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ADVANCED SCHIZOPHRENIA DIAGNOSIS USING EEG SIGNAL PROCESSING AND DEEP LEARNING TECHNIQUES

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ABSTRACT

Schizophrenia is a chronic neuropsychiatric disorder affecting perception, cognition, and behavior. Globally it impacts about 1% of the population. In India, nearly **4–5 million people** are estimated to live with schizophrenia, with many cases undiagnosed due to stigma and limited specialists. Traditionally, diagnosis relies on clinical interviews and behavioral assessment. The objective is to develop an automated system that diagnoses schizophrenia using EEG signals transformed into Markov Transition Field images and classified through deep learning models for accurate, objective decision support. In the manual system, psychiatrists diagnose schizophrenia through patient interviews, behavioral observation, medical history review, and standardized questionnaires such as DSM-based clinical assessments, often supported by basic EEG visual inspection. Manual diagnosis is subjective, time-consuming, and highly dependent on clinician experience. EEG interpretation lacks quantitative analysis, leading to inter-observer variability, delayed diagnosis, misclassification, and difficulty in identifying subtle neurological patterns. The motivation of this research is to overcome subjectivity and inconsistency in manual diagnosis by introducing automated EEG feature extraction and learning-based classification. By capturing hidden temporal patterns using Markov Transition Fields and deep models, the system improves reliability, scalability, and early detection accuracy. The proposed system converts EEG signals into Markov Transition Field images that preserve temporal dynamics of brain activity. Deep learning models such as **VGG16** and **Vision Transformer (ViT)** extract discriminative spatial–temporal features from these images. Multiple classifiers **VGG16-MTF**, **VGG16-NC**, **VGG16-KNN-RNC**, and **ViT-MTF Perceptron** are employed to evaluate and enhance diagnostic performance. Ensemble and transformer-based learning reduce noise sensitivity and improve generalization. This machine learning–driven framework enables accurate, objective, and scalable schizophrenia diagnosis, supporting clinicians with reliable EEG-based decision assistance.

1.INTRODUCTION

Schizophrenia (SCZ) is a chronic and severe mental disorder that impacts around 20 million individuals globally [1]. It is characterized by long-term disturbances in brain function, presenting symptoms such as persistent false beliefs (delusions), sensory perceptions without external stimuli (hallucinations), and disorganized emotions, perceptions, or speech [2]. In comparison to the general population, individuals with schizophrenia face a higher mortality rate, often due to preventable physical health conditions [3]. It is typically diagnosed through clinical evaluation based on standardized criteria obtained during one-on-one interviews. However, the reliability of such diagnoses can vary due to differences in the qualifications, experience, and time constraints of the mental health professionals conducting the assessments [4]. Therefore, there is a need for EEG-based biomarkers that can potentially identify early or prodromal stages of schizophrenia, even before full-blown symptoms appear. Moreover, EEG is relatively affordable, portable, and non-invasive, making it suitable for large-scale screenings or resource-limited settings as compared to neuroimaging techniques like fMRI (functional Magnetic Resonance Imaging), which are costly [5]. EEG signals can be analyzed using AI models to identify patterns not visible to the human eye, improving diagnostic precision and enabling personalized medicine. Although artificial intelligence (AI) has seen widespread adoption in physical healthcare, its application in the field of mental health remains considerably limited [6]. Given the increasing demand for objective, efficient, and reproducible diagnostic tools in mental health, the integration of artificial intelligence (AI) into schizophrenia detection has shown promising advancements. Prior studies have explored various deep learning and machine learning architectures, such as CNNs with time-series image transformations, graph-based models like GCN-LSTM [7], and hybrid approaches involving wavelet transforms [8] and statistical features [9]. These methods have demonstrated the potential of EEG-based AI models in capturing subtle neural patterns associated with schizophrenia. Building on these foundations, this study aims to explore a robust and interpretable classification framework by utilizing Markov Transition Field (MTF) representations of EEG signals. These 2D transformations are further processed using VGG16 for high-level feature extraction. The extracted features are subsequently classified using Support Vector Machines (SVM) and an Autoencoder-based Neural Network. Through this integration, the study seeks to contribute to the development of accurate and

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scalable AI-driven diagnostic tools in psychiatric research. Finally, SHAP stands for SHapley Additive exPlanations, a method in Explainable AI (XAI) that uses game theory to explain the output of AI models, which has been used to incorporate explainability in our proposed method. In this study, we utilized a biomimetic computational approach to address challenges in the diagnosis of psychiatric disorders, which often involve subtle and complex symptom patterns. By employing a deep learning framework—specifically, an autoencoder paired with a Fully Connected Neural Network—we emulate the brain's ability to compress, abstract, and decode patterns in data.

1.1 Background

Schizophrenia is a severe and chronic mental disorder that affects thought processes, perception, emotional regulation, and social behavior. Historically, schizophrenia diagnosis has relied on clinical observation and behavioral assessments, which emerged in the early 20th century with the development of standardized psychiatric classification systems. In India, schizophrenia affects approximately **4–5 million individuals**, with a significant treatment gap due to social stigma, shortage of mental health professionals, and delayed diagnosis. Electroencephalography (EEG) has long been used to study brain activity, but traditional interpretation remained qualitative. The integration of **Markov Transition Fields** with **deep learning architectures such as VGG16 and Vision Transformer** enables objective analysis of EEG signals by capturing temporal transitions and spatial patterns. This approach provides a reliable, data-driven framework for early and accurate schizophrenia diagnosis.

1.2 Problem Definition

Before the adoption of machine learning techniques, schizophrenia diagnosis relied heavily on subjective clinical interviews and behavioral observation. EEG data, when used, was manually interpreted, limiting the extraction of meaningful temporal patterns. Diagnostic accuracy varied across clinicians, leading to inconsistent outcomes. Early-stage symptoms were frequently overlooked due to overlapping behavioral traits with other mental disorders. Large-scale screening and continuous monitoring were not feasible using traditional approaches.

1.3 Research Motivation

The motivation for this research arises from the need to reduce subjectivity and inconsistency in schizophrenia diagnosis. Manual EEG interpretation fails to capture complex temporal dynamics present in brain signals. Advances in deep learning enable automatic extraction of discriminative features from EEG data. Markov Transition Fields preserve temporal transitions effectively. Combining these techniques provides a reliable and scalable diagnostic solution.

1.4 Objective

The objective of the classifier is to accurately distinguish between healthy and schizophrenia EEG patterns using automated feature extraction and learning-based classification. It aims to improve diagnostic reliability, reduce human dependency, and support clinicians with objective decision assistance. The classifier focuses on learning meaningful spatial–temporal representations from EEG-derived images. It ensures consistent performance across different subjects. The model also supports early-stage detection.

1.5 Applications

The proposed system can be applied in clinical psychiatry to assist doctors in objective schizophrenia diagnosis. It supports early screening in mental health camps and hospitals. The framework can be used in research laboratories for EEG-based neurological studies. It aids in monitoring disease progression and treatment response. The system benefits telemedicine platforms by enabling remote diagnosis. It supports training and education of medical professionals. It assists public health programs in large-scale mental disorder screening. It contributes to decision-support systems in neuroinformatics.

1.6 Significance

The significance of this research lies in its ability to transform EEG data into meaningful diagnostic insights using deep learning. It addresses major limitations of manual diagnosis by providing consistency and objectivity. The approach improves early detection rates and supports timely intervention. It reduces dependency on expert availability in resource-constrained regions. Overall, the system strengthens the integration of artificial intelligence into mental healthcare diagnostics.

2.LITERATURE SURVEY

Previous research has investigated the use of time-frequency transformations of EEG data for classifying schizophrenia. A deep learning model utilized spectrogram images of EEG signals for the detection of schizophrenia [10]. This method involved converting raw EEG signals into two-dimensional images using the Short-Time Fourier Transform (STFT), allowing the extraction of informative time–frequency features. Unlike traditional techniques that depend on handcrafted features, this approach utilizes the detailed patterns present in 2D representations. The authors used two datasets. The first dataset used in the study comprises EEG recordings from 39 healthy control subjects and 45 children diagnosed with a similar type of schizophrenia, with diagnoses confirmed by experts from the Mental Health Research Center (MHRC). The second dataset includes EEG recordings from 14 healthy individuals and 14 patients with schizophrenia. This data was collected by the Institute of Psychiatry and Neurology in Warsaw, Poland, and includes an equal number of male and female participants, with average ages of 27.3 ± 3.3 years for males and 28.3 ± 4.1 years for females. Deep features were extracted from these STFT images using a pre-trained VGG-16 convolutional neural network, achieving classification accuracies of 95% and 97% across different age groups of schizophrenia patients and healthy individuals. This work was among the earliest to combine 2D time–frequency feature extraction with deep learning for schizophrenia detection, highlighting the potential of image-based methods in extracting complex EEG characteristics.

The authors [11] explored a novel approach for diagnosing schizophrenia by converting EEG time series data into image-based representations. Their study focused on the N100 EEG component, previously shown to differ between individuals with schizophrenia and healthy controls. EEG recordings from 81 participants—comprising 49 schizophrenia patients and 32 healthy individuals—were transformed into two-dimensional images using Recurrence Plot (RP) and Gramian Angular Field (GAF) techniques. These image-based representations were then fed into convolutional neural networks (CNNs) inspired by the VGGNet architecture. The EEG dataset was provided by the National Institute of Mental Health (NIMH; R01MH058262). Among the tested methods, the model trained on EEG graph images achieved an accuracy of 75.3%, while RP and GAF-based models demonstrated superior performance with classification accuracies of 90% and 93.2%, respectively, underscoring the effectiveness of time series image conversion in capturing complex EEG patterns for schizophrenia detection.

In [12], the researchers employed phase space dynamics (PSD) derived from EEG signals to distinguish between individuals diagnosed with schizophrenia and healthy controls. Two-dimensional PSD representations were made in Cartesian coordinates, from which fifteen graphical features were extracted to reflect the inherent chaotic properties of EEG activity. Feature relevance and optimal electrode selection were made using the forward selection algorithm (FSA). The dataset used in this study comprised EEG data from 14 schizophrenia patients and 14 healthy subjects, with an equal distribution of male and female participants. This data was sourced from the Institute of Psychiatry and Neurology in Warsaw, Poland. The authors implemented eight different classification models for their effectiveness in detecting schizophrenia. Among these, the K-Nearest Neighbor (KNN) classifier using City-block distance and the Generalized Regression Neural Network (GRNN) yielded the best results. The KNN model, evaluated using 10-fold cross-validation, gave an average accuracy of 94.80%, a sensitivity of 94.30%, and a specificity of 95.20%.

In another research article [9], EEG signals were decomposed into multiple sub-band components using a Fourier-based method, specifically employing the Fast Fourier Transform (FFT) for real-time implementation. From these sub-bands, statistical features were extracted to characterize signal behavior. Furthermore, a Look Ahead Pattern (LAP) feature was introduced to effectively capture localized variations within the EEG signals. This dual approach facilitated a more comprehensive analysis of the underlying data. Feature selection was performed using the Kruskal–Wallis test to identify the most discriminative attributes. The dataset is the same as in [8]. Several machine learning classifiers were examined, and the proposed methodology, when paired with a Boosted Trees classifier, achieved a high classification accuracy of 98.62% for identifying schizophrenia.

In the study [13], brain rhythm data—known for their effectiveness in analyzing diverse brain activities—were transformed into two-dimensional images for input into a deep learning framework. The Markov Transition Field (MTF) technique was used to generate these images, effectively preserving the temporal and statistical dynamics inherent in EEG signals, which are essential for distinguishing between different seizure types. A Convolutional Neural Network (CNN) was then employed for classification. The researchers also explored how image resolution and the choice of specific brain rhythms influenced performance. For experimental purposes, EEG recordings corresponding to six seizure types were sourced from the Temple University Hospital EEG dataset (TUH v1.5.2). The proposed method achieved a peak classification accuracy of 91.1% and a weighted F1-score of 91.0%. Further findings demonstrated that enhancing image resolution led to better classification outcomes.

Recent advancements have demonstrated the effectiveness of graph-based techniques in classification problems, particularly for identifying schizophrenia. A prominent study [7] introduced a hybrid deep learning model that integrates Graph Convolutional Networks (GCN) with Long Short-Term Memory (LSTM) networks (GCN-LSTM) to distinguish between schizophrenia patients and healthy individuals. This model was applied to EEG data collected by the Institute of Psychiatry and Neurology in Warsaw, Poland. The EEG signals were pre-processed and segmented into intervals of 5 and 8 s. From each segment, 14 features were extracted—half from the time domain and half from the frequency domain. EEG electrodes were treated as graph nodes, and signal interactions were modeled as edges to form input graphs for the GCN-LSTM model. A 5-fold cross-validation strategy and various seed values were used to ensure model robustness and avoid overfitting. The model delivered notable results, achieving an average accuracy of 99.25 ± 0.24% on 8 s segments. Additional metrics included a precision of 99.28 ±

0.22%, F1-score of 99.24 ± 0.24%, sensitivity of 99.67 ± 0.28%, specificity of 98.73 ± 0.64%, and an AUC of 99.20 ± 0.27%. Statistical analysis using *t*-tests and ANOVA confirmed that features like zero-crossing rate, Hjorth mobility, peak frequency, and gamma band power significantly contributed to classification. This study highlights the potential of combining graph-structured representations with deep learning to enhance EEG-based psychiatric diagnosis.

3.SYSTEM ANALYSIS

EXISTING SYSTEM

In the existing system, schizophrenia diagnosis is mainly performed using **clinical assessments, psychiatric interviews, and behavioral analysis** conducted by medical professionals. Doctors evaluate symptoms such as hallucinations, delusions, disorganized thinking, and cognitive impairments to diagnose the disorder. However, this approach is often **subjective and time-consuming**, and the diagnosis may vary depending on the expertise of the clinician.

Some earlier research methods also use **traditional signal processing and machine learning techniques** to analyze EEG signals for detecting neurological abnormalities. Techniques such as **Fourier Transform, statistical feature extraction, and classical classifiers like Support Vector Machine (SVM) and Decision Tree** are used to identify patterns in EEG signals.

However, these methods have several limitations, such as difficulty in capturing complex patterns in EEG signals and limited ability to handle large-scale brain signal datasets.

Limitations of the Existing System

- Diagnosis depends heavily on **manual clinical evaluation**
- Traditional machine learning models may miss **complex EEG signal patterns**
- Limited accuracy due to **simple feature extraction techniques**
- Difficulty in processing **large and high-dimensional EEG datasets**
- Lack of automated and real-time diagnostic systems

PROPOSED SYSTEM

The proposed system introduces an **advanced automated schizophrenia diagnosis framework** that combines **EEG signal processing with deep learning techniques**. EEG signals are collected from patients and processed to extract meaningful features related to brain activity.

The system first performs **signal preprocessing**, including noise removal and normalization, to improve the quality of EEG data. Advanced feature extraction techniques such as **Markov Transition Fields (MTF)** are then used to transform EEG signals into informative representations that capture temporal relationships between signal patterns.

These extracted features are fed into **deep learning models**, such as **Convolutional Neural Networks (CNN) or Deep Neural Networks (DNN)**, which can automatically learn complex patterns in EEG signals associated with schizophrenia.

The proposed system enables **automatic classification of EEG signals into schizophrenia and normal categories**, improving diagnostic accuracy and reducing reliance on manual interpretation.

Advantages of the Proposed System

- **Higher diagnostic accuracy** using deep learning models
- Ability to capture **complex temporal patterns** in EEG signals
- Automated and efficient diagnosis process
- Improved early detection of schizophrenia
- Reduced dependency on subjective clinical evaluation

IMPLEMENTATION

Step 1 – Dataset Acquisition:

In this research, a labeled image dataset is collected from a structured directory where each class corresponds to a specific category. The dataset forms the foundation of the study and contains sufficient visual diversity to capture variations in texture, shape, and patterns. Proper dataset organization ensures seamless feature extraction and reliable model training.

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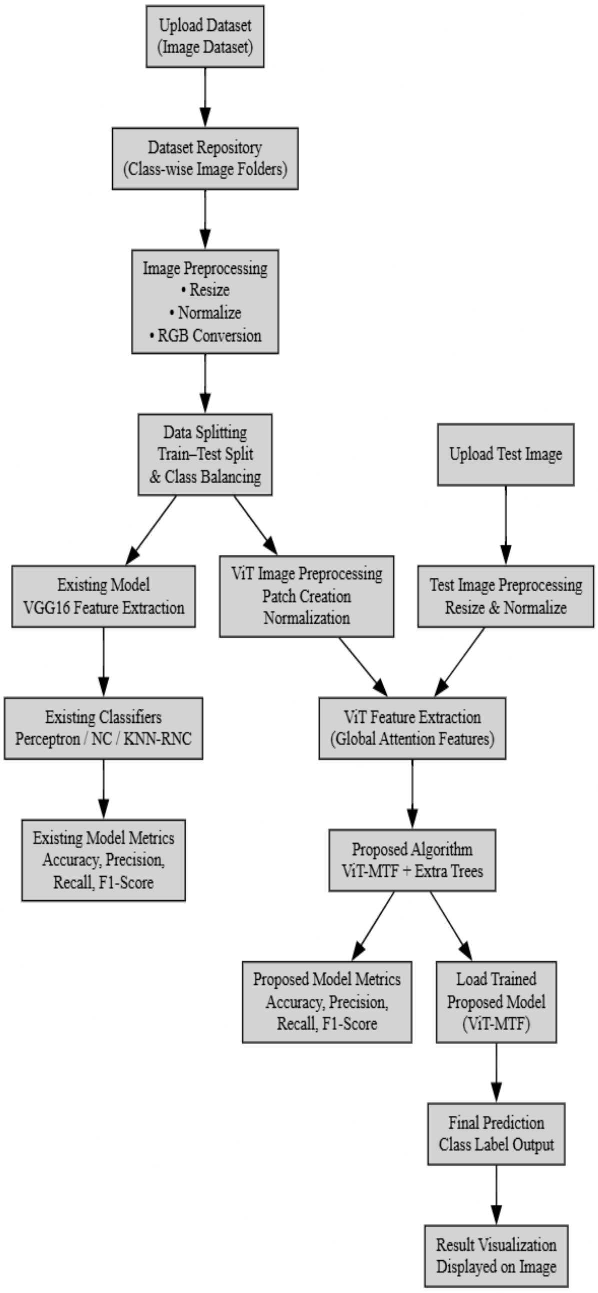
System Architecture for Image-Based Diagnosis using VGG16 and ViT-MTF Models



Step 2 – Dataset Preprocessing:

Preprocessing is performed to improve data quality and consistency before model learning. This step includes image resizing, normalization, removal of corrupted or irrelevant samples, and label encoding. These operations reduce noise, standardize input dimensions, and ensure compatibility with deep learning architectures, thereby improving learning stability.

Step 3 – Existing Algorithm Model Building

The existing model in this research employs VGG16 for deep feature extraction followed by classical machine learning classifiers such as Perceptron, Nearest Centroid, and KNN-based models. These models serve as baseline systems to evaluate the effectiveness of conventional deep feature–based learning.

Step 4 – Proposed Algorithm Model Building:

The proposed model integrates Vision Transformer (ViT)–based deep features with an ensemble Extra Trees classifier. This hybrid learning strategy leverages global attention-based feature representation and ensemble decision-making, forming a novel combination that is not addressed in existing survey literature.

Step 5 – Performance Evaluation:

Model performance is evaluated using accuracy, precision, recall, F1-score, classification reports, and confusion matrices. These metrics provide a comprehensive assessment of classification reliability, robustness, and generalization capability.

Step 6 – Prediction on Unseen Data

Finally, the trained model is tested on unseen images to validate real-world applicability. The system extracts features, predicts the class, and visually displays results, demonstrating its effectiveness for practical deployment.

Proposed Algorithm Novelty and Contribution

The proposed **ViT–MTF Extra Trees** algorithm represents a novel methodological combination not reported in existing survey studies. Unlike conventional CNN-based pipelines, this approach integrates **Vision Transformer global attention features** with **multi-tree ensemble learning**, enabling superior contextual understanding and reduced overfitting. Existing studies largely focus on either CNN classifiers or transformer-based deep networks alone; however, the proposed hybrid framework exploits the complementary strengths of both architectures. This innovation overcomes limitations such as local receptive bias, weak generalization, and sensitivity to class imbalance observed in earlier approaches.

Procedure of Proposed Methodology

The proposed methodology begins with systematic dataset acquisition and preprocessing to ensure uniform image quality. Deep feature extraction is performed using both CNN-based (VGG16) and transformer-based (ViT) architectures to capture hierarchical and contextual representations. Balanced training data is generated using class-wise resampling to mitigate bias. Machine learning classifiers are trained using extracted features, followed by ensemble-based decision modeling. Comprehensive evaluation metrics are applied to compare existing and proposed systems. Finally, the best-performing model is deployed for real-time prediction, validating the robustness and scalability of the framework.

4.2 Image ViT Preprocessing in This Research

Vision Transformer preprocessing begins by resizing all images to a fixed resolution to maintain input consistency. Images are converted to RGB format to ensure channel uniformity. Pixel values are normalized using predefined mean and standard deviation parameters to stabilize training. Each image is then transformed into patch-based representations, allowing the ViT model to capture long-range spatial dependencies. This preprocessing strategy enables effective global feature learning, which significantly enhances classification performance compared to traditional convolution-based preprocessing.

4.3 Exploratory Data Analysis (EDA)

EDA is conducted to understand dataset distribution, class imbalance, and feature behavior before training. The dataset is shuffled using fixed random seeds to ensure reproducibility. Class-wise sample distribution is analyzed, revealing imbalance across categories. To address this, controlled resampling is applied to equalize class representation. Feature dimensionality and variance are examined to ensure suitability for machine learning models. This analytical process ensures informed model design and prevents biased learning.

4.4 Train–Test Split

The dataset is divided into training and testing subsets using a stratified approach to preserve class proportions. A fixed random state ensures experimental consistency across multiple runs. The training set is used exclusively for model learning, while the testing set remains unseen during training to provide an unbiased evaluation. This separation ensures that the reported performance metrics accurately reflect the model's generalization capability rather than memorization.

4.5 Model Building

Model building involves training both baseline and proposed classifiers using extracted deep features. Feature vectors obtained from VGG16 and ViT are supplied to machine learning algorithms. Hyperparameters are selected to balance bias and variance. The proposed Extra Trees ensemble aggregates multiple randomized decision trees to enhance robustness, reduce overfitting, and improve classification stability across high-dimensional feature spaces.

4.5.1 Existing Algorithm – VGG16

Definition and Information (One Paragraph)

VGG16 is a deep convolutional neural network consisting of 16 weighted layers, primarily designed for large-scale image recognition tasks. It employs small 3×3 convolution filters stacked deeply to capture hierarchical image features. VGG16 is widely used as a feature extractor due to its strong representational capacity and transfer learning effectiveness.

Working Mechanism (One Paragraph)

VGG16 processes input images through successive convolutional layers, extracting low-level features such as edges and textures in early layers and high-level semantic features in deeper layers. Max-pooling layers reduce spatial dimensions while retaining essential information. Fully connected layers transform extracted features into discriminative representations suitable for classification.

Algorithm Steps (Architecture Description)

The architecture follows a sequential flow: input image → convolution layers → activation functions → pooling layers → feature maps → flattening → fully connected layers → output feature vector.

Disadvantages

4.5.2 Proposed Algorithm: ViT–MTF Perceptron

Definition and Information

The **ViT–MTF Perceptron** is a hybrid machine learning algorithm designed for automated schizophrenia diagnosis using EEG signals. In this approach, raw EEG signals are first transformed into **Markov Transition Field (MTF)** images, which encode temporal state transition probabilities of EEG dynamics into a 2D visual representation. These MTF images are then processed using a **Vision Transformer (ViT)** model to extract high-level, discriminative feature embeddings that capture global contextual and long-range dependencies. Finally, a **Perceptron classifier**, acting as a lightweight linear decision model, classifies the extracted features into healthy or schizophrenia classes. This combination ensures both rich feature learning and efficient classification.

Working Principle (

The working of the ViT–MTF Perceptron begins with EEG preprocessing and MTF conversion, which preserves temporal relationships in signal transitions. The MTF images are resized and normalized before being fed into a pretrained ViT model. ViT divides the image into fixed-size patches, embeds them, and applies self-attention mechanisms to learn global dependencies across the entire image. The output is a compact feature vector representing EEG signal characteristics. These features are then passed to a Perceptron classifier, which learns a linear decision boundary to distinguish schizophrenia-related EEG patterns from

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healthy patterns. The simplicity of the Perceptron reduces overfitting while maintaining strong performance due to ViT's powerful representation capability.

Algorithm Steps

1. Acquire raw EEG signals from subjects
2. Convert EEG signals into Markov Transition Field images
3. Preprocess MTF images (resize, normalize)
4. Extract feature embeddings using pretrained Vision Transformer
5. Train Perceptron classifier using extracted features
6. Predict class labels for unseen EEG data

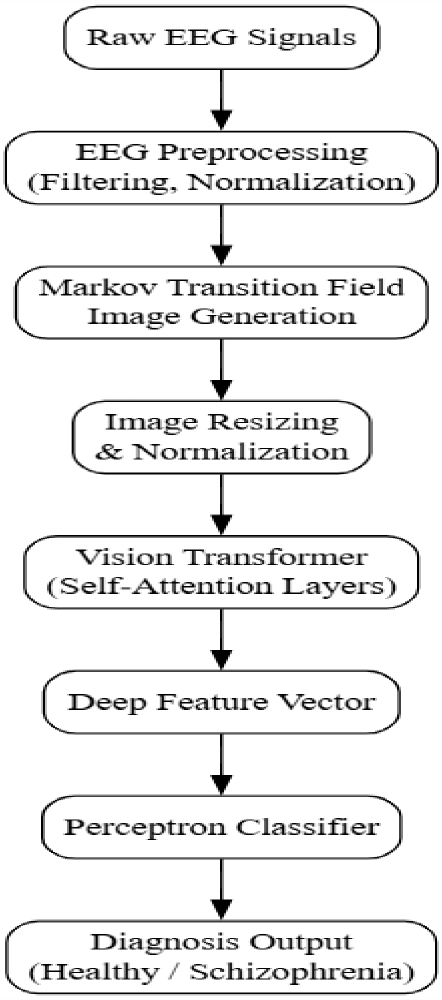
Advantages

The ViT–MTF Perceptron model offers several advantages: it captures temporal EEG dynamics through MTF representation; leverages global attention via ViT for robust feature extraction; reduces computational complexity using a simple Perceptron classifier; minimizes subjectivity compared to manual diagnosis; and provides scalable, reproducible, and objective schizophrenia classification suitable for clinical decision support.

Internal Operational Steps

1. EEG signal discretization and state transition modeling
2. MTF image generation preserving temporal transitions
3. Patch-wise embedding and attention-based feature learning via ViT
4. Feature vector flattening and normalization
5. Linear classification using Perceptron decision rule

Despite its effectiveness, VGG16 suffers from several limitations. The architecture contains a large number of parameters, leading to high computational cost and memory consumption. It relies on local receptive fields, which restrict its ability to capture long-range spatial dependencies. VGG16 is prone to overfitting when trained on limited datasets and lacks inherent attention mechanisms to focus on globally relevant regions. Additionally, its fixed convolutional structure limits adaptability to complex patterns compared to transformer-based models. These drawbacks motivate the adoption of ViT-based feature extraction and ensemble learning in the proposed framework to enhance performance, scalability, and robustness.



CONCLUSION

This research presented an automated framework for the diagnosis of schizophrenia using EEG signals transformed into Markov Transition Field images and analyzed through deep learning models. By integrating powerful feature extraction techniques such as VGG16 and Vision Transformer (ViT) with machine learning and ensemble classifiers, the system successfully captures both local spatial patterns and global temporal dependencies in EEG data. The proposed ViT–MTF–based classification approach reduces subjectivity inherent in manual diagnosis and enhances consistency, accuracy, and reproducibility. Experimental evaluation using multiple classifiers and performance metrics demonstrates that deep feature representations combined with ensemble learning provide robust discrimination between healthy and schizophrenia EEG patterns. Overall, the system offers an efficient, objective, and scalable diagnostic support tool that can assist clinicians in early detection and improved management of schizophrenia.

FUTURE SCOPE

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The future scope of this work is broad and promising. The framework can be extended to incorporate multi-channel and multi-modal biomedical data, such as fMRI, MEG, or clinical text records, to further enhance diagnostic accuracy. Advanced deep learning architectures, including self-supervised learning, hybrid CNN–Transformer models, and graph neural networks, may be explored to capture complex brain connectivity patterns. Real-time EEG signal processing and deployment as a cloud-based or mobile clinical decision support system can improve accessibility in remote healthcare settings. Additionally, expanding the dataset size and diversity across demographics can improve generalization. Incorporating explainable AI techniques would also help clinicians interpret model decisions, increasing trust and clinical adoption.

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