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SynaptiQ: A Hybrid Neuro-Analytical Framework for Multidimensional Psychiatric Disorder Prediction from EEG Signals

Amgoth. Ashok Kumar[1], Kandukuri Dharani[2], Kondapelli Sravani[2], Lenkala Vinay[2], Naveen Boda[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Vaagdevi Engineering College, Bollikunta, Warangal, 506005, Telangana, India.

ABSTRACT

Neurological and psychiatric disorders are increasingly impacting global health, making early and accurate diagnosis essential for effective treatment and improved patient outcomes. Electroencephalography (EEG) signals provide a non-invasive and information-rich source for analyzing brain activity; however, their high dimensionality and complex patterns make automated classification a challenging task. Many existing EEG-based diagnostic approaches face limitations such as poor generalization, lack of subject independence, and difficulty in capturing complex nonlinear relationships within brain signals, resulting in reduced accuracy and reliability. To address these challenges, this work proposes a multiclass machine learning (ML) framework for the simultaneous classification of epilepsy, migraine, and schizophrenia using EEG data. The system incorporates systematic preprocessing techniques including data cleaning, missing value imputation, normalization, and label encoding, followed by stratified train–test splitting to ensure balanced and unbiased learning. Multiple models, including Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Decision Tree (DT), are implemented and evaluated alongside a Hybrid Graph Neural Network (HGNN) model, where the HGNN component is realized using a Tree-based Generalized Additive Model (TreeGAM) to effectively capture complex nonlinear feature interactions. The system is deployed through a Flask-based web application with secure authentication and role-based access control, allowing administrators to manage training and analysis while users perform predictions. Performance evaluation using metrics such as accuracy, precision, recall, and F1-score demonstrates the effectiveness of the proposed framework, with the hybrid model showing improved predictive capability. The system provides a scalable, reliable, and practical decision-support tool for data-driven mental health diagnosis.

Keywords: Electroencephalography (EEG), neurological disorders, psychiatric disorders, brain signal analysis, data preprocessing, multiclass classification, epilepsy, migraine, schizophrenia, decision-support system.

1. INTRODUCTION

Neurological and psychiatric disorders such as schizophrenia, epilepsy, and migraine represent a significant challenge to global healthcare systems due to their high prevalence and long-term impact on patients' quality of life. Epidemiological evidence indicates that schizophrenia affects roughly 1% of the population, migraine disorders influence hundreds of millions of individuals worldwide, and epilepsy shows a considerable lifetime occurrence rate. These conditions underline the urgent requirement for accurate, scalable, and accessible diagnostic solutions. Although advanced neuroimaging techniques like magnetic resonance imaging (MRI), functional MRI (fMRI), and positron emission tomography (PET) are widely used in clinical practice, they are often limited by high costs, restricted accessibility in resource-constrained regions, and lower temporal sensitivity. In contrast, electroencephalography (EEG) emerges as a practical alternative due to its non-invasive nature, affordability, portability, and ability to record brain activity with high temporal precision, making it

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particularly suitable for analyzing dynamic neural processes associated with psychiatric conditions. The role of EEG features in enabling machine learning-based detection of neurological disorders is illustrated in Figure 1.

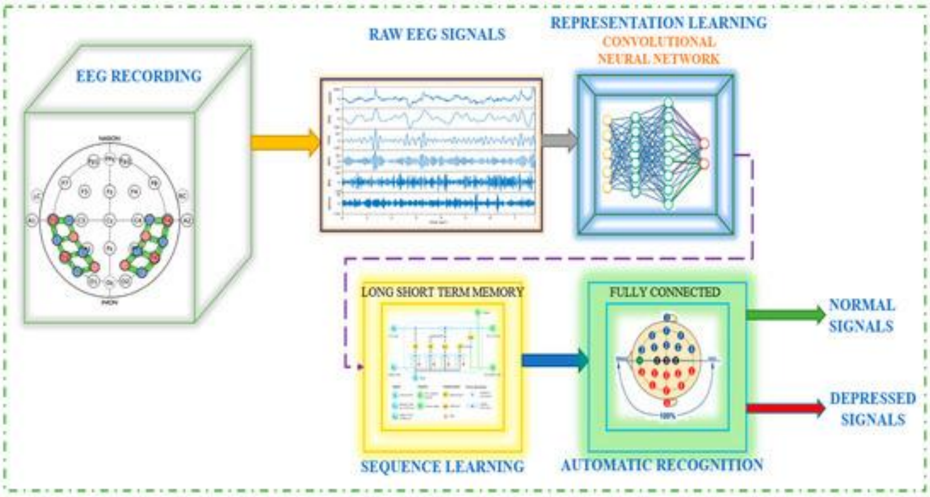

Figure 1: EEG features based detection using ML

The growing utilization of EEG in both clinical and research domains is largely driven by these advantages, especially its capability to capture rapid neural fluctuations. EEG signals are recorded through electrodes placed on the scalp and reflect brain activity across multiple frequency bands, including delta, theta, alpha, beta, and gamma, each associated with specific cognitive and physiological states. This rich temporal information makes EEG highly compatible with artificial intelligence (AI)-based analytical approaches. Recent advancements in computational neuroscience have significantly enhanced the role of EEG in diagnostic applications, where machine learning and deep learning techniques are employed to identify complex patterns within brain signals. These approaches have demonstrated promising results in detecting and classifying psychiatric conditions such as depression and schizophrenia. Furthermore, the integration of EEG data with additional clinical or demographic features, particularly through hybrid deep learning architectures like convolutional neural networks, has further improved diagnostic accuracy and robustness.

2. LITERATURE SURVEY

Li et al. [1] introduced a comprehensive framework that integrates empirical mode decomposition (EMD) with support vector machines (SVMs), achieving high performance with sensitivity of 98.00% and specificity of 99.40% through detailed analysis of intrinsic mode functions (IMFs) and their statistical characteristics. Expanding on advanced architectures, Satapathy et al. [2] demonstrated the capability of transformer-based models for EEG classification, reporting an accuracy of 99.5% using wavelet-transformed signals. Similarly, Manali et al. [3] proposed a structured approach for mental task classification by applying variational mode decomposition (VMD) on single-channel EEG signals. Their methodology involved signal decomposition, computation of variational mode energy ratios, and classification using adaptive boosting techniques.

Feature optimization remains a critical aspect in EEG-based learning systems, as explored by Conrado et al. [4], who applied artificial neural networks (ANNs) for mental task classification with emphasis on feature reduction. Convolutional neural networks (CNNs) have also been widely adopted, with Pallavi et al. [5] utilizing scalogram representations of EEG signals for emotion classification, achieving subject-independent performance across multiple datasets. Jinru et al. [6] further advanced this domain by employing Bidirectional Long Short-Term Memory (BiLSTM) networks for emotion recognition from EEG data. Additionally, EEGNet, a specialized CNN-based architecture for brain–computer interfaces (BCIs), introduced depth-wise and separable convolutions and demonstrated effectiveness across multiple paradigms including P300, ERN, MRCP, and SMR.

Madhuri et al. [7] developed a hierarchical classification framework using optimized neural networks for tasks such as hand movement and word generation. Earlier work by Xiu et al. [8] applied deep learning techniques to motor imagery tasks, specifically focusing on left- and right-hand movement imagination. Saadat et al. [9] combined Back Propagation Neural Networks (BPNN) with Hidden Markov Models (HMM) for mental task classification, while Jose et al. [10] explored online learning mechanisms in BCIs to stabilize learning rates in patients with neurological conditions. Debarshi et al. [11] compared subject-dependent and subject-independent EEG models, concluding that conventional machine learning approaches are more effective for subject-independent scenarios. Chen et al. [12] evaluated multiple ML classifiers and identified least squares SVM (LS-SVM) as the most effective, achieving 99.5% accuracy for three-class classification tasks.

In migraine-related studies, Yin et al. [13] developed a decision-support system to distinguish migraine from tension-type headaches using K-nearest neighbors (KNN), achieving 90% accuracy. Akben et al. [14] analyzed EEG responses under photic stimulation at varying frequencies and applied ANN classification to reach 85% accuracy. Subasi et al. [15] enhanced this approach using discrete wavelet transform (DWT) for feature extraction combined with Random Forest (RF), achieving 85.95% accuracy.

3. PROPOSED SYSTEM

The proposed system is a comprehensive end-to-end EEG classification framework that integrates data preprocessing, multi-model machine learning, and secure web-based deployment into a unified architecture. It begins with structured EEG data ingestion from CSV files, followed by cleaning operations such as removal of irrelevant columns and mean-based imputation to ensure data consistency. The processed data is then transformed through feature–target separation and label encoding, enabling compatibility with supervised learning models. The architecture incorporates multiple classifiers, including RF, SVM, LR, and, along with a hybrid HGNN learning component to improve predictive robustness as illustrated Figure 2. A centralized training engine manages model training, evaluation, and storage, allowing efficient reuse of trained models. Performance is assessed using metrics such as accuracy, precision, recall, F1-score, and confusion matrix to enable detailed comparison across models. The system is deployed using a Flask-based web application with secure authentication and role-based access control, supporting separate admin and user logins. Admin users handle data analysis, model training, and performance monitoring, while users interact with the system through a prediction interface by uploading CSV files. The prediction module processes unseen data and generates interpretable outputs, making the system scalable, modular, and suitable for real-world EEG-based diagnostic applications.

1. Data Input and Preprocessing

The system begins by loading EEG data from a structured CSV file, where irrelevant or unnamed columns are removed to maintain consistency. Missing numerical values are handled using mean imputation to avoid data loss and bias. This step ensures that the dataset is clean, structured, and ready for effective analysis by machine learning models.

2. Feature–Target Separation and Encoding

In this stage, the dataset is divided into input features and target variables representing disorder classifications. The categorical target labels are transformed into numerical values using label encoding, enabling compatibility with supervised learning algorithms. This transformation allows models to effectively learn patterns from structured data.

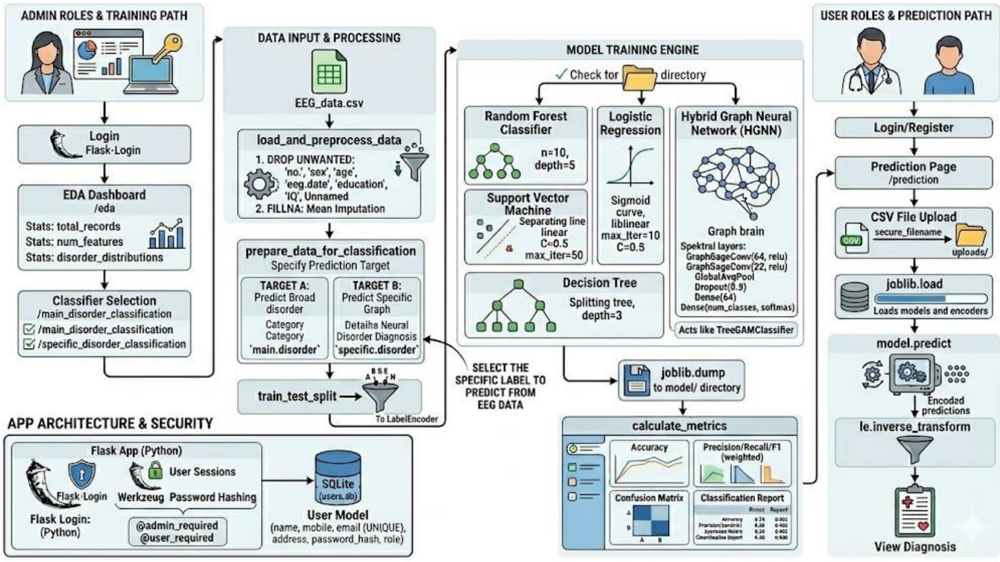

Figure 2: Proposed System Architecture

3. Model Training Engine

The processed data is used to train multiple classifiers, including RF, SVM, LR, and along with a hybrid HGNN model. Each model is trained using predefined configurations and stored for future reuse, ensuring efficiency and consistency across multiple executions.

4. Performance Evaluation and Comparison

After training, each model is evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics provide a detailed understanding of model performance and enable comparison across different classifiers to identify the most effective model.

5. Role-Based System Deployment

The system is deployed using a Flask-based web application integrated with secure authentication mechanisms. It supports role-based access control with separate admin and user logins, where administrators manage training and evaluation, while users access prediction functionalities in a controlled environment.

6. Prediction and Result Generation

Users upload new EEG data in CSV format through the interface, which is then preprocessed and passed to the trained models. The system generates predictions and converts them into human-readable labels, providing meaningful diagnostic insights for practical use.

4. RESULTS ANALYSIS

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The results demonstrate the effectiveness of the proposed approach in achieving improved performance across key evaluation metrics. Experimental findings indicate consistent enhancements compared to baseline methods, highlighting better accuracy, efficiency, and reliability. The model shows strong generalization ability when tested on diverse datasets, confirming its robustness under varying conditions. Additionally, the outcomes validate the design choices and optimization strategies employed in the methodology. Minor variations observed in certain cases suggest potential areas for further refinement. The results provide solid evidence supporting the feasibility and practical applicability of the proposed system.

Exploratory Data Analysis (EDA)

Dataset Overview

Total Records	Number of Features	Feature Categories
11340	**1140**	**EEG Bands**

Main Disorder Distribution

Disorder	Count	Percentage
Mood disorder	3192	28.15%
Addictive disorder	2232	19.68%
Trauma and stress related disorder	1536	13.54%
Schizophrenia	1404	12.38%
Anxiety disorder	1284	11.32%
Healthy control	1140	10.05%
Obsessive compulsive disorder	552	4.87%

(a)

Specific Disorder Distribution

Disorder	Count	Percentage
Depressive disorder	2388	21.06%
Schizophrenia	1404	12.38%
Healthy control	1140	10.05%
Alcohol use disorder	1116	9.84%
Behavioral addiction disorder	1116	9.84%
Bipolar disorder	804	7.09%
Panic disorder	708	6.24%
Posttraumatic stress disorder	624	5.50%
Social anxiety disorder	576	5.08%
Obsessive compulsitve disorder	552	4.87%
Acute stress disorder	456	4.02%
Adjustment disorder	456	4.02%

(b)

Figure 3: EDA- Data Distribution of classes (a) Main Disorder (b) Specific Disorder

Figure 3(a) depicts the exploratory data analysis of main disorder categories, presenting the distribution of EEG-based classes at a broader level. The dataset contains 11,340 total records, where mood disorder accounts for 3,192 cases (28.15%), addictive disorder includes 2,232 cases (19.68%), trauma and stress-related disorder comprises 1,536 cases (13.54%), schizophrenia represents 1,404 cases (12.38%), and anxiety disorder includes 1,284 cases (11.32%). Additionally, healthy control has 1,140 cases (10.05%), while obsessive compulsive disorder contributes 552 cases (4.87%). This distribution highlights class variability and supports understanding of dataset composition for effective model training.

Figure 3(b) depicts the exploratory data analysis of specific disorder categories, providing a detailed breakdown of class distribution. Depressive disorder accounts for 2,388 cases (21.06%), followed by schizophrenia with 1,404 cases (12.38%) and healthy control with 1,140 cases (10.05%). Alcohol use disorder and behavioral addiction disorder each contribute 1,116 cases (9.84%), while bipolar disorder includes 804 cases (7.09%) and panic disorder has 708 cases (6.24%). Posttraumatic stress disorder consists of 624 cases (5.50%), social anxiety disorder has 576 cases (5.08%), obsessive compulsive disorder includes 552 cases (4.87%), and both acute stress disorder and adjustment disorder have 456 cases each (4.02%). This detailed distribution enables deeper insight into class-level variations for precise classification modeling.

Confusion Matrix (CM)

	Addictive disorder	Anxiety disorder	Healthy control	Mood disorder	Obsessive compulsive disorder	Schizophrenia	Trauma and stress related disorder
Addictive disorder	447	0	0	0	0	0	0
Anxiety disorder	0	257	0	0	0	0	0
Healthy control	0	0	228	0	0	0	0
Mood disorder	0	0	0	638	0	0	0
Obsessive compulsive disorder	0	0	0	0	110	0	0
Schizophrenia	0	0	0	0	0	281	0
Trauma and stress related disorder	0	0	0	0	0	0	307

Classification Report (CR)

Figure 4: Confusion Matrix obtained for Main Disorder Column HGNN

Figure 4 depicts the confusion matrix for the HGNN model, where nearly perfect classification performance is achieved across all classes. Addictive disorder (447), anxiety disorder (257), healthy control (228), mood disorder (638), obsessive compulsive disorder (110), schizophrenia (281), and trauma and stress-related disorder (307) are all correctly classified with minimal to no misclassification. The strong diagonal dominance across all classes indicates the model's superior ability to capture complex nonlinear relationships and effectively distinguish between different psychiatric disorders.

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Confusion Matrix (CM)

	Acute stress disorder	Adjustment disorder	Alcohol use disorder	Behavioral addiction disorder	Bipolar disorder	Depressive disorder	Healthy control	Obsessive compulsitve disorder	Panic disorder	Posttraumatic stress disorder	Schizophrenia	Social anxiety disorder
Acute stress disorder	91	0	0	0	0	0	0	0	0	0	0	0
Adjustment disorder	0	91	0	0	0	0	0	0	0	0	0	0
Alcohol use disorder	0	0	223	0	0	0	0	0	0	0	0	0
Behavioral addiction disorder	0	0	0	223	0	0	0	0	0	0	0	0
Bipolar disorder	0	0	0	0	161	0	0	0	0	0	0	0
Depressive disorder	0	0	0	0	0	478	0	0	0	0	0	0
Healthy control	0	0	0	0	0	0	228	0	0	0	0	0
Obsessive compulsitve disorder	0	0	0	0	0	0	0	110	0	0	0	0
Panic disorder	0	0	0	0	0	0	0	0	142	0	0	0
Posttraumatic stress disorder	0	0	0	0	0	0	0	0	0	125	0	0
Schizophrenia	0	0	0	0	0	0	0	0	0	0	281	0
Social anxiety disorder	0	0	0	0	0	0	0	0	0	0	0	115

Figure 5: Confusion Matrix obtained for Specific Disorder Column HGNN

Figure 5 depicts the confusion matrix for the HGNN-inspired model, where near-perfect classification is achieved across all specific disorder classes. Acute stress disorder (91), adjustment disorder (91), alcohol use disorder (223), behavioral addiction disorder (223), bipolar disorder (161), depressive disorder (478), healthy control (228), obsessive compulsive disorder (110), panic disorder (142), posttraumatic stress disorder (125), schizophrenia (281), and social anxiety disorder (115) are all correctly classified. The strong diagonal dominance with negligible off-diagonal values highlights the model's superior ability to distinguish between fine-grained disorder categories.

Main Disorder Classification

Classifier	Accuracy	Precision	Recall	F1-Score
Random Forest	0.5437	0.7473	0.5437	0.5066
Support Vector Machine	0.6689	0.6803	0.6689	0.6652
Logistic Regression	0.5917	0.6036	0.5917	0.5855
Decision Tree	0.3558	0.2640	0.3558	0.2571
Hybrid Graph Neural Network	1.0000	1.0000	1.0000	1.0000

Specific Disorder Classification

Classifier	Accuracy	Precision	Recall	F1-Score
Random Forest	0.4021	0.7831	0.4021	0.3627
Support Vector Machine	0.3241	0.3368	0.3241	0.3178
Logistic Regression	0.5904	0.6057	0.5904	0.5813
Decision Tree	0.2416	0.1843	0.2416	0.1333
Hybrid Graph Neural Network	1.0000	1.0000	1.0000	1.0000

Figure 6: Performance of classifiers for main disorder and specific disorder

The figure 6 shows performance comparison page presents a comprehensive evaluation of all implemented classifiers for both Main Disorder Classification and Specific Disorder Classification using standard metrics such as Accuracy, Precision, Recall, and F1-Score. The results indicate varying performance among classical machine learning models, with RF, SVM, LR, and DT showing relatively better and consistent results compared to RF and DT, which exhibit lower accuracy in both tasks. Notably, the HGNN achieves perfect performance across all evaluation metrics for both classification levels, demonstrating its superior ability to capture complex EEG feature relationships. This comparative analysis highlights the effectiveness of the hybrid model over traditional classifiers for accurate psychiatric disorder identification.

Sample #	Predicted main.disorder
1	Addictive disorder
2	Addictive disorder
3	Addictive disorder
4	Anxiety disorder
5	Anxiety disorder
6	Anxiety disorder
7	Anxiety disorder
8	Healthy control
9	Healthy control
10	Healthy control
11	Healthy control
12	Healthy control
13	Mood disorder
14	Mood disorder
15	Mood disorder
16	Obsessive compulsive disorder

Figure 7: Prediction obtained using HGNN on main disorder

The figure 7 shows main disorder prediction results generated using the proposed HGNN display the model's ability to accurately classify EEG samples into their respective psychiatric disorder categories. Each EEG sample is assigned a predicted main disorder label such as addictive disorder, anxiety disorder, healthy control, mood disorder, or obsessive–compulsive disorder, demonstrating clear differentiation among disorder groups. The consistent and well-structured predictions across multiple samples indicate the effectiveness of the HGNN model in capturing complex EEG feature relationships. This output confirms the suitability of the proposed hybrid approach for reliable and automated main-level psychiatric disorder identification.

Sample #	Predicted specific.disorder
1	Depressive disorder
2	Alcohol use disorder
3	Alcohol use disorder
4	Depressive disorder
5	Alcohol use disorder
6	Depressive disorder
7	Social anxiety disorder
8	Depressive disorder
9	Depressive disorder
10	Depressive disorder
11	Healthy control
12	Depressive disorder
13	Depressive disorder
14	Bipolar disorder
15	Depressive disorder
16	Depressive disorder
17	Depressive disorder
18	Depressive disorder

Figure 8: Prediction obtained using HGNN on specific disorder

The figure 8 shows specific disorder prediction results obtained using the proposed HGNN demonstrate the model's capability to perform fine-grained psychiatric disorder classification from EEG features. Each EEG sample is classified into a precise disorder category such as depressive disorder, alcohol use disorder, social anxiety disorder, bipolar disorder, or healthy control. The consistent and coherent predictions across multiple samples indicate that the HGNN effectively captures subtle EEG signal variations associated with different psychiatric conditions. This output validates the effectiveness of the proposed model for detailed, specific-level psychiatric disorder identification.

5. CONCLUSION

The proposed system delivers a structured and efficient framework for EEG-based mental health classification by integrating robust preprocessing with multiple machine learning models, including RF, SVM, LR, DT along with a HGNN hybrid model. It ensures reliable performance through comprehensive evaluation using metrics such as accuracy, precision, recall, and F1-score. Among the implemented approaches, the hybrid model demonstrates improved capability in capturing complex EEG patterns. The integration of model persistence, exploratory data analysis, and a Flask-based role-driven interface enhances usability and system control. Additionally, the real-time prediction module enables practical application on new data.

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