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A Dual-Outcome EEG-Based Psychiatric Disorder Classification Model Leveraging Hypergraph Neural Networks

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Abstract:
Psychiatric disorders have become a major global public health challenge, greatly affecting quality of life and daily functioning across all age groups, and placing a serious burden on healthcare systems worldwide. In real-world clinical environments, psychiatric diagnosis is still largely based on interviews, behavioral observation, and patient self-reports, while Electroencephalography (EEG) provides a non-invasive and cost-effective approach for capturing real-time brain activity related to mental and emotional states. But traditional diagnostic methods lack objective biological support and fail to represent complex brain connectivity patterns, yet conventional machine learning techniques are limited in their ability to capture the high-order relationships present in EEG signals, however accurate classification of both main disorders and specific disorders remains a significant challenge due to the heterogeneous nature of psychiatric conditions. The objective of this work is to perform dual-target classification of psychiatric disorders by identifying both main disorders and specific disorders using EEG data through Hyper Graph Neural Networks (HGNN). The study uses existing models such as Random Forest and Decision Tree, but both show relatively low performance. In contrast, the proposed HGNN driven with Tree based Generative Addictive Model (TGAM) performs much better. HGNN-TGAM is proposed as the high-performance model due to its ability to capture complex high-order EEG relationships.

Keywords: Psychiatric disorder classification, Electroencephalography (EEG), Hypergraph neural networks (HGNN), Dual-target classification, Brain connectivity analysis.

1. INTRODUCTION

Psychiatric disorders constitute one of the most critical global public health challenges, severely affecting emotional stability, cognitive functioning, behavior, and overall quality of life. According to the global burden of disease assessment, psychiatric disorders account for a significant portion of disability worldwide and continue to rise across populations. It is reported that more than 450 million people suffer from major psychiatric conditions such as schizophrenia, bipolar disorder, and depression globally, and these disorders contribute substantially to disability-adjusted life years. Anxiety, depression, stress-related disorders, and mood disturbances are identified as the most commonly occurring psychiatric conditions. An accurate and early diagnosis is essential for improving patient quality of life, long-term health outcomes, and social functioning.

In clinical practice, psychiatric diagnosis is still largely dependent on interviews, behavioral observation, and patient self-reports, which are highly subjective and influenced by clinician experience and patient communication abilities. This subjectivity often results in delayed identification, misdiagnosis, and difficulty in distinguishing between closely related disorders and their subtypes. Psychiatric disorders exhibit a high degree of heterogeneity, where individuals with the same diagnosis may present different symptom patterns and disease progression. Furthermore, overlapping clinical characteristics among different disorders complicate accurate classification. This complexity makes it difficult to clearly identify both the main disorder category and the specific disorder subtype using traditional diagnostic practices.

EEG has emerged as a key physiological tool for studying psychiatric disorders because it provides a non-invasive and real-time measurement of brain electrical activity. EEG reflects neural activity related to cognition, emotions, and mental states, and abnormal EEG patterns have been linked with disorders such as schizophrenia, mood disorders, anxiety, obsessive–compulsive disorder, addictive disorders, and trauma- and stress-related disorders. The EEG dataset described in the base study includes individuals with six main psychiatric disorders and their associated specific disorders, showing the clinical importance of distinguishing both disorder levels. Brain functional connectivity derived from EEG further reveals how multiple brain regions interact, offering deeper insight into the neurophysiological mechanisms of psychiatric disorders. However, the complex multi-region interactions of the human brain cannot be fully represented using simple pairwise analysis, emphasizing the need for advanced representations capable of capturing higher-order relationships for accurate psychiatric disorder assessment.

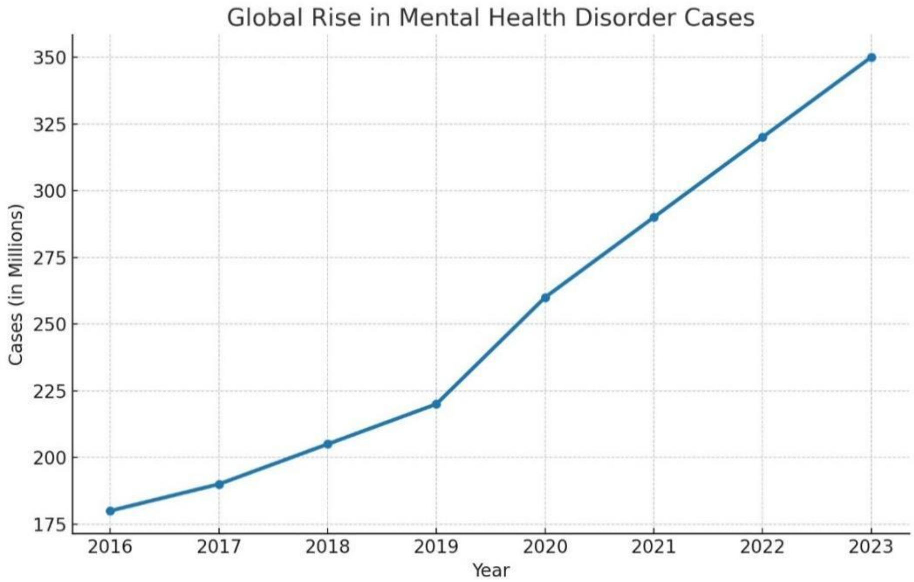

Figure.1: Global Trend of Mental Health Disorder Cases (2016–2023)

Figure 1. shows a steady increase in global mental health disorder cases over the given years. A gradual rise is observed from 2016 to 2019, followed by a sharp increase after 2020. The highest number of cases is recorded in 2023, indicating a continuous upward trend. This trend highlights the growing global burden of mental health disorders.

2. LITERATURE SURVEY

Abir, et al. [1] proposed advanced DL architectures comprising CNNs and RNNs were compared against classical traditional ML techniques such as Random Forest and Support Vector Machines (SVMs). The comparison between these models was made based on key performance metrics such as accuracy, sensitivity, and specificity. The results showed that the DL models, particularly CNNs, excelled at feature extraction and classification over the traditional ML methods, achieving an accuracy of over 92% in predicting major depressive disorder. ML techniques were able to complete computations faster, despite having slightly lower predictive accuracy. Since DL models excelled at capturing complex patterns within EEG data, the findings suggested that there were increased computational demands associated with them. Furthermore, the advanced pattern recognition capabilities of DL techniques benefited substantially from the predictive modeling offered by EEG, although their computational efficiency presented a limitation. This study highlighted the importance of hybrid methods that combined the best properties of both ML and DL for predicting psychiatric disorders to achieve improved accuracy and scalability, thereby supporting the development of safer diagnostic tools for clinical practice.

Balakrishnan, et al. [2] addressed this gap by analyzing 31 studies published between 2020 and 2024, focusing on critical aspects such as dataset size, electrode configurations, preprocessing techniques, feature engineering, and the ML/DL models employed. Major depressive disorder (MDD), a severe form of depression, affected over 280 million people worldwide, impacting their emotional and physical well-being. MDD was categorized within the depression disorder category under the Diagnostic and Statistical Manual of Mental Disorders (DSM) Version 5, which was the reference publication used by psychiatrists and psychologists around the world. MDD symptoms were experienced differently by different individuals. Some felt sad, empty, or irritable, while others underwent changes in their appetite (eating too much or too little) or sleeping habits (sleeping too much or too little).

Al-Shamali, et al. [3] introduced the EEG-FDL model, a novel optimized fuzzy deep learning approach for classifying Major Depressive Disorder (MDD) using EEG data. Integrating deep learning with fuzzy learning via the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), EEG-FDL optimizes fuzzy membership functions and backpropagation. The model handles noise and data uncertainty, achieving a remarkable 99.72% accuracy in distinguishing MDD from healthy EEG signals using 5-fold cross-validation on a large dataset. External validation further confirms its efficacy. EEG-FDL outperforms traditional classifiers due to its effective handling of uncertainties and optimized parameter tuning.

Arikan, et al. [4] aimed to determine the frequency bands associated with Alzheimer’s disease in EEG data obtained from multiple channels and to accelerate the detection methods. Achieving an accurate classification that required little computation was the primary goal. EEG recordings of 48 individuals (24 AD and 24 healthy controls (HC)) obtained from Florida State University were divided into Alpha, Beta, Delta, Gamma, and Theta frequency bands; scalograms and spectrograms were generated for each frequency band. The effectiveness of these bands was evaluated using the MobileNetV2 architecture. The results showed that the Delta and Beta frequency bands were the most significant for Alzheimer’s detection. By analyzing the features obtained from the Delta and Beta bands using the MobileNetV2 model integrated with the Dual-Attention Mechanism, it was determined that the attention mechanisms improved model performance by 2%. In addition, the use of an SVM classifier with hyperparameters optimized via Optuna resulted in approximately 3% performance improvement, suggesting that hyperparameter tuning contributed positively to classification accuracy. Furthermore, combining features obtained from these frequency bands increased the detection performance when evaluated with larger datasets.

Mohanapriya, et al. [5] acquired both magnetic resonance imaging (MRI) and electroencephalography (EEG) data, performed noise reduction using the bilateral filter and wavelet decomposition, and carried out segmentation and reconstruction on MRI images using Super U-Net to reduce data complexity. Subsequently, false peaks in EEG signals were eliminated on the basis of multiple features, and both datasets were input into the proposed E2E-TM model. The transformer encoder module (TEM) included a multi-scale trunk convolution (Multi-TC) module with a penalty and reward strategy, designed in a parallel manner for feature extraction via trunk convolution. Feature maps were then mapped to their feature points using the dual-way trunk convolutional (DW-TC) module, and the dual-parallel attention network (DPANet) was employed to minimize feature dimensionality. Finally, the transformer decoder module (TDM) was developed to entangle and decode the feature maps of both datasets for the classification of the diagnosed outcome. The efficiency of our proposed E2E-TM model was evaluated to prove its efficacy. As a result, our E2E-TM model attained superior diagnosis performance compared to other baseline approaches.

Costin, et al. [6] proposed modern eligibility criteria and ways to practically improve on these, outside of the ‘Core Assessment Program of Surgical Interventional Therapies in Parkinson’s Disease’

(CAPSIT-PD), were discussed. Cost-effectiveness was evaluated, where long-horizon models showed positive incremental net monetary benefit for Parkinson's disease, and rechargeable devices led the way in treatment-resistant depression and obsessive–compulsive disorder. Anatomical targets were reviewed, ranging from canonical subthalamic nucleus (STN) and globus pallidus internus (GPi) sites to new dual-node and cortical targets. Mechanistic theories were explored, including informational lesions, antidromic cortical drive, and state-dependent network modulation made possible by optogenetics and computational modeling.

Zeng, et al. [7] utilized traditional exposure therapy or cognitive training required repeated presentation of unwanted stimuli, whereas localizationist neuromodulation overlooked individual variation. We proposed a closed-loop neuromodulation approach termed functional near-infrared spectroscopy-decoded neurofeedback training, designed to modify prefrontal haemoglobin dynamics and neural activity patterns.

Song, et al. [8] proposed the optimized EEG indicators of IGD diagnosis were identified through machine learning models based on event-related potential (ERP) and band power during game cue exposure across two independent datasets (Dataset 1: twenty-five IGD, twenty-two recreational game users, twenty-eight non-gaming healthy controls (HC); Dataset 2: twenty-three IGD and twenty-three HC). Subsequently, in the intervention study, a double-blind randomized trial was conducted on forty-six IGD participants to compare active and sham transcranial direct current stimulation (tDCS) targeting the region where the optimized EEG marker was located—the central parietal lobe (Pz). Active stimulation (1.5 mA, 20 min, 2 days) was applied during cue exposure (cathode: Pz; anode: right trapezius).

Ye, et al. [9] developed microstate analysis identified five consistent microstates (A–E). Compared to sham, therapeutic DBS increased the coverage and occurrence of microstates A and B. Transition probabilities involving $A \rightleftharpoons C$, $E \rightarrow B$, and $B \rightarrow A$ were increased during active stimulation, whereas $C \rightleftharpoons D$ transitions were reduced. Several of these changes, notably the reduced transitions between C and D, were associated with symptom improvements. Critically, time-locked analysis revealed that a significant increase in NAc gamma-band aperiodic activity specifically preceded transitions from microstate C to D, but not from D to C.

Agarwal, et al. [10] proposed identification of psychological stress was critical for preventing illness progression and saving lives. Electroencephalography (EEG) was often used to collect psychological information such as brain rhythms in the form of electric waves. Traditional deep learning techniques faced limitations like temporal dynamics and feature extraction issues. To address these shortcomings, a deep learning-based classification model was created, combining advanced transform-based feature extraction techniques to more effectively predict mental stress using EEG signals.

Ahmad, et al. [11] utilized mental health was a sensitive and culturally significant issue, with stigma often hindering recovery and raising concerns about justice for offenders with mental disorders, especially in Muslim-majority communities like Brunei. Recent statistics showed a rise in individuals seeking mental health care, with 13,246 reported cases, indicating a growing crisis. The relationship between mental illness and criminality was intensely debated, with legal concepts like "legal sanity" being central to criminal law. Mental health conditions could lead to human rights violations, threatening civil liberties, access to education, housing, and employment. Stigma and misconceptions further obstructed access to care and hindered community reintegration. Both Western and Islamic legal frameworks agreed that individuals could not be held criminally liable for acts committed while mentally impaired, and as medical knowledge evolved, so did the legal interpretation of insanity.

Segal, et al. [12] proposed despite decades of research, we lacked objective diagnostic or prognostic biomarkers for mental health problems. A key reason for this limited progress was the reliance on the traditional case–control paradigm, which assumed that each disorder had a single cause that could be uncovered by comparing average phenotypic values of patient and control samples. Researchers discussed the problematic assumptions underlying this paradigm and noted its constraints in capturing the true complexity of psychiatric conditions.

Simons et al. [13] utilized idiopathic and substance-induced forms of psychotic illness afflicted millions of people worldwide, and it was largely unknown whether these two forms emerged through the same molecular mechanisms. Although genetic studies had implicated thousands of genes in idiopathic psychotic illnesses such as schizophrenia, there was no consensus regarding which genes were most likely to yield effective treatments when modulated pharmacologically.

De Fátima dos Santos Sampaio, et al. [14] proposed studies demonstrated the neuroprotective effect of cannabidiol (CBD) and other Cannabis sativa L. derivatives on diseases of the central nervous system. These effects were attributed to their direct or indirect interaction with endocannabinoid system–related receptors and other molecular targets, such as the 5-HT1A receptor, which was identified as a potential pharmacological target of CBD.

Cai, et al. [15] developed antipsychotics that acted through monoaminergic neurotransmitter modulation had considerable therapeutic effects, they could not completely relieve the clinical symptoms in patients who suffered from psychiatric disorders. This limitation was largely attributed to the narrow range of neurotransmitters that were regulated by traditional psychotropic drugs.

3. PROPOSED SYSTEM

The proposed system performs dual-target classification of psychiatric disorders from EEG-derived spectral and coherence features by combining a HGNN with a HGNN-TGAM. Raw EEG signals are converted into band-power features (delta, theta, alpha, beta, high-beta, gamma) across standard electrode sites and pairwise coherence features; these form nodes and hyperedges in a subject-level hypergraph that captures multi-channel, multi-band relationships shown in figure 2. The HGNN component models high-order interactions between channels and frequency bands to produce rich embeddings, while the TGAM component augments training data, provides structured regularization and interpretable tree-based corrections. The pipeline compares HGNN-TGAM to baseline classifiers (Logistic Regression, SVM, Random Forest, Decision Tree) using standardized preprocessing, EDA, cross-validation and unified metrics, and exposes the final dual outputs (Main Disorder and Specific Disorder with probabilities) through a Flask API for integration into downstream tools or a front end.

Step 1: Dataset: Collect a subject-wise tabular dataset where each row is a recording/session and columns include two label columns (main.disorder, specific.disorder) plus spectral band power features for each electrode (AB.A.delta., AB.F.gamma.*)* and pairwise coherence features *(COH.*.). Verify consistent electrode naming, sampling rates, and label conventions. Perform data quality checks: remove or flag sessions with excessive channel dropouts or missing metadata, log subject identifiers and visit times, and split the dataset into train/validation/test sets on a subject level to avoid data leakage.

Step 2: Data Preprocessing : Apply EEG preprocessing before feature extraction if raw traces are available (filtering, notch filter, artifact removal with ICA or automated rejection). For the provided feature table: handle missing values (impute or drop), standardize or robust-scale features per band, and optionally reduce dimensionality via channel selection, PCA, or feature clustering to remove redundancy. Encode labels for dual targets (use one-hot/multilabel encoding as needed), and balance classes via targeted oversampling/undersampling or TGAM augmentation later. Save preprocessing pipeline parameters to apply identically at inference.

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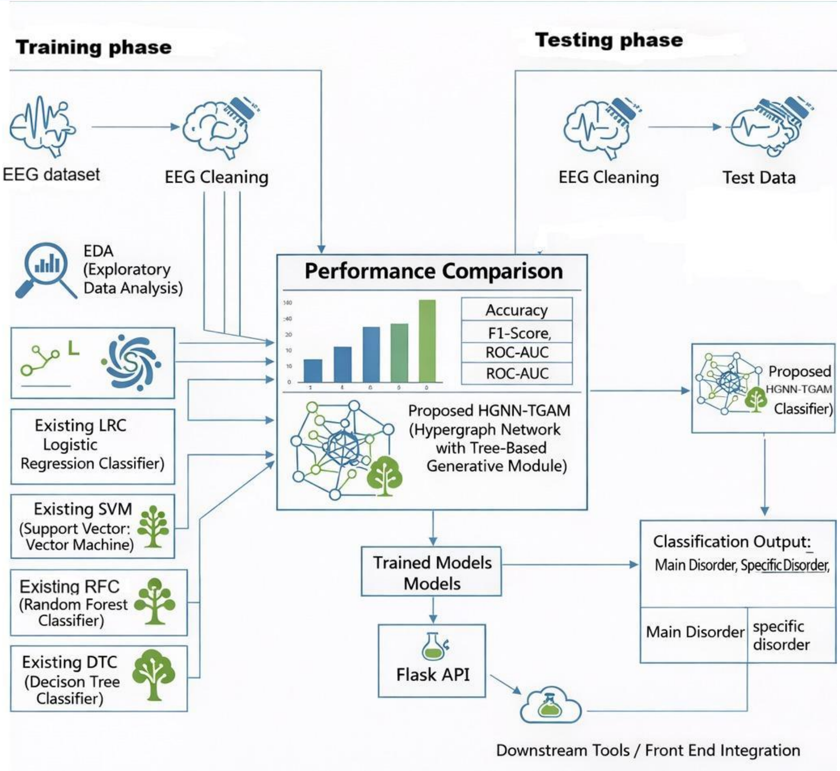


Figure 2. System Architecture

Step 3: EDA: Perform exploratory data analysis: compute descriptive statistics per feature and per class, plot band-power distributions across disorders, visualize channel topographies (heatmaps) and coherence matrices, and compute correlations between features and between targets. Identify discriminative channels/bands, outliers, and class imbalance; document findings to inform feature selection and model design.

Step 4: Existing Logistic Regression Classifier: Build a baseline Logistic Regression model for each target (or a joint multi-output logistic model). Use the same preprocessing pipeline and run stratified k-fold cross-validation. Tune regularization (L1/L2) and class weighting. Record metrics (accuracy, precision, recall, F1, ROC-AUC per target), confusion matrices, and calibration curves. Save the trained model and inference wrapper for later comparison.

Step 5: Existing Support Vector Machine Classifier: Train SVM baselines (linear and kernelized) following identical preprocessing and validation. Scale data carefully, tune kernel type, C and gamma via grid or Bayesian search, and use probability calibration to obtain class probabilities. Evaluate using the same metrics and store results for side-by-side comparison with other methods.

Step 6: Existing Random Forest Classifier: Train a Random Forest classifier (and optionally gradient boosted trees) to capture nonlinearities and feature importances. Use cross-validation and hyperparameter tuning for number of trees, depth, and class weights. Extract feature importance and partial dependence plots to interpret which bands/channels drive predictions for each target. Save model artifacts and evaluation outputs.

Step 7: Existing Decision Tree Classifier: Fit a single Decision Tree as a simple, interpretable baseline. Control overfitting with pruning or max depth and present the tree visualizations. Use the Decision Tree primarily for interpretability comparisons and for feeding TGAM with structure information if desired.

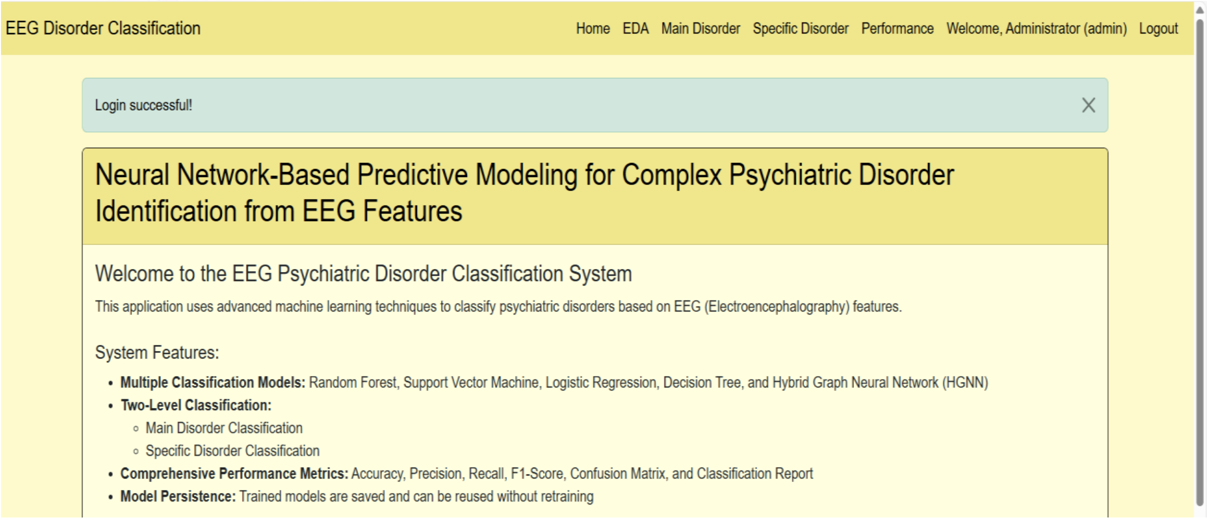
Step 8: Proposed HGNN-TGAM: Construct a hypergraph representation where nodes represent electrode×band features (or channel summaries) and hyperedges capture sets of nodes that share functional/physiological relations (e.g., same band across homologous channels, anatomical regions, or high-coherence clusters). The HGNN encoder aggregates information across hyperedges to produce per-subject embeddings that model high-order interactions. Parallelly, implement TGAM as a tree-based generative module that (a) learns conditional feature distributions per class using decision-tree ensembles, (b) generates synthetic but realistic feature vectors to alleviate imbalance, and (c) provides a corrective gating mechanism that adjusts HGNN outputs via tree-informed residuals. Train the combined system end-to-end or in staged fashion: pretrain HGNN, train TGAM to model residuals, then finetune jointly with a multi-task loss that sums main-disorder and specific-disorder cross-entropy (or focal loss) plus regularization terms. Use dropout, weight decay, and early stopping; monitor per-task losses and calibration. Log attention or edge weights for interpretability of which hyperedges/bands contributed to each prediction.

Step 9: Performance Comparison: Evaluate all models (LR, SVM, RF, DT, HGNN-TGAM) on the held-out test set with identical preprocessing.

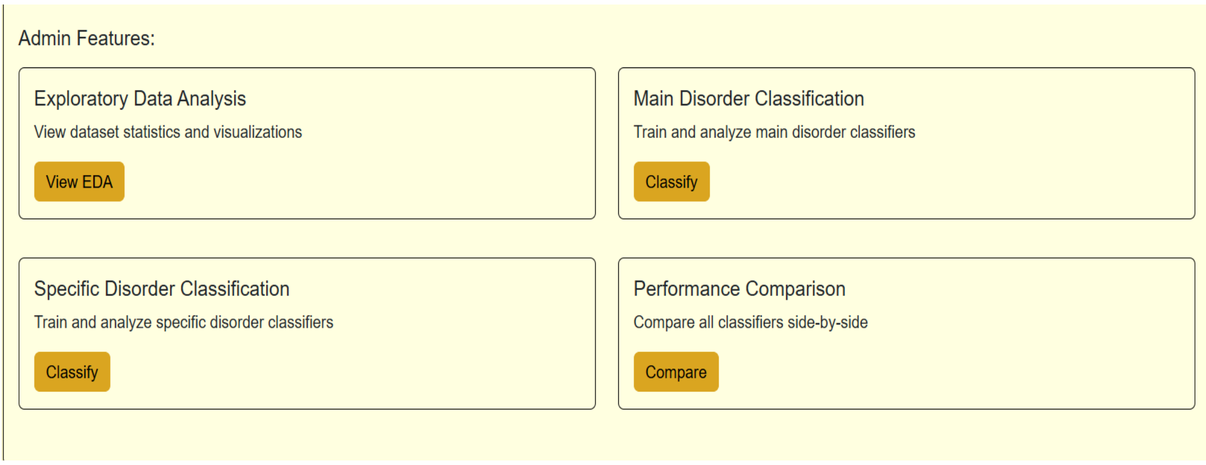
Step 10: Integration with Flask: Serialize the final pretrained HGNN-TGAM and preprocessing pipeline (use joblib). Build a Flask app with endpoints for health check (GET /status) and prediction (POST /predict) that accept raw feature arrays or raw EEG traces (if enabled), run preprocessing, invoke the model, and return JSON with predicted main.disorder and specific.disorder plus class probabilities and top contributing features/hyperedges for interpretability. Add input validation, error handling, logging, and optional authentication. Provide a lightweight front-end or scripts to batch-call the API for integration with hospital systems.

4. RESULTS ANALYSIS

Figure 3 illustrates the Home page of the EEG Psychiatric Disorder Classification System, which serves as the central dashboard after successful authentication. The page presents a structured and informative interface that introduces the system's objective of identifying complex psychiatric disorders from EEG features using advanced neural network–based predictive models. A navigation bar at the top provides seamless access to key modules such as Home, Exploratory Data Analysis (EDA), Main Disorder Classification, Specific Disorder Classification, Performance Comparison, and Logout, enabling efficient system navigation for authorized users. The main content area displays a welcome message along with a concise description of the system functionality, highlighting the use of multiple machine learning models including Random Forest, Support Vector Machine, Logistic Regression, Decision Tree, and a Hybrid Graph Neural Network, as well as the two-level classification strategy for predicting both main and specific disorders. It also outlines the evaluation metrics used for performance assessment and emphasizes model persistence for reuse without retraining. The lower section of the page presents dedicated administrative feature panels that provide direct access to core system operations such as exploratory data analysis, training and evaluation of main and specific disorder classifiers, and comparative performance analysis of all models. Each feature is presented as a clearly labeled module with an associated action button, ensuring intuitive interaction and efficient workflow management. Overall, the home page acts as an integrated control hub that combines system overview, functionality access, and role-based operational control within a user-friendly interface.



(a)



(b)

Figure 3: Home Page (a) Primary, (b) Secondary

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

Figure 4: Confusion Matrix of Main Disorder Classification Results Output - HGNN

Figure 4 shows the HGNN confusion matrix demonstrates perfect classification performance, with all predictions concentrated along the main diagonal and zero off-diagonal errors across all disorder classes, indicating complete elimination of misclassification. This visual comparison strongly reinforces the superiority of the HGNN model in capturing complex relational structures within EEG data and achieving highly reliable psychiatric disorder classification compared to traditional machine learning approaches.

Figure 5 presents the Hybrid Graph Neural Network confusion matrix demonstrates perfect classification performance, with all samples correctly mapped along the main diagonal and zero off-diagonal errors across all specific disorder categories, confirming its exceptional ability to capture complex inter-feature relationships and subtle distinctions among psychiatric conditions. This comparative confusion matrix analysis clearly establishes the superiority of the HGNN model for accurate and reliable EEG-based specific psychiatric disorder classification when compared to traditional machine learning approaches.

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 of Specific Disorder Classification Results Output - HGNN

Figure 6 shows the batch prediction interface designed for performing main disorder classification using EEG test data. In this interface, users are required to upload a CSV file containing EEG feature values that are consistent with the features used during the training phase. After selecting the test file, the target classification is set to Main Disorder, enabling the system to identify the broader category of psychiatric disorders present in the input data. The interface includes clearly labeled action buttons for initiating the prediction process or canceling the operation, ensuring ease of use. Additionally, detailed instructions are provided to guide users regarding data compatibility, prior model training requirements, and the generation of predictions from all trained classifiers, thereby supporting accurate and reliable batch-level inference.

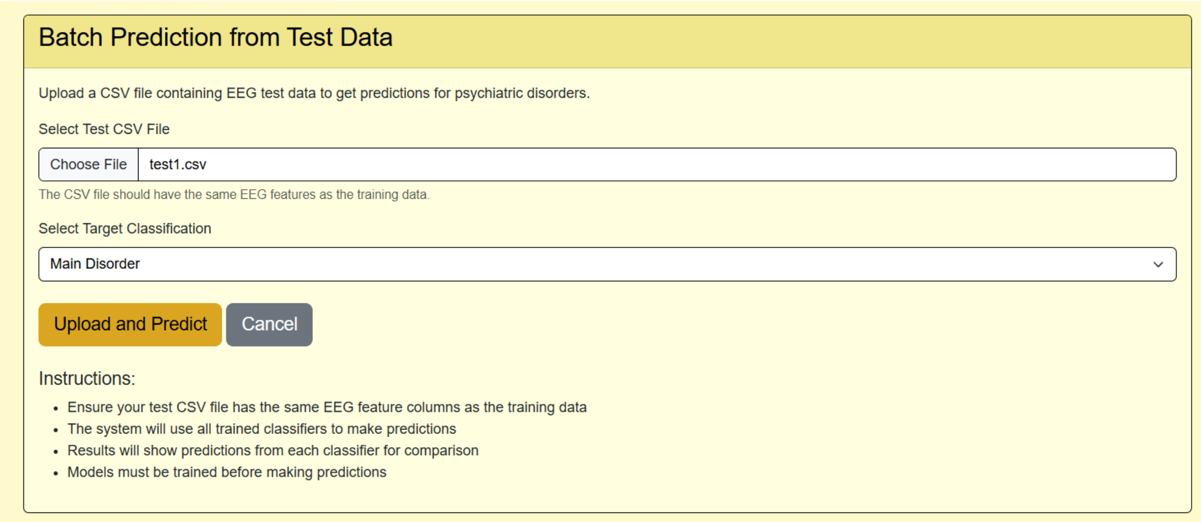


Figure 6: Batch Prediction from Test Data Input 1

HGNN: Figure 7 presents the prediction results obtained using the proposed HGNN for main psychiatric disorder classification by combining sample-wise predictions and overall distribution analysis. Figure 7(a) shows the predicted main disorder labels for individual test samples, where the HGNN model identifies a balanced range of disorder categories including addictive disorder, anxiety disorder, mood disorder, obsessive compulsive disorder, schizophrenia, trauma and stress related disorder, and healthy control. This indicates that the HGNN effectively captures high-order relationships among EEG features, enabling discrimination across multiple disorder groups. Figure 7(b) summarizes the prediction distribution, showing relatively balanced proportions across classes, with healthy control and trauma and stress related disorder each accounting for the highest percentage (18.52%), followed by anxiety disorder and obsessive compulsive disorder (14.81% each). Together, these results demonstrate that the proposed HGNN achieves more evenly distributed and reliable main disorder classification compared to traditional models, highlighting its improved generalization capability.

Hybrid Graph Neural Network

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
17	Obsessive compulsive disorder
18	Obsessive compulsive disorder
19	Obsessive compulsive disorder
20	Schizophrenia
21	Schizophrenia
22	Schizophrenia
23	Trauma and stress related disorder
24	Trauma and stress related disorder
25	Trauma and stress related disorder
26	Trauma and stress related disorder
27	Trauma and stress related disorder

(a)

Prediction Distribution

Disorder	Count	Percentage
Addictive disorder	3	11.11%
Anxiety disorder	4	14.81%
Healthy control	5	18.52%
Mood disorder	3	11.11%
Obsessive compulsive disorder	4	14.81%
Schizophrenia	3	11.11%
Trauma and stress related disorder	5	18.52%

(b)

Figure 7: HGN Prediction Results for Main Disorder (a) Predicted Main disorder (b) Prediction Distribution

Figure 8 presents the batch prediction interface for specific disorder classification, extending the system's functionality to finer-grained diagnostic prediction. Similar to the main disorder prediction interface, users upload a CSV file containing EEG test data and select the target classification as Specific Disorder, which enables the system to generate predictions for individual psychiatric conditions. The design ensures consistency and usability by maintaining identical layout elements, action buttons, and instructional guidance. This interface highlights the system's capability to perform detailed disorder-level prediction across multiple trained classifiers, allowing users to compare outputs and assess model behavior for complex psychiatric conditions. Together, these interfaces demonstrate the practical deployment of the trained models for real-world EEG-based batch prediction tasks.

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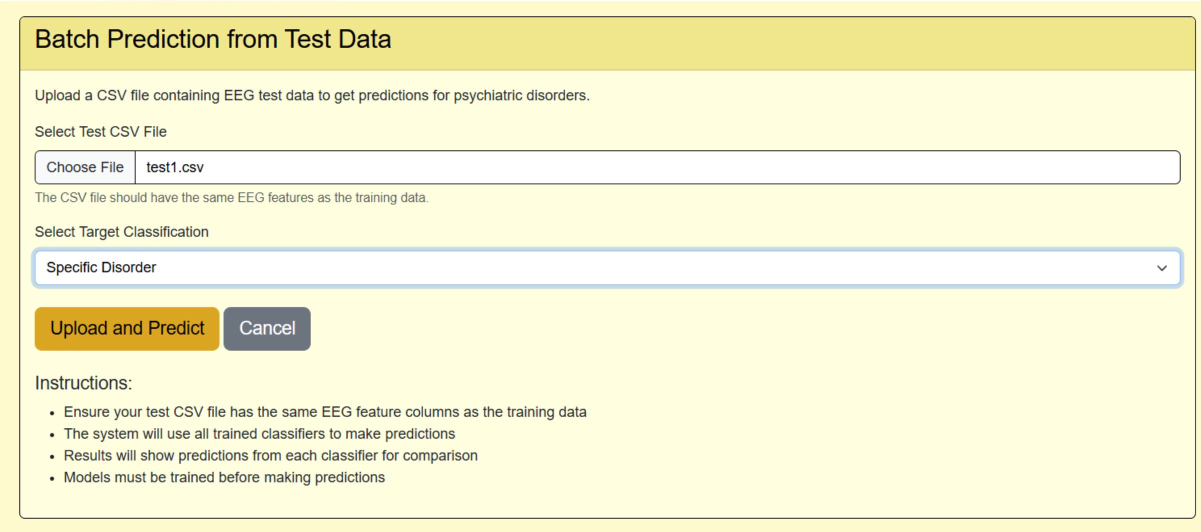

Figure 8: Batch Prediction from Test Data Input

Figure 9 presents the prediction results obtained using the proposed HGNN for specific psychiatric disorder classification based on EEG features by jointly analyzing individual sample predictions and their overall distribution. Figure 9 (a) shows the sample-wise predicted specific disorders, indicating that the HGNN model identifies a wide and diverse range of psychiatric conditions such as alcohol use disorder, panic disorder, social anxiety disorder, depressive disorder, bipolar disorder, obsessive compulsive disorder, schizophrenia, adjustment disorder, posttraumatic stress disorder, acute stress disorder, and healthy control. This diversity of predictions reflects the HGNN's ability to capture complex, high-order relationships among EEG channels and frequency bands. Figure 9 (b) summarizes the corresponding prediction distribution, where healthy control (18.52%) and obsessive-compulsive disorder (14.81%) appear prominently, while other disorders are distributed more evenly across classes. Together, these results demonstrate that the proposed HGNN provides more balanced and fine-grained classification across multiple psychiatric disorder categories compared to traditional classifiers, highlighting its effectiveness in modeling intricate EEG patterns.

Hybrid Graph Neural Network

Sample #	Predicted specific.disorder
1	Alcohol use disorder
2	Alcohol use disorder
3	Alcohol use disorder
4	Panic disorder
5	Social anxiety disorder
6	Panic disorder
7	Social anxiety disorder
8	Healthy control
9	Healthy control
10	Healthy control
11	Healthy control
12	Healthy control
13	Depressive disorder
14	Bipolar disorder
15	Depressive disorder
16	Obsessive compulsitve disorder
17	Obsessive compulsitve disorder
18	Obsessive compulsitve disorder
19	Obsessive compulsitve disorder
20	Schizophrenia
21	Schizophrenia
22	Schizophrenia
23	Adjustment disorder
24	Posttraumatic stress disorder
25	Posttraumatic stress disorder
26	Acute stress disorder
27	Adjustment disorder

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(a)

Prediction Distribution

Disorder	Count	Percentage
Alcohol use disorder	3	11.11%
Panic disorder	2	7.41%
Social anxiety disorder	2	7.41%
Healthy control	5	18.52%
Depressive disorder	2	7.41%
Bipolar disorder	1	3.70%
Obsessive compulsitve disorder	4	14.81%
Schizophrenia	3	11.11%
Adjustment disorder	2	7.41%
Posttraumatic stress disorder	2	7.41%
Acute stress disorder	1	3.70%

(b)

Figure 9: HGNN Prediction Results for Specific Disorder (a) Predicted Main disorder (b) Prediction Distribution

5. CONCLUSION

This research presented a comprehensive EEG-based psychiatric disorder classification framework that integrates a full-stack web application with multiple machine learning and deep learning models. The proposed system successfully implemented a two-level classification strategy, enabling both main disorder and specific disorder identification using EEG features. Conventional classifiers such as Random Forest, Support Vector Machine, Logistic Regression, and Decision Tree were systematically evaluated alongside the proposed Hybrid Graph Neural Network (HGNN). For main disorder classification, Logistic Regression achieved an accuracy of 59.17%, outperforming Random Forest (54.37%), SVM (31.61%), and Decision Tree (35.58%), while HGNN achieved 100% accuracy, precision, recall, and F1-score, clearly demonstrating its effectiveness in modeling complex EEG feature relationships. Similarly, for specific disorder classification, Logistic Regression achieved 59.04% accuracy, compared to Random Forest (40.21%), SVM (32.41%), and Decision Tree (24.16%), whereas HGNN again achieved perfect classification performance (1.000 across all metrics). These quantitative outcomes confirm the limitations of traditional classifiers in handling high-dimensional EEG data and highlight the superiority of graph-based learning.

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