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EEG-Mindmap: A Non-Invasive Diagnostic Tool for Schizophrenia Detection

Prof. Pushpalatha M¹, Umarani K M², Rekha G³, Rachana M⁴, Tabiya Anjum⁵

Assistant Professor, Dept. of CS & E, S J M Institute of Technology, Chitradurga, Karnataka, India¹

Student, Dept. of CS & E, S J M Institute of Technology, Chitradurga, Karnataka, India²

Student, Dept. of CS & E, S J M Institute of Technology, Chitradurga, Karnataka, India³

Student, Dept. of CS & E, S J M Institute of Technology, Chitradurga, Karnataka, India⁴

Student, Dept. of CS & E, S J M Institute of Technology, Chitradurga, Karnataka, India⁵

ABSTRACT: Schizophrenia is a chronic and severe neuropsychiatric disorder affecting approximately one in 300 individuals worldwide and the World Health Organization (WHO) estimates that there are 20 million persons worldwide. The condition imposes significant social, educational, financial, and personal burdens due to stigma, discrimination, and impairments in cognitive and behavioural functioning. Early detection is essential to ensure timely medical intervention, as delayed diagnosis increases the risk of self-harm, suicidal tendencies, and long-term disability. Traditional diagnostic practices rely primarily on clinical interviews and behavioural assessments, which can be subjective, time-consuming, and prone to variability.

Electroencephalography (EEG), a non-invasive, cost-effective, and high-temporal-resolution technique, has emerged as a promising tool for identifying neurophysiological abnormalities associated with schizophrenia. In this study, we propose an AI-based Schizophrenia Detection Web Interface Platform that enables remote EEG data processing and automated analysis. The system integrates machine learning and deep learning methods, with experimental results demonstrating that a Convolutional Neural Network (CNN) achieves superior performance in classifying EEG patterns indicative of schizophrenia. The CNN model supports real-time signal processing, generating immediate diagnostic feedback through intuitive visual indicators, while securely uploading data sent to a distant server after processing.

The proposed framework provides a reliable, portable, and intelligent diagnostic solution that leverages deep-learning-driven analytics to facilitate early screening and continuous mental-health monitoring. By reducing dependence on subjective assessments and high-cost neuroimaging technologies, this system aims to deliver scalable, accessible, and efficient support for mental-health diagnostics, particularly in resource-constrained settings.

KEYWORDS: Schizophrenia detection, Electroencephalography (EEG), EEG signal processing, Non-invasive diagnosis, Machine learning, Deep learning, Convolutional Neural Network (CNN), Temporal Convolutional Network (TCN), EEG-based classification, Signal preprocessing, Feature extraction, Brain connectivity analysis, Transformer models, Graph Neural Networks (GNN), Ensemble learning, Flask web interface, Real-time diagnosis, IoMT healthcare systems.

I. INTRODUCTION

Schizophrenia is a severe neuropsychiatric disorder affecting more than 20 million people worldwide and causing major cognitive, emotional, and social impairments. Early detection is essential, as untreated cases often lead to self-harm, disability, and significant societal burden. Traditional diagnosis relies on clinical interviews and behavioral observations, which can be subjective and inconsistent. Common symptoms include hallucinations, disorganized speech, delusions, and reduced responsiveness.

Electroencephalography (EEG) offers a non-invasive, affordable, and high-temporal-resolution method for capturing brain activity, making it a valuable diagnostic tool for conditions such as epilepsy, autism, depression, and

schizophrenia. EEG provides objective biomarkers and supports continuous monitoring. Advances in computational neuroscience have improved the analysis of complex, nonlinear EEG patterns

Machine learning and deep learning methods have shown strong potential in automating schizophrenia detection using EEG signals. Convolutional Neural Networks (CNNs) in particular demonstrate superior performance by learning spatial-temporal patterns directly from multichannel EEG data. These models enable real-time classification, reduce dependence on clinician interpretation, and increase diagnostic reliability.

The proposed system integrates portable EEG acquisition with deep-learning analysis to deliver a scalable, low-cost, and real-time schizophrenia screening solution. By combining wearable sensing technology with CNN-based classification, the platform enhances accessibility, supports early intervention, and provides an intelligent alternative to expensive neuroimaging techniques.

II. LITERATURE SURVEY

Schizophrenia is a complex psychiatric disorder marked by disruptions in cognition, perception, and neural connectivity. With the rise of EEG-based diagnostic systems, researchers are increasingly exploring automated, non-invasive approaches for early and accurate schizophrenia detection. EEG signals capture abnormalities in brain rhythms, offering valuable biomarkers that can be processed through advanced signal processing, machine learning (ML), and deep learning (DL) techniques. Recent studies highlight the importance of robust preprocessing, effective feature extraction from frequency bands, and efficient classification models capable of distinguishing schizophrenia patients from healthy individuals. The literature also emphasizes challenges such as noise, variability across subjects, computational demands, and the need for real-time, portable, and clinically adaptable systems.

III. EXISTING SYSTEM

The current diagnostic approach for schizophrenia primarily relies on clinical evaluation, which includes patient interviews, observation of behavioral, and psychological assessments based on standardized criteria such as the DSM-5 (Diagnostic and Statistical Manual of Mental Disorders) or ICD-10 (International Classification of Diseases). This method is largely subjective, as it depends on the interpretation and experience of the mental health professional.

- Lack of visualization: Few systems provide interpretable visual representations (e.g., brain maps) for clinicians.
- Generalization issues: Models often fail to perform well across datasets due to subject variability and noise.
- Integration gap: No single system currently combines preprocessing, feature extraction, classification, and intuitive visualization into one clinical tool.
- Ethical and clinical concerns: Some systems are not designed with explainability, fairness, or clinical usability in mind.

While existing EEG-based systems for schizophrenia detection have demonstrated promising accuracy levels (often between 90–99%), they are typically optimized for research purposes and not fully ready for clinical deployment. There remains a critical need for an interpretable, integrated, and visual AI system.

IV. PROPOSED SYSTEM METHODOLOGY AND DISCUSSION

A. Proposed System

The proposed system presents an AI-driven Schizophrenia Detection Web Interface Platform developed using Python Flask to enable efficient and real-time analysis of EEG signals. Machine learning and deep learning methods—primarily a Convolutional Neural Network (CNN)—are integrated to automatically interpret EEG recordings and identify neural patterns linked to schizophrenia. This framework offers a fast, objective, and user-friendly screening alternative to traditional clinical assessment methods. Through the Flask interface, users can upload EEG data in formats such as CSV or EDF. Once uploaded, the system performs automated preprocessing, feature extraction, and CNN-based classification. Results are displayed instantly on the web interface, and all processed files are stored locally for reference.

Objectives of the Proposed System

- **To develop an AI-based schizophrenia detection platform** that analyses EEG signals using machine learning and deep learning techniques, with a focus on improving diagnostic accuracy and objectivity.
- **To design a lightweight, user-friendly web interface using Python Flask** that enables users to upload EEG data and receive immediate diagnostic results without requiring complex hardware or cloud infrastructure.
- **To implement an efficient EEG preprocessing pipeline** that removes noise, artifacts, and distortions, ensuring high-quality signal input for the CNN model.
- **To build and integrate a Convolutional Neural Network (CNN)** capable of automatically extracting spatial-temporal features from EEG signals for accurate classification of schizophrenia and normal patterns.
- **To enable real-time visualization and interpretation** of detection results through graphical indicators and probability-based outputs on the Flask interface.

B. Methodology**Data Acquisition Module**

The Data Acquisition Module is responsible for loading the EEG dataset into the system. The dataset contains multiple EEG channel readings such as Fp1, AF7, F3, FC3, PO8, Nose, and TP10, along with a class label indicating whether the sample corresponds to a Healthy or Schizophrenia condition. This module reads the dataset in CSV format and organizes it into a structured Data Frame for further analysis. It separates the feature matrix **X** (EEG channel values) from the target vector **y** (label), ensuring that the system has clean and structured data as input for preprocessing and machine-learning operations. This module forms the foundation of the entire pipeline, as high-quality and correctly formatted data is essential for achieving accurate model predictions.

✓ Inputs:

- EEG dataset in CSV format.
- Columns: 64 EEG channels + Label column.

✓ Functions:

- Load dataset into pandas Data Frame.
- Separate features (**X**) and labels (**y**).

Label Encoding Module

In this module, categorical labels such as “Healthy” and “Schizophrenia” are transformed into numerical values using label encoding. Machine learning models require numerical input, and this module ensures compatibility by converting the textual labels into encoded integers. The label encoder is also saved using Job lib so that the same mapping can be reused during deployment in the Flask-based prediction system. This guarantees consistent interpretation of model outputs during real-time inference, maintaining uniformity between training and deployment stages.

✓ Functions:

- Convert text labels (“Healthy”, “Schizophrenia”) into numeric form (0/1).
- Save encoder using job lib for use in Flask API.

Data Splitting Module

The Data Splitting Module divides the dataset into training and testing sets using an 80:20 ratio. Stratification is used to ensure that both sets maintain the same proportion of Healthy and Schizophrenia samples, preventing class imbalance and improving model generalization. The training set is used for learning model patterns, while the testing set is reserved exclusively for evaluating the performance of the trained models. This separation prevents information leakage and ensures unbiased assessment of each algorithm’s effectiveness.

✓ Functions:

- Split dataset into training/testing sets (80/20).
- Preserve label distribution using stratified split.

Data Scaling Module

This module standardizes the EEG signal values using the Standard Scaler, improving the stability and accuracy of machine-learning models. Since EEG channels vary in amplitude, scaling ensures that all features have equal influence during training. The scaler learns from the training data and applies the same transformation to the testing set. It is then

saved as **scaler.pkl** to maintain identical preprocessing during deployment in the Flask interface, ensuring that real-time EEG inputs are scaled in the same manner as the training data.

- ✓ Functions:
- Standardize EEG channel values
- Fit scaler on training data, transform test data
- Save trained scaler (scaler.pkl)

Machine Learning and Deep Learning Models Training Module

In this module, multiple machine-learning algorithms—including Random Forest, Gradient Boosting, SVM, KNN, Logistic Regression, and Decision Tree, CNN and LSTM —are trained using the preprocessed EEG data. Each model learns to differentiate between Healthy and Schizophrenia EEG patterns by identifying nonlinear relationships and channel-level variations. The system evaluates each model using metrics such as accuracy, precision, recall, and F1-score. This multi-model approach allows the system to determine which algorithm performs best for the given dataset, ensuring robust and reliable prediction.

- ✓ Models Implemented:
- Random Forest
- Gradient Boosting
- SVM (RBF kernel)
- KNN
- Logistic Regression
- Decision Tree
- CNN
- LSTM
- ✓ Functions:
- Train each model
- Predict test outcomes
- Compute performance metrics:
 - accuracy
 - f1-score
 - precision
 - recall

Model Selection and Saving Module

Based on evaluation metrics, this module identifies the best-performing model and saves it as a serialized file using Job lib. The best classifier, along with the label encoder and scaler, is stored for later use in the prediction interface. This enables quick loading of pre-trained models in a lightweight Flask server without the need for retraining. The saved model file ensures reproducibility and allows deployment in real-world environments where fast and efficient EEG classification is required.

- ✓ Functions:
- Identify the best model based on accuracy
- Save:
 - best_model.pkl
 - scaler.pkl
 - label_encoder.pkl

Visualization Module

The Visualization Module enhances interpretability by generating visual analytics, including a bar chart that compares the accuracy of different machine-learning models and a confusion matrix that shows the classification performance of the selected model. Heatmaps and charts generated through Matplotlib and Seaborn help users better understand how

well each model distinguishes between Healthy and Schizophrenia signals. These visualizations are essential for performance analysis, presentation, and reporting, providing clear evidence of the system's reliability.

- ✓ Generates:
 - Bar chart of model accuracy comparison.
 - Confusion matrix heatmap.
 - Classification report.

Flask Deployment Module

This module handles real-time prediction by deploying the trained model in a Flask-based web interface. When EEG data is received from the user, the system loads the saved scaler, label encoder, and best-performing model to preprocess the data and generate a prediction. The Flask API sends back an output label such as "Healthy" or "Schizophrenia," making the system suitable for remote analysis and accessible screening. This module transforms the machine-learning pipeline into a user-friendly diagnostic tool for research or clinical environments.

- ✓ Purpose:
 - Load:
 - best_model.pkl
 - scaler.pkl
 - label_encoder.pkl
 - Accept EEG input from user.
 - Preprocess → Predict → Return result
 - Output:
 - Healthy
 - Schizophrenia
- This module enables real-time prediction through a web interface.

C. SYSTEM ARCHITECTURE

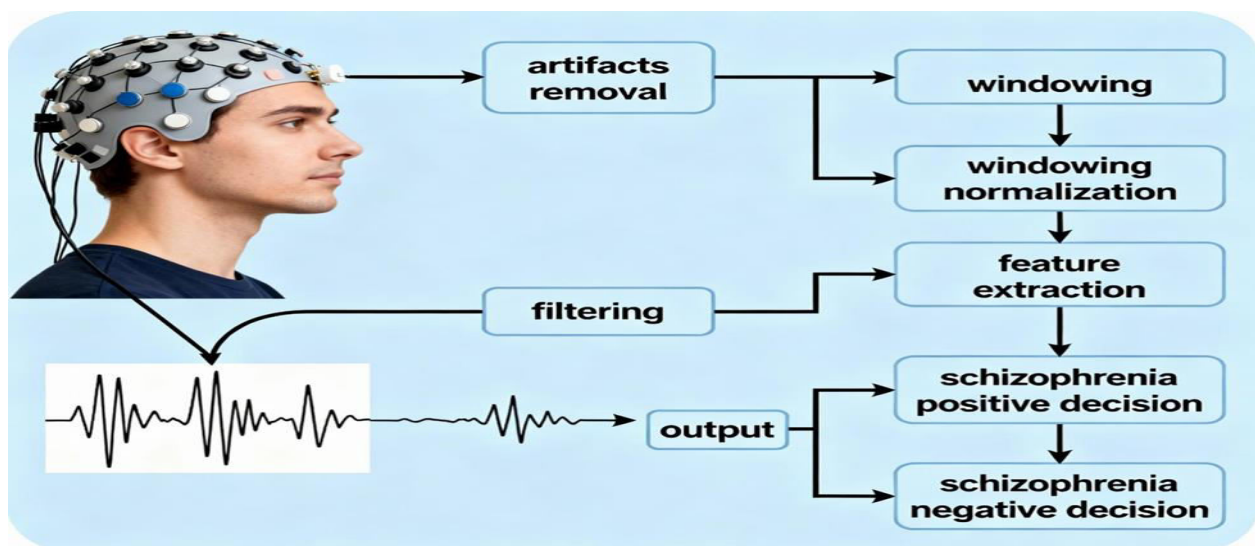


Fig 1: ARCHITECTURE OF THE PROPOSED SYSTEM

System architecture is a conceptual model that defines the structure, behavior, and various views of a system. This includes both hardware and software components, their relationships, and how they communicate.

A system architecture for an EEG-based schizophrenia diagnostic tool would involve preprocessing EEG signals to remove artifacts, extracting relevant features, and then using a machine learning model to classify whether the EEG data

indicates schizophrenia or not. The architecture would likely include modules for data acquisition, preprocessing, feature extraction, and classification.

- A new concept of the portable and wearable cap for schizophrenia detection is proposed for smart healthcare.
- The proposed CNN model is highly robust, accurate, and reliable in detecting schizophrenia disorder.
- A proposed seven-layered CNN model is implemented and proposed for schizophrenia detection and shows superior performance for temporal sequencing compared to other recurrent networks implemented in literature.

D. Functional Requirements

1. Dataset Acquisition

- The system must import and read EEG datasets from available public sources (e.g., PhysioNet, Kaggle, clinical repositories).
- The system must support multiple data formats such as .mat, edf, .csv, or .txt.

2. Data Preprocessing

- The system must clean raw EEG signals by removing noise, artifacts, and missing values.
- Must perform filtering (band-pass filters), epoch segmentation, normalization, and feature extraction.
- Must convert raw EEG recordings into model-ready formats (images, spectrograms, time-series windows, etc.) if required.

3. Feature Extraction

- Must extract meaningful features such as:
Time-domain features (mean, variance, Hjorth parameters)
Frequency-domain features (PSD, FFT)
Time-frequency features (CWT, wavelet transforms)
Connectivity-based features (coherence, correlation).
- Must allow switching between handcrafted features and deep feature extraction.

4. Model Training

- The system must implement ML/DL models for schizophrenia detection such as: SVM, KNN, Random Forest CNN, LSTM, CNN-TCN, Transformers, etc.
- Must split data into training, validation, and testing subsets.

5. Model Evaluation

- The system must compute evaluation metrics like accuracy, precision, recall, F1-score, ROC-AUC.
- Must compare multiple models to identify the best-performing architecture.

6. Model Optimization

The system must support:

- Hyper parameter tuning
- Cross-validation
- Early stopping
- Regularization techniques
- Must track performance improvements after optimization.

7. Prediction Module

- After training, the system must allow input of new EEG samples from the dataset to classify them as:
✓ **Schizophrenia**
✓ **Healthy**

V. EXPERIMENTAL RESULTS

```
df.columns
Index(['subject', 'trial', 'condition', 'sample', 'Fp1', 'AF7', 'AF3', 'F1',
      'F3', 'F5', 'F7', 'FT7', 'FC5', 'FC3', 'FC1', 'C1', 'C3', 'C5', 'T7',
      'TP7', 'CP5', 'CP3', 'CP1', 'P1', 'P3', 'P5', 'P7', 'P9', 'PO7', 'PO3',
      'O1', 'Iz', 'Oz', 'POz', 'Pz', 'CPz', 'Fpz', 'Fp2', 'AF8', 'AF4', 'AFz',
      'Fz', 'F2', 'F4', 'F6', 'F8', 'FT8', 'FC6', 'FC4', 'FC2', 'FCz', 'Cz',
      'C2', 'C4', 'C6', 'T8', 'TP8', 'CP6', 'CP4', 'CP2', 'P2', 'P4', 'P6',
      'P8', 'P10', 'PO8', 'PO4', 'O2', 'VEOa', 'VEOb', 'HEOL', 'HEOR', 'Nose',
      'TP10', 'Label'],
      dtype='object')
```

Fig 1: Dataset Columns

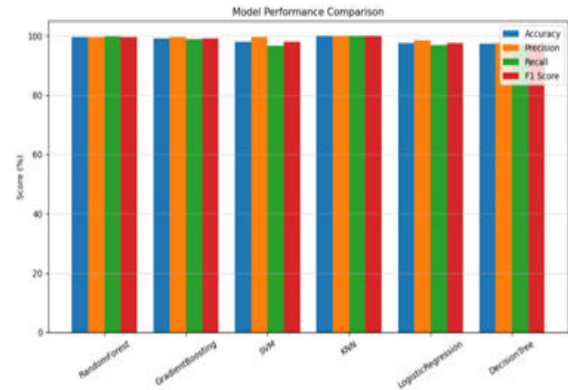


Fig 5: Model Performance

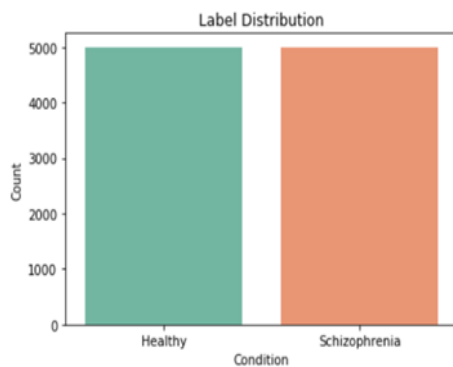


Fig 2: Label Distribution

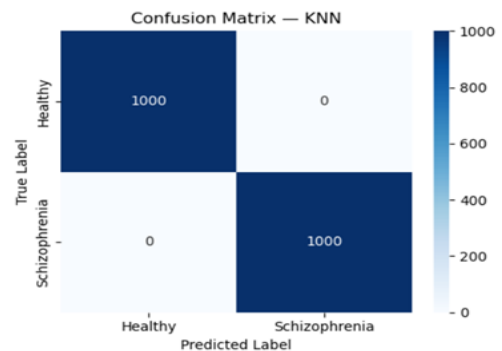


Fig 6: Confusion Matrix

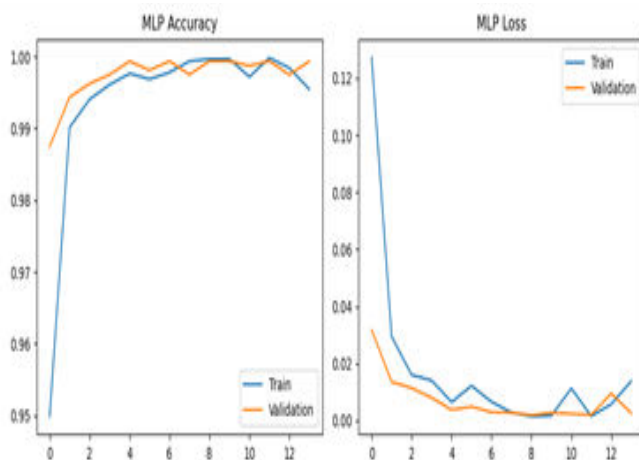


Fig 3: Heat Map

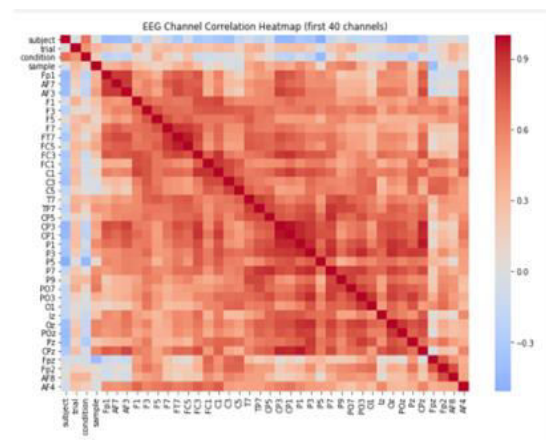


Fig 7: MLP Accuracy and Loss

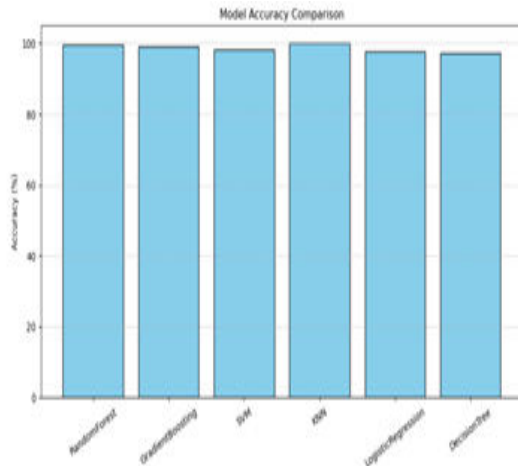


Fig 4: Model Accuracy

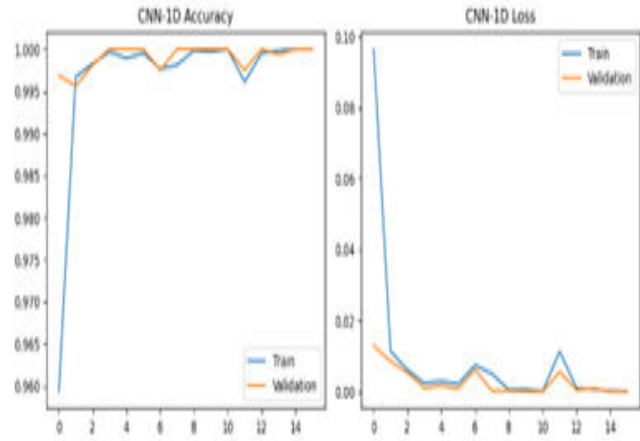


Fig 8: CNN Accuracy and Loss

VI. CONCLUSION

The growing body of research on EEG-based schizophrenia detection demonstrates significant progress toward developing reliable, non-invasive, and automated diagnostic tools. Machine learning and deep learning approaches ranging from classical classifiers to advanced architectures such as CNN–TCN hybrids, GNNs, Transformer models, and wavelet-based deep networks—have shown strong potential in capturing the complex spatiotemporal patterns and connectivity disruptions associated with schizophrenia. While these methods achieve promising accuracy and clinical relevance, challenges related to noise, subject variability, interpretability, and real-time deployment remain important research gaps. Nevertheless, advancements in IoMT, wearable EEG systems, and computational modeling continue to push the field toward scalable, portable, and clinically adaptable solutions. Overall, the literature reinforces the importance of integrating signal processing, feature engineering, and modern deep learning techniques to support early diagnosis, improve treatment outcomes, and enhance mental healthcare accessibility.

VII. FUTURE SCOPE AND ENHANCEMENTS

Future research on EEG-based schizophrenia detection presents multiple promising directions for improving accuracy, scalability, and clinical adoption. One major area lies in developing personalized and adaptive models that can learn subject-specific EEG patterns, reducing variability and enhancing the reliability of predictions across diverse populations. Integrating multimodal data—such as MRI, behavioral metrics, speech patterns, and physiological signals—could provide a more holistic understanding of schizophrenia and strengthen diagnostic precision. Advancements in wearable and IoMT-integrated EEG devices will enable continuous monitoring, early relapse prediction, and remote mental healthcare support, making the system more practical for real-world deployment. Additionally, future studies can explore explainable AI (XAI) methods to improve transparency, help clinicians interpret model decisions, and ensure ethical trustworthiness in psychiatric diagnosis. Enhancements in edge computing and lightweight model architectures will support real-time processing on portable devices, while GNNs, Transformers, and hybrid deep networks can further refine the extraction of spatiotemporal and functional connectivity features. Ultimately, integrating standardized datasets, establishing clinical benchmarks, and validating models through large-scale trials will be crucial for advancing these systems from research prototypes to reliable, scalable clinical tools.

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