study was limited by imbalanced data, small sample size, and single-site acquisition.

Padmavathi *et al.* [20] proposed an automated diagnostic framework for schizophrenia detection using EEG signals collected from 36 patients and 36 healthy controls. After preprocessing with filtering and independent component analysis to eliminate noise and artifacts, the signals were processed through an 11-layer convolutional recurrent deep neural network built with convolution and LSTM layers, LeakyReLU activations, dropout regularization, and softmax classification. The model was trained and validated using cross-validation and random partitioning methods, demonstrating strong performance in feature extraction and classification. The integration of convolutional layers for spatial features and LSTM layers for temporal dependencies enhanced the model's ability to capture complex EEG patterns. The findings confirmed the potential of an end-to-end deep learning approach for reliable diagnosis of schizophrenia. However, limitations included the small dataset size, high computational requirements, interpretability challenges, and risk of overfitting due to model complexity.

Aksoy *et al*. [21] examined schizophrenia detection using an EEG dataset collected from 39 healthy adolescents and 45 diagnosed patients. EEG signals were recorded from 16 channels, with four channels selected for detailed analysis. Preprocessing involved discrete wavelet transform for frequency decomposition, statistical feature extraction, and dimensionality reduction with principal component analysis. Classical machine learning methods including logistic regression, k-nearest neighbors, random forest, decision tree, naive Bayes, and support vector machine were applied alongside a quantum support vector machine (QSVM) implemented on the IBM Quantum Lab. Findings indicated that QSVM with Pauli X and Z feature maps performed with higher effectiveness compared to classical models. The study demonstrated that quantum approaches could enhance schizophrenia detection while emphasizing limitations caused by dependence on simulator environments, qubit constraints, and increased execution time when circuit complexity grew.

Hussain *et al*. [22] proposed a lightweight one-dimensional convolutional neural network with an ensemble-like approach to classify schizophrenia from EEG signals. The study employed a benchmark dataset of 84 adolescents, including 45 diagnosed with schizophrenia and 39 healthy controls, recorded across 16 EEG channels. The signals were segmented into smaller trials, and data augmentation was applied to address data scarcity. The pyramidal CNN model, designed with minimal parameters, offered efficiency and avoided overfitting issues. Results indicated strong performance and revealed that temporal and frontal brain regions played a critical role in discrimination, with beta and gamma frequency bands showing notable associations with schizophrenia. The method reduced complexity compared to existing deep models while providing robust classification. Reported limitations included the small dataset size, lack of severity-based stratification, and absence of information on schizophrenia subtypes, medication influence, and illness phases.

Zhang *et al*. [23] conducted a study using T1-weighted MRI scans from the SchizConnect database, comprising 887 structural brain images from BrainGluSchi, COBRE, and NMorphCH datasets. The authors developed a modified 3D VGG-11 model with batch normalization and squeeze-excitation blocks (SE-VGG-11BN) to classify schizophrenia patients from healthy controls. Preprocessing involved skull stripping, affine registration, and down-sampling, followed by data augmentation. The model achieved an AUC of 0.987, outperforming the benchmark model and other CNN architectures, including DenseNet and ResNet. Grad-CAM analysis revealed subcortical and ventricular regions as key for classification, aligning with existing neuroimaging findings. Limitations included high computational cost, modest sample size, potential loss of anatomical detail due to down-sampling, and the absence of pre-trained model fine-tuning.

Grover et al. [24] presented Schizo-Net, a model for schizophrenia diagnosis using EEG-based brain connectivity indices and deep learning. The EEG dataset, sourced from the Institute of Psychiatry and Neurology in Warsaw, included recordings from 14 patients and 14 healthy controls. After extensive preprocessing using EEGLAB, artifact removal was performed through ASR and ICA. Six brain connectivity features—PLV, PLI, PDC, DTF, SL, and COR—were extracted, capturing various aspects of brain synchronization and directional flow. Multiple deep neural network architectures were trained and validated using Monte Carlo cross-validation with stratification. Findings revealed that causality-based features like DTF and PDC offered richer diagnostic insights than phase synchronization metrics. Significant connectivity differences were observed in frontal and occipital brain regions of patients.

Limitations included the exclusive focus on alpha frequency bands and equal weight assignment to all neural models during the late fusion process.

3. Research Gap

- Reliance on small, imbalanced, and geographically constrained EEG datasets causes overfitting, weak cross-population generalization, and reduced external validity.
- Minimal use of multi-site and cross-modal validation restricts the establishment of robust, generalizable biomarkers.
- Computationally intensive architectures with millions of parameters limit scalability in real-time and resource-constrained clinical settings.
- Extensive hyperparameter tuning increases reproducibility challenges and hinders clinical translation.
- Overuse of handcrafted features (spectral power, entropy, connectivity indices) restricts capture of full spatiotemporal EEG dynamics.
- Converting EEG into 2D surrogate representations (spectrograms, Markov Transition Fields, transfer entropy) introduces temporal distortions, information loss, and preprocessing overhead.
- Data augmentation strategies (GANs, VAEs) improve diversity but introduce instability, long convergence times, and synthetic artifacts.
- Limited integration of explainable AI (XAI), with many models functioning as black boxes despite the clinical need for interpretability.
- Persistent difficulty in separating physiological artifacts (e.g., ocular, muscular, cardiac noise) from pathological neural patterns undermines signal reliability and diagnostic precision.

4. Motivation of the Study

Schizophrenia is a chronic and highly disabling psychiatric disorder that represents one of the most complex challenges to global public health due to its early onset, lifelong course, and profound clinical and socioeconomic consequences. Typically emerging in late adolescence or early adulthood, it disrupts critical stages of personal, cognitive, and social development and is characterized by enduring disturbances in thought processes, perception, emotional regulation, and behavior. These impairments severely compromise functional capacity, diminish quality of life, and contribute to elevated rates of premature mortality, primarily attributable to comorbid medical conditions and heightened vulnerability to suicide. Although the disorder affects approximately one percent of the global population, its impact extends far beyond individual suffering, creating long-term economic burdens associated with unemployment, loss of productivity, and the need for sustained clinical and social support. Despite decades of research, schizophrenia continues to be among the most difficult psychiatric conditions to diagnose at an early stage with accuracy and consistency. Conventional diagnostic frameworks, including the DSM-5 and ICD-10, rely predominantly on clinical interviews, subjective observations, and patient self-reports. While these approaches provide standardized criteria, they remain vulnerable to variability across clinicians and fail to adequately capture the subtle neurobiological changes that precede overt psychosis, thereby delaying intervention at a stage where treatment outcomes could be significantly improved. Neuroimaging modalities such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) have generated important insights into altered connectivity and brain function in schizophrenia, but their routine use is limited by high cost, technical complexity, and restricted accessibility in most clinical contexts. Electroencephalography (EEG), by contrast, represents a practical, cost-effective, and non-invasive modality with superior temporal resolution, capable of identifying abnormal neural oscillations and connectivity patterns associated with the disorder in real time. Although promising, traditional EEG analysis has depended largely on handcrafted features such as coherence and spectral power, which are constrained in their ability to capture the multidimensional dynamics of brain activity in schizophrenia. The motivation for this study arises from the urgent need to establish diagnostic frameworks that are objective, scalable, and clinically feasible. By harnessing the advantages of EEG signals within a more advanced analytical paradigm, the proposed research seeks to facilitate earlier, more accurate detection of schizophrenia, enabling timely intervention, improved clinical management, and a reduction in the heavy medical and societal burden imposed by this disorder.

5. Objectives of the Study

- To design and implement a novel hybrid deep learning model for automated detection of schizophrenia from EEG signals, capable of capturing both localized neural oscillations and broader temporal dynamics.
- To apply advanced EEG preprocessing techniques, including missing value imputation, Z-score normalization, overlapping segmentation, and data augmentation, in order to enhance data quality, reduce noise, and mitigate class imbalance for robust model training.

- To integrate explainable AI (XAI) approaches, such as feature attribution methods, for identifying discriminative electrode regions and temporal patterns, thereby ensuring interpretability, clinical trust, and alignment with established neurophysiological markers of schizophrenia.
- To conduct rigorous model evaluation using stratified validation protocols and quantitative performance metrics including accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC, benchmarking against conventional diagnostic methods to demonstrate reliability and clinical applicability.

6. Scope of the Study

Schizophrenia detection research occupies a pivotal role in advancing diagnostic precision, clinical reliability, and accessibility within mental healthcare. Although schizophrenia is highly prevalent and associated with lifelong impairment, conventional diagnostic methods that rely on clinician observation, patient self-report, and structured interviews remain constrained by subjectivity, variability, and delayed recognition of prodromal stages. Neuroimaging techniques such as functional magnetic resonance imaging and magnetoencephalography provide valuable insights into structural and functional alterations, yet their cost, infrastructure demands, and technical complexity limit their routine clinical application, particularly in resource-limited settings. In contrast, electroencephalography offers a pragmatic alternative, being portable, cost-effective, and capable of capturing neural oscillatory abnormalities with high temporal resolution. The proposed research will advance a hybrid deep learning framework that utilizes EEG signals to enhance the early and accurate detection of schizophrenia. The framework will incorporate rigorous preprocessing techniques to manage signal noise, segmentation strategies to preserve temporal dependencies, and data augmentation to mitigate dataset scarcity. By integrating hybrid neural architectures, the study will enable robust feature representation that captures both localized neural dynamics and global connectivity disruptions characteristic of schizophrenia. Evaluation will be performed using standard performance metrics such as sensitivity, specificity, precision, recall, and F1-score, ensuring comprehensive assessment of diagnostic reliability. In addition, explainable mechanisms will be integrated to provide transparency regarding the discriminative features that guide classification decisions, thereby fostering trust and clinical interpretability. This work will also emphasize scalability and adaptability, ensuring that the framework remains computationally efficient and viable for real-world application across diverse healthcare environments. Ultimately, the proposed study will not only establish a methodological advancement in EEG-based analysis but will also contribute to more equitable, timely, and objective schizophrenia diagnosis, supporting improved clinical decision-making and reducing the broader health and socioeconomic burdens associated with this disorder.

7. Proposed Methodology

EEG provides a reliable, non-invasive, and cost-effective means of capturing neural activity with high temporal resolution, making it particularly suitable for the research of schizophrenia. In this research, a novel hybrid deep learning framework will be designed to automatically detect schizophrenia from EEG recordings. The complete workflow of the proposed methodology is illustrated in Figure 1. The principal objective is to develop a robust binary classification system capable of differentiating between EEG signals recorded from individuals diagnosed with schizophrenia and those from healthy controls.

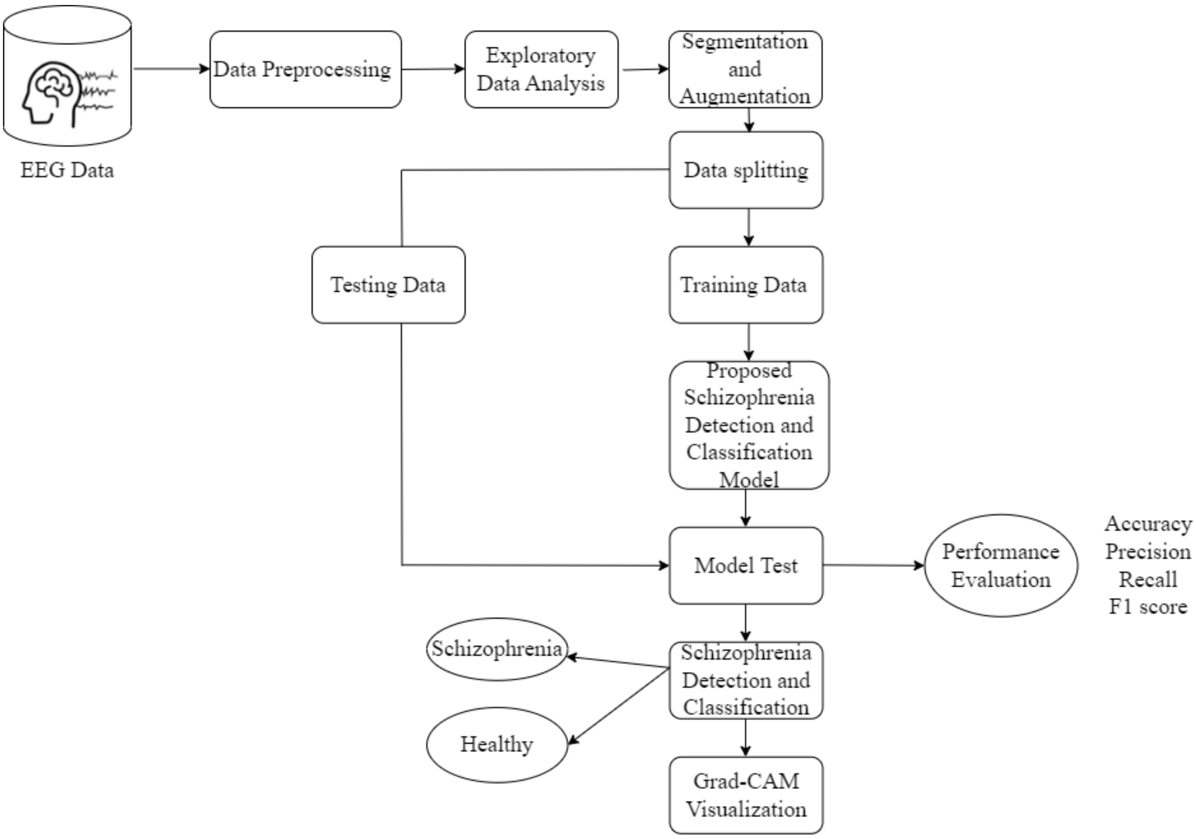

Fig. 1. Block Diagram of Proposed Methodology

The dataset will be sourced from publicly available repositories to ensure diversity and accessibility, comprising EEG recordings that capture brain activity across multiple cortical regions through standardized electrode placement protocols. Following dataset acquisition, preprocessing will be undertaken to improve the quality and consistency of signals. Missing values will be addressed using established imputation techniques or segment removal where appropriate, and normalization will be performed to place all signals on a standardized scale. Z-score normalization will be employed to stabilize variations across subjects and sessions, thereby enhancing training efficiency and improving model convergence.

Exploratory Data Analysis (EDA) will be performed to study the characteristics and distribution of the dataset. Visualizations such as heatmaps will be generated to examine correlations between electrode signals, while descriptive statistics will be compiled to provide insights into class distribution, variance, and electrode-specific activity patterns. These analyses will provide an informed basis for both preprocessing decisions and model optimization strategies. Preprocessed signals will be segmented into smaller overlapping trials to increase sample size, reduce computational complexity, and highlight discriminative features. Data augmentation techniques will be implemented to mitigate the limitations posed by dataset scarcity and to enhance generalizability across populations. Hyperparameter tuning will be systematically applied to optimize performance, focusing on factors such as learning rates, batch sizes, and trial lengths.

The novel hybrid deep learning model will be developed to extract meaningful representations from EEG signals by combining complementary learning strategies, ensuring that both localized neural activity and broader temporal dynamics are captured effectively. Evaluation will be conducted using a stratified split of the dataset into training, validation, and testing subsets to ensure balanced representation of classes. Performance assessment will rely on established metrics including accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC, providing a comprehensive evaluation of classification effectiveness and robustness. In addition, explainable AI (XAI) methods will be incorporated to ensure interpretability of predictions. Feature attribution techniques will be employed to highlight the electrodes and temporal regions most influential in the classification process, thereby aligning computational results with clinically meaningful insights.

The final framework will provide binary outputs, classifying input EEG signals as schizophrenia or healthy control, while also presenting interpretable evidence to support its decision-making process. By integrating rigorous preprocessing, a novel hybrid deep learning model, and explainable analysis, this study will establish an intelligent, scalable, and clinically applicable methodology for the early and accurate detection of schizophrenia.

8. Implementation Feasibility

The proposed schizophrenia detection framework will be implemented, trained, and evaluated on the Google Collaboratory platform using Python. Google Collaboratory provides a free, cloud-based environment with GPU and TPU support, allowing efficient processing of EEG signals and rapid model training. Its integration with widely used Python libraries such as TensorFlow, Keras, and PyTorch ensures seamless implementation of advanced deep learning architectures, while libraries like MNE and SciPy support EEG signal preprocessing and analysis. The platform's scalability will enable experimentation with large datasets and diverse model configurations without requiring extensive local computational resources. Furthermore, its collaborative and accessible environment will facilitate reproducibility, transparency, and cost-effectiveness, making it an ideal choice for validating the proposed hybrid deep learning framework for schizophrenia detection.

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