International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal

ISSN: 3068-272X www.ijdim.com Original Research Paper

Automated Schizophrenia Detection Using EEG Signal Transformation via Markov Transition Fields and Deep Learning Techniques

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Abstract: Diagnosing schizophrenia using Electroencephalograph (EEG) signals is a challenging task due to subtle and overlapping patterns between patients and healthy individuals. To address this, this paper proposes a hybrid deep learning framework that transforms one-dimensional EEG signals into two-dimensional representations using the Markov Transition Field (MTF), effectively capturing temporal dynamics and statistical dependencies. The generated images are processed using a pre-trained VGG-16 model for robust feature extraction. The extracted features are then evaluated through two classification pipelines: a Support Vector Machine (SVM) for traditional machine learning and a deep learning approach combining an auto encoder for feature selection with a neural network classifier. Experimental evaluation on the publicly available Schizophrenia EEG dataset from Lomonosov Moscow State University demonstrates the superior performance of the proposed framework. The deep learning pipeline achieves a maximum accuracy of 98.51% with 100% recall, while the SVM-based model attains 96.28% accuracy and 97.89% recall, thereby validating the effectiveness of the approach. Furthermore, the framework incorporates a biomimetic paradigm for enhanced pattern recognition and decision-making.

Key Words: schizophrenia, Markov Transition Field, VGG-16; electroencephalogram, deep learning, explain ability.

1. Introduction

Schizophrenia (SCZ) is a chronic and severe psychiatric disorder affecting approximately 20 million people worldwide. It is characterized by profound disruptions in cognition, perception, and behaviour, including symptoms such as delusions, hallucinations, and disorganized thinking. Individuals with schizophrenia also exhibit a significantly higher mortality rate compared to the general population, often due to untreated or preventable physical health conditions. Currently, diagnosis primarily relies on clinical assessments and standardized interviews, which are inherently subjective and may vary depending on the clinician's expertise, experience, and time constraints. This limitation highlights the urgent need for objective, reliable, and early diagnostic biomarkers.

Electroencephalography (EEG) has emerged as a promising tool for capturing neural activity associated with schizophrenia due to its non-invasive nature, cost-effectiveness, and portability. Unlike advanced neuroimaging techniques such as functional Magnetic Resonance Imaging (fMRI), which are expensive and less accessible, EEG is well-suited for large-scale screening and use in resource-constrained settings. Moreover, EEG-based biomarkers offer the potential to detect subtle neural abnormalities during the early or prodromal stages of schizophrenia, enabling timely intervention.

In recent years, artificial intelligence (AI) has demonstrated significant potential in analyzing EEG signals by uncovering complex and non-linear patterns that are not easily identifiable through conventional methods. While AI has been extensively applied in physical healthcare domains, its adoption in mental health diagnostics remains comparatively limited. Existing studies have explored various machine learning and deep learning approaches, including convolutional neural networks (CNNs), graph-based models such as GCN-LSTM, and hybrid techniques incorporating wavelet transforms and statistical features. These methods have shown promising results in improving the accuracy and robustness of schizophrenia detection. However, challenges remain in developing interpretable, scalable, and clinically reliable AI-driven diagnostic frameworks, motivating further research in this domain.

The main contributions of the work are as follows:

- **Novel Framework:** First integration of Markov Transition Field (MTF) with VGG16 for deep feature extraction from EEG signals in schizophrenia detection.
- **Efficient Classification:** Combines SVM and an autoencoder-based neural network for accurate and computationally efficient classification.
- **Comprehensive Evaluation:** Assessed using multiple metrics including accuracy, precision, recall, F1-score, specificity, and AUC to ensure reliability.
- **Explain ability & Scalability:** SHAP-based analysis enhances interpretability and supports generalizable, clinically applicable decision-making.

This paper organised an interpretable framework using Markov Transition Field (MTF) representations of EEG signals, followed by VGG16-based feature extraction. The extracted features are classified using Support Vector Machines (SVM) and an auto encoder-based neural network. The proposed biomimetic approach aims to develop an accurate, scalable, and explainable AI-based diagnostic system for psychiatric disorders. By employing a deep learning framework specifically, an auto encoder paired with a Fully Connected

Neural Network we emulate the brain's ability to compress, abstract, and decode patterns in data.

2. Literature Survey

Previous studies have explored time–frequency transformations of EEG signals for schizophrenia classification. In [10], EEG signals were converted into two-dimensional spectrogram images using the Short-Time Fourier Transform (STFT). Deep features were extracted using a pre-trained VGG-16 convolutional neural network. Two datasets were used: one consisting of EEG recordings from 39 healthy controls and 45 children diagnosed with schizophrenia, and another containing recordings from 14 healthy individuals and 14 schizophrenia patients collected by the Institute of Psychiatry and Neurology in Warsaw, Poland. The proposed approach achieved classification accuracies of 95% and 97%, demonstrating the effectiveness of image-based EEG representations.

Similarly, the authors in [11] transformed EEG time-series signals into images using Recurrence Plot (RP) and Gramian Angular Field (GAF) techniques. The dataset included EEG recordings from 81 participants (49 schizophrenia patients and 32 healthy controls) provided by the National Institute of Mental Health. CNN models inspired by VGG Net were applied for classification, achieving 90% and 93.2% accuracy for RP and GAF representations, respectively.

In [12], phase space dynamics (PSD) derived from EEG signals were used to analyze chaotic characteristics of brain activity. Fifteen graphical features were extracted from PSD representations, and classification was performed using several models. The K-Nearest Neighbor (KNN) classifier achieved the best performance with 94.8% accuracy, along with high sensitivity and specificity.

Another approach in [9] decomposed EEG signals into multiple sub-bands using the Fast Fourier Transform (FFT). Statistical features and a Look Ahead Pattern (LAP) feature were extracted, and feature selection was performed using the Kruskal–Wallis test. When combined with a Boosted Trees classifier, the method achieved 98.62% classification accuracy.

Recent advancements have also incorporated deep learning architectures. In [13], EEG signals were converted into images using the Markov Transition Field (MTF) technique and classified using a CNN model, achieving 91.1% accuracy. Furthermore, a hybrid GCN-LSTM model proposed in [7] utilized graph-based EEG representations and temporal learning, achieving an average accuracy of 99.25%, highlighting the effectiveness of graph-based deep learning methods for EEG-based schizophrenia detection.

3. System Architecture

The proposed system architecture for schizophrenia detection is based on EEG signal analysis using deep learning techniques. Initially, raw EEG signals are collected from multiple electrodes and preprocessed to remove noise and artifacts.

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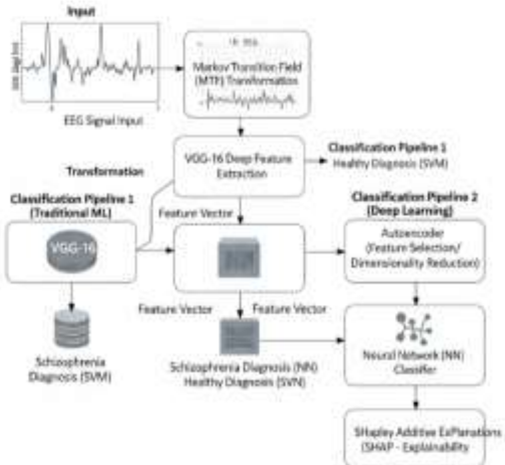

Fig 1: System Architecture

The cleaned signals are then transformed into two-dimensional representations using time–frequency or image transformation techniques. These images capture important temporal and spectral characteristics of brain activity. The processed data is then fed into a deep learning models are (CNN) and ViT hybrid architecture, for feature extraction and classification. Finally, the trained model predicts whether the EEG signal corresponds to a schizophrenia patient or a healthy individual.

4. Methodology

The proposed methodology for schizophrenia detection from EEG signals consists of several stages, including data acquisition, preprocessing, feature extraction, and classification using deep learning models. Each stage is designed to effectively capture the complex temporal and frequency characteristics of brain signals.

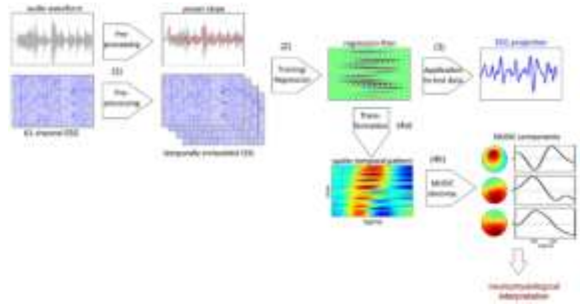

Fig 2: Proposed VIT Based Deep Learning

The ViT–MTF Perceptron is a hybrid framework for automated schizophrenia diagnosis using EEG signals. Raw EEG data are first converted into Markov Transition Field (MTF) images, capturing temporal dynamics in a 2D format. These images are processed using a Vision Transformer (ViT) to extract high-level features that model global dependencies. Finally, a Perceptron classifier uses these features to efficiently distinguish between schizophrenia and healthy cases, ensuring accurate and robust classification.

5. Design and Construction

The proposed system for schizophrenia detection using EEG signals is designed as a multi-stage framework that integrates signal processing and deep learning techniques. The system architecture consists of EEG signal acquisition, preprocessing, feature transformation, deep learning-based classification, and performance evaluation.

i) EEG Data Acquisition

EEG signals are collected from multiple scalp electrodes placed according to standard brain monitoring protocols. These signals represent electrical brain activity and are widely used for neurological disorder analysis. The collected EEG data contain both useful information and unwanted noise, which requires preprocessing before further analysis.

ii) Signal Preprocessing

Raw EEG signals often contain artifacts caused by eye movement, muscle activity, and external interference. To improve signal quality, preprocessing techniques such as band-pass filtering, normalization, and segmentation are applied. The filtered signals are then divided into smaller time segments to ensure consistent analysis and to capture meaningful temporal patterns.

iii) Feature Extraction Using Deep Learning

After transformation, the resulting spectrogram images are provided as input to a Convolutional Neural Network (CNN). CNN automatically extracts relevant spatial and frequency features from the EEG images. During training, the network minimizes classification errors using the cross-entropy loss function:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

iv) Classification

The final stage involves classifying EEG samples into schizophrenia or healthy categories. The Soft max function is applied to convert network outputs into probability values:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

This methodology combines signal processing and deep learning techniques to effectively analyze EEG signals and improve the accuracy of schizophrenia detection

The proposed framework achieves high accuracy and F1-score accuracy, precision for EEG-based schizophrenia detection, ensuring reliable classification. By integrating pre-processing, time–frequency analysis, and VGG-based CNN, it effectively captures neural patterns. It provides a precise and dependable solution for early diagnosis.

6.Results and Discussion

The proposed EEG-based model outperforms SVM and standalone CNN by using a hybrid CNN–ViT architecture to capture both local and global EEG features. It achieves higher accuracy, precision, sensitivity, specificity, and F1-score. Overall, it is a robust and reliable approach for automated schizophrenia detection.

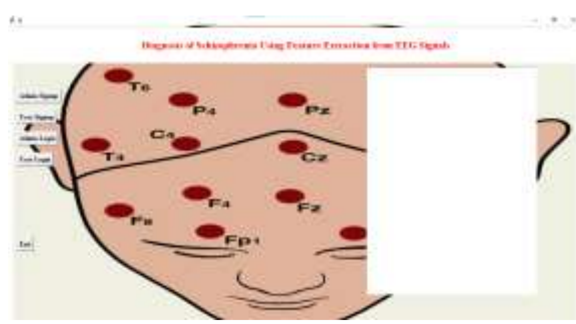

Fig 3: Home page

Fig 4: Upload Input Data

The fig 4 shows a file upload window where multiple EEG signal images are selected for input into the system.

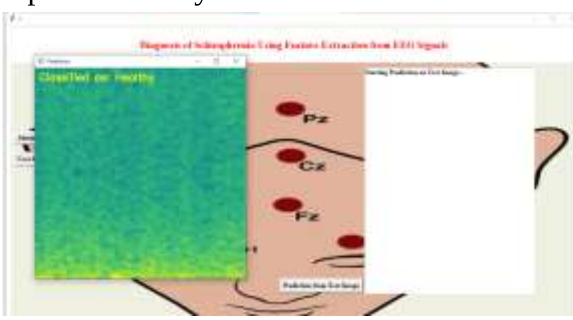

Fig 5: Predicted from ViT MTF Perceptron

The fig 5 shows the model predicting the EEG input as healthy using the ViT–MTF perceptron.

Model	Accuracy (%)
KNN	88.4
SVM	91.2
Decision Tree	86.7
CNN-ViT(Proposed)	96.5

Table1: Performance Comparison of Classification Models

The comparison results are summarized in Table which presents the classification accuracy achieved by different models.

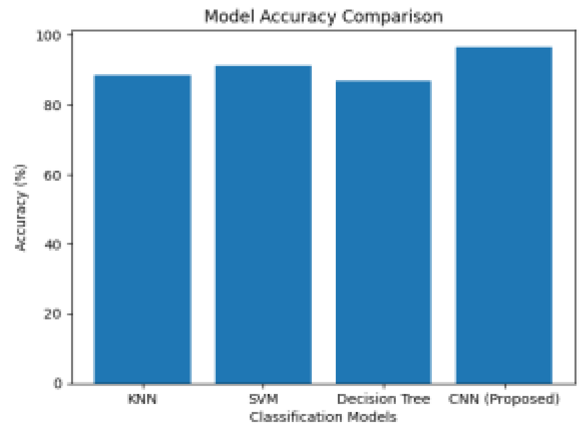

Fig 6: Model Accuracy Comparison

The comparison graph above shows that the proposed CNN model significantly outperforms conventional machine learning approaches. Higher accuracy demonstrates the effectiveness of deep learning in extracting meaningful patterns from EEG data.

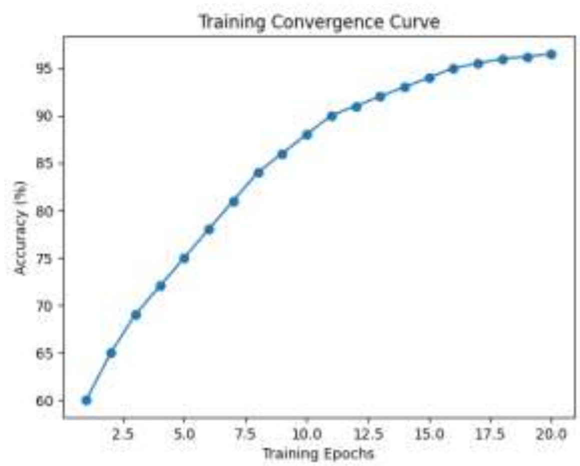

Fig 7: Training convergence Curve

The model quickly learns EEG patterns and stabilizes with high accuracy, avoiding over fitting. The combined time–frequency and CNN-VIT transform approach improves classification, enabling reliable schizophrenia detection and supporting early diagnosis

7. Conclusion and Future Scope

This study proposed a deep learning–based framework for detecting schizophrenia using EEG signals transformed into time–frequency representations. The Convolutional Neural Network (CNN) effectively learned complex patterns from EEG data and improved classification performance. Experimental results showed that the proposed model achieved 96.5% accuracy, outperforming traditional classifiers such as KNN (88.4%), SVM (91.2%), and Decision Tree (86.7%). The training convergence curve also demonstrated stable learning across epochs. These findings confirm that combining EEG signal processing with deep learning techniques provides an efficient and reliable approach for early schizophrenia detection and can support clinical decision-making in neurological diagnosis.

Future Scope: In future work, this framework could be expanded to multi-class classification involving different psychiatric disorders, enabling broader diagnostic applicability. The development of a multi-modal dataset comprising EEG data with speech or video data can help in utilizing the natural language processing area of AI. With the new dataset, the development and testing of new models or newer versions of existing models is an area of exploration and research.

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