# Psychiatric Disease Detection Using Machine Learning

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***Abstract*—Psychiatric disorders pose significant diagnostic challenges due to their reliance on subjective assessments and overlapping symptoms, often leading to delayed or inaccurate diagnoses. This study proposes a machine learning approach using preprocessed electroencephalogram (EEG) signals to detect and classify psychiatric conditions objectively. Leveraging power spectral density and functional connectivity features from a dataset of 945 subjects, including patients with schizophrenia, mood disorders, anxiety disorders, and healthy controls, we employ Random Forest and LightGBM classifiers. Our methodology aims to enhance diagnostic accuracy, enable early detection, and support personalized treatment by identifying neurophysiological patterns.**

## I. Introduction

Psychiatric disorders are among the most complex and poorly understood medical conditions due to the absence of definitive biological markers. Current diagnostic methods rely heavily on subjective clinical interviews and symptom checklists, as outlined in the DSM and ICD, leading to significant challenges.

### A. Subjectivity and Diagnostic Overlap

Psychiatric diagnoses are based on observed behaviors and self-reported symptoms, which vary widely between clinicians and patients. Many disorders (e.g., depression, anxiety, PTSD) exhibit overlapping symptoms, complicating differential diagnosis. The DSM and ICD categorize disorders based on symptoms rather than underlying neurobiology, leading to heterogeneity within diagnoses—two individuals with the same diagnosis may have distinct neurophysiological dysfunctions.[1]

### B. Inefficient and Trial-Based Treatment Approaches

The absence of objective biomarkers forces psychiatrists to rely on trial-and-error prescribing, often leading to prolonged suffering, adverse side effects, and poor treatment outcomes. Research suggests that symptom-based classification limits treatment personalization, preventing therapies from targeting the root causes of psychiatric conditions.

### C. Limitations of Current Neuroimaging Methods

While fMRI and PET scans provide insights into brain function, they are expensive, time-consuming, and impractical for routine psychiatric diagnosis. EEG is a low-cost, portable alternative, but raw EEG data is noisy and complex, requiring advanced computational techniques to extract meaningful patterns.[2]

### D. Lack of Comprehensive EEG-Based Classification

Most previous EEG-machine learning (ML) studies focus on single disorders (e.g., only schizophrenia or depression), failing to capture the spectrum of psychiatric illnesses. Few studies compare multiple disorders simultaneously, which limits their clinical applicability in real-world diagnosis.

### E. Significance of the Problem

The challenges in psychiatric diagnosis and treatment have far-reaching medical, social, and economic consequences.

*1) Global Burden of Psychiatric Disorders:* Mental health conditions contribute to 4.9% of global disability-adjusted life years (DALYs), with disorders like depression and anxiety affecting hundreds of millions worldwide. The World Health Organization (WHO) estimates that mental health conditions cost the global economy $2.5 trillion annually, projected to rise to $6 trillion by 2030.

*2) Diagnostic Delays and Misclassification:* Schizophrenia takes an average of 1.5 years to diagnose correctly, leading to delayed treatment and worsening prognosis. Bipolar disorder is misdiagnosed as depression in 40% of cases, often leading to inappropriate medication that can worsen symptoms.

*3) The Need for Objective, Data-Driven Biomarkers:* EEG provides real-time brain activity measurements, offering quantifiable features such as alpha power (linked to schizophrenia) and theta connectivity (linked to mood disorders). Machine learning models trained on EEG data have shown ¿90% classification accuracy for some psychiatric conditions, demonstrating a promising alternative to subjective clinical assessments.

### F. The Role of EEG and Machine Learning in Psychiatric Diagnosis

Emerging research suggests that EEG-based ML models could revolutionize psychiatric diagnosis by overcoming many of the limitations of current methods.[3]

*1) Advancing Precision Psychiatry:* ML-EEG models can stratify patients based on neurophysiological subtypes, enabling personalized treatments rather than symptom-based therapy. For example, a patient diagnosed with depression might show abnormal theta connectivity, suggesting a different treatment than someone with gamma-band dysfunction.

*2) Early Detection and Preventive Interventions:* EEG changes often appear before full-blown symptoms, allowing proactive interventions rather than reactive treatments. For example, alpha asymmetry in EEG has been shown to predict future depression risk, enabling preventive care.

*3) Improving Diagnostic Accuracy and Reducing Errors:* Machine learning can distinguish between schizophrenia and bipolar disorder (67.84% accuracy) and panic disorder vs. social anxiety disorder (70.47% accuracy), reducing misdiagnosis.[3]

*4) Bridging the Gap Between Research and Clinical Practice:* The NIMH's Research Domain Criteria (RDoC) initiative emphasizes biological measures for psychiatric classification. EEG-ML approaches align with RDoC's vision, mapping symptoms to underlying neural circuits rather than relying on phenomenological symptom descriptions.

### G. Challenges and Ethical Considerations

While EEG-ML presents significant advantages, its clinical implementation must address key challenges:

- **Data Privacy and Ethical Concerns:** This data is highly sensitive, requiring robust data protection policies so that not anyone with the EEG can know what the patient is facing.
- **Interpretability and Trust:** Clinicians need explainable AI models to trust EEG-based predictions.
- **Generalization and Bias:** EEG datasets may not capture ethnic, gender, or age-related variations, leading to potential bias in ML predictions.

## II. Data Description

The dataset utilized in this study consists of preprocessed EEG signals obtained from psychiatric patients and healthy controls. The original EEG recordings were transformed into quantitative features prior to publication, enabling more efficient analysis while preserving key neurophysiological patterns.

### A. Data Acquisition and Source

- **Source:** Seoul Metropolitan Government-Seoul National University (SMG-SNU) Boramae Medical Center, Seoul, South Korea [4]
- **Collection Period:** January 2011 to December 2018
- **Subjects:** 945 participants (age range: 18-70 years)
- **Composition:** Includes both psychiatric patients and healthy controls

### B. Data Characteristics

The dataset contains two primary types of preprocessed features: [3]

- **Power Spectral Density (PSD):** Computed using Fast Fourier Transform (FFT) across standard frequency bands (delta, theta, alpha, beta, gamma)
- **Functional Connectivity:** Represented by coherence measures between electrode pairs

### C. Diagnostic Categories

The dataset encompasses six major psychiatric disorder categories, further divided into nine specific diagnoses:

- Schizophrenia (n = 117)
- Mood Disorders (n = 266):
  - Depressive Disorder (n = 119)
  - Bipolar Disorders (n = 67)
- Anxiety Disorders (n = 107):
  - Panic Disorder (n = 59)
  - Social Anxiety Disorders (n = 48)
- Obsessive-Compulsive Disorder (n = 46)
- Addictive Disorders (n = 186):
  - Alcohol Use Disorder (n = 93)
  - Behavioral Addiction (n = 93)
- Trauma/Stress-Related Disorders (n = 128):
  - PTSD (n = 52)
  - Acute Stress Disorder (n = 38)
  - Adjustment Disorder (n = 38)

## III. Data Preprocessing

Given that the original EEG signals were already preprocessed, our preprocessing pipeline focuses on preparing the derived features for machine learning analysis.

### A. Initial Processing Steps

- **Column Standardization:**
  - Removal of unique identifier columns
  - Renaming of features for improved readability
- **Missing Data Handling**

### B. Feature Engineering

- **Outlier Detection:**
  - Statistical methods for identifying extreme values
  - Robust handling of outliers to minimize data distortion
- **Data Transformation:**
  - Log transformation for skewed distributions
  - Normalization/standardization for feature scaling
- **Categorical Encoding:**
  - Appropriate encoding of diagnostic labels
  - Handling of any demographic categorical variables

### C. Quality Assurance

- Verification of preprocessing steps through statistical summaries
- Validation of data integrity throughout transformation pipeline
- Documentation of all preprocessing decisions for reproducibility

## IV. Feature Extraction

Based on the dataset publisher's analysis [4], we identified the most discriminative features for each psychiatric disorder category. The optimal feature combinations were determined to be:

These feature combinations will serve as the primary inputs for training our machine learning models, with the objective of developing the most effective classifier for each disorder category.

TABLE I
OPTIMAL FEATURE COMBINATIONS BY DISORDER

| Disorder | Most Effective Features |
|---|---|
| Depression disorder | Delta band functional connectivity (FC) |
| Bipolar disorder | Delta band power spectral density (PSD) + FC |
| Panic disorder | Whole spectrum PSD |
| Social anxiety disorder | Theta band FC |
| Alcohol use disorder | Whole spectrum PSD |
| Behavioral addiction disorder | Delta band PSD |
| Post-traumatic stress disorder | Beta band PSD |
| Acute stress disorder | Beta band PSD + FC |
| Adjustment disorder | Alpha band FC |

Additionally, we will conduct a comparative analysis using:

- The complete PSD features across all frequency bands
- Intelligence quotient (IQ) measurements

This dual approach will enable us to:

1) Validate the publisher's recommended feature selections
2) Assess whether comprehensive spectral analysis provides improved classification performance
3) Evaluate the potential contribution of cognitive metrics to diagnostic accuracy

## V. CLASSIFICATION TECHNIQUES

Detecting psychiatric disorders derived from electroencephalogram (EEG) signals requires a robust and effective machine learning model. Two prominent candidates for this project are the Random Forest Classifier and the LightGBM Classifier (Light Gradient Boosting Machine). The Random Forest Classifier is a widely adopted ensemble method that leverages multiple decision trees to achieve reliable classification, valued for its simplicity and robustness. In contrast, the LightGBM Classifier, a high-performance gradient boosting framework, is engineered for speed, scalability, and superior accuracy on complex datasets. The mechanics, key parameters, and specific advantages of both models will be explored in the context of psychiatric disease detection.

### A. Random Forest Classifier

Random Forest is a widely used machine learning model designed for classification tasks. The term "forest" stems from its structure, which comprises multiple "decision trees." Each tree is independently trained using a bootstrap sample of the dataset and operates by evaluating a randomized subset of features when making splits. This approach enhances the model's robustness and overall predictive performance. [5]

*1) How It Works:* The main mechanism of the Random Forest algorithm operates through the following steps:

1) **Bootstrap Sampling**
Each decision tree within the Random Forest is trained on a distinct dataset generated through bootstrap sampling. This technique involves randomly drawing data points from the original dataset with replacement, allowing some data points to appear multiple times in the training set while others may be excluded.
2) **Random Feature Selection**
When a decision tree creates a split, it evaluates only a random subset of features rather than the full feature set. For classification tasks, this subset typically consists of the square root of the total number of features, while in regression tasks, a slightly larger subset is often selected. This method reduces correlation between trees and enhances the model's overall robustness.
3) **Tree Construction**
Each decision tree independently grows by using its specific bootstrap sample and the selected subset of features. Splitting continues until predefined stopping criteria are met, such as forming pure nodes, reaching a minimum number of samples per node, or reaching maximum tree depth.
4) **Final Prediction (Ensemble Decision)**
Once all decision trees are fully constructed, their predictions are aggregated to produce the final output:
   - For classification problems, the Random Forest combines the individual class predictions from all trees and selects the majority class (majority voting).
   - For regression problems, it averages the predicted numerical values across all trees.

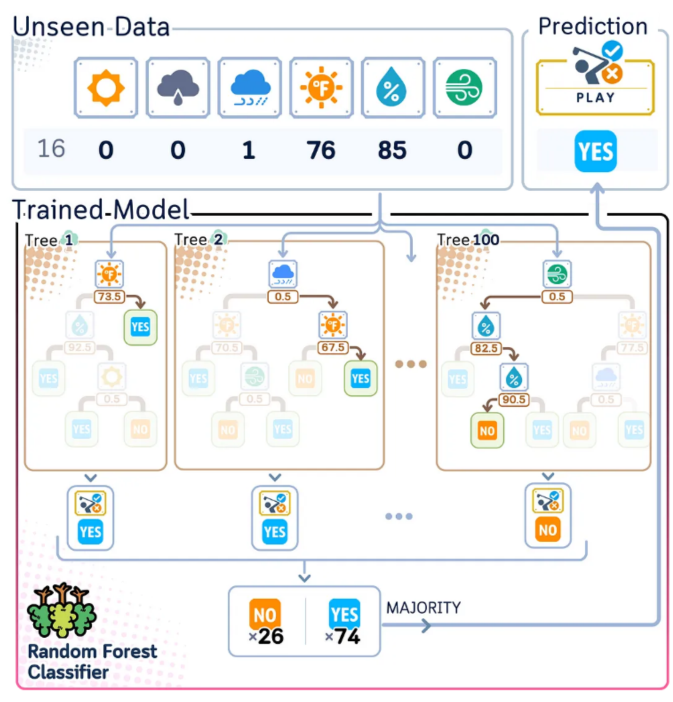


Fig. 1. Majority vote from 100 decision trees analyzing features.

*2) Random Forest-Specific Parameters:*

- **oob_score**
This uses leftover data (out-of-bag samples) to check how well the model works. This gives you a way to test your model without setting aside separate test data. It's especially helpful with small datasets. [6]

- **n_estimators**
  This parameter controls how many trees to build (default is 100). To find the optimal number of trees, track the OOB error rate as you add more trees to the forest. The error typically drops quickly at first, then levels off. The point where it stabilizes suggests the optimal number—adding more trees after this gives minimal improvement while increasing computation time.
- **bootstrap**
  This decides whether each tree learns from a random sample of data (True) or uses all data (False). The default (True) helps create different kinds of trees, which is key to how Random Forests work. Only consider setting it to False when you have very little data and can't afford to skip any samples.
- **n_jobs**
  This controls how many processor cores to use during training. Setting it to -1 uses all available cores, making training faster but using more memory. With big datasets, you might need to use fewer cores to avoid running out of memory.

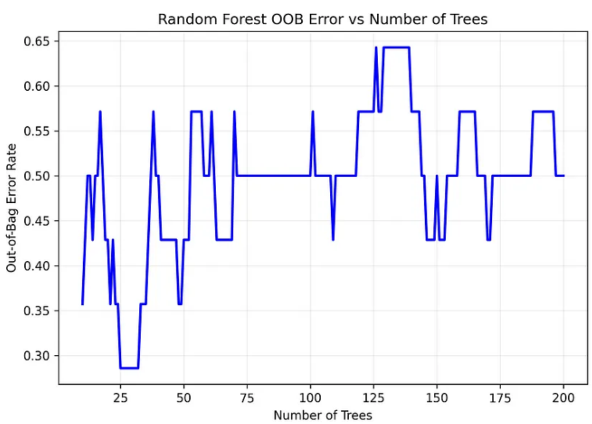


Fig. 2. Majority vote from 100 decision trees analyzing features.

*3) Why Use Random Forest for Psychiatric Disease Detection?:* The Random Forest Classifier is a highly suitable model for the task of detecting psychiatric disorders using power spectral density (PSD) values derived from EEG signals. Here are the key reasons why this model can be a right choice for this application

1) **Accessibility for Novices**
   The Random Forest Classifier is particularly advantageous for individuals new to machine learning. Its default parameters are robust and effective, allowing users to achieve meaningful results without requiring extensive knowledge of complex hyperparameter optimization. This enables a focus on data analysis rather than intricate model configuration.
2) **Compatibility with PSD Features**
   PSD values represent numerical data, quantifying power across various frequency bands (e.g., delta, theta, alpha). The Random Forest Classifier excels at identifying patterns within such structured, numerical datasets, associating elevated theta power with anxiety.
3) **Robustness to Noisy Data**
   EEG-derived data, such as PSD values, is often susceptible to noise from artifacts. The Random Forest Classifier mitigates this challenge effectively by averaging predictions across multiple decision trees, thereby reducing the impact of outliers and irregularities in the data.
4) **Effective Multi-Class Classification**
   Psychiatric disease detection frequently involves distinguishing between multiple diagnostic categories (e.g., depression, anxiety, schizophrenia) rather than a binary outcome. The Random Forest Classifier is inherently designed to handle multi-class problems, aggregating votes from its ensemble of trees to assign data points to the appropriate class.
5) **Insight into Feature Importance**
   Post-training, the model provides access to feature importance metrics, revealing which PSD features most significantly influence classification outcomes. This capability is invaluable in psychiatric research, offering potential insights that could inform clinical understanding and practice.

*4) Potential Downsides for Using Random Forest:*

- **Imbalance**
  If the dataset has way more "normal" people than "schizophrenia" cases, it might be necessary to add `class_weight='balanced'` to make it fairer.
- **Speed**
  If we have thousands of PSD samples, it might be slower than other models.

### *B. LightGBM Classifier*

The LightGBM Classifier (Light Gradient Boosting Machine) is a high-performance machine learning model optimized for classification tasks. It belongs to the gradient boosting family, where it constructs an ensemble of decision trees sequentially to improve predictive accuracy. Unlike traditional models, LightGBM is designed for speed and scalability, making it particularly effective for large or complex datasets. The "Light" in its name reflects its efficiency in memory usage and computation time, achieved through innovative techniques in tree construction.[7]

*1) How It Works:* The LightGBM algorithm operates through the following steps:

1) **Gradient Boosting**
   LightGBM builds decision trees one at a time, where each tree corrects the errors of the previous ones. It uses a mathematical approach called gradient descent to minimize prediction errors, focusing on the data points that are hardest to classify correctly.
2) **Leaf-Wise Tree Growth**
   Unlike traditional level-wise growth (where all nodes at the same level split simultaneously), LightGBM grows

trees by splitting the leaf that offers the greatest reduction in error. This targeted approach makes it more efficient, though it risks overfitting if not controlled.

3) **Histogram-Based Learning**
To speed up training, LightGBM groups continuous features (like PSD values) into discrete bins or "histograms." Instead of evaluating every possible split point, it only checks these bins, drastically reducing computation time while maintaining accuracy.

4) **Final Prediction (Ensemble Decision)**
Once all trees are built, LightGBM combines their outputs:
   - For classification, it calculates a score for each class across all trees and selects the class with the highest score (akin to weighted voting).
   - For regression, it averages the predictions.

*2) Key LightGBM Parameters:* LightGBM's performance depends on several core parameters that control model structure and training. Here are the most important ones[8]:

- **objective**
  Defines the loss function (e.g., regression, binary, or multiclass).
- **num_leaves**
  Maximum leaves per tree (higher = more complex, but risk of overfitting).
- **learning_rate**
  Step size for gradient descent (lower = slower but more precise training).
- **max_depth**
  Limits tree depth to control overfitting.
- **min_data_in_leaf**
  Minimum samples required in a leaf (higher = smoother predictions).
- **feature_fraction**
  Fraction of features used per tree (improves diversity).
- **bagging_fraction**
  Fraction of data sampled per iteration (reduces overfitting).
- **L1 (lambda_l1) & L2 (lambda_l2)**
  Regularization terms to penalize large weights.

*3) Why Use LightGBM for Psychiatric Disease Detection?:* The LightGBM Classifier is exceptionally well-suited for detecting psychiatric disorders using power spectral density (PSD) values derived from electroencephalogram (EEG) signals.

1) **Superior Speed and Scalability**
LightGBM leverages histogram-based learning to efficiently process PSD data, enabling rapid training and prediction. This scalability is particularly advantageous for expanding EEG datasets or iterative experimentation, delivering high performance without compromising accuracy.

2) **Enhanced Pattern Recognition**
LightGBM's gradient boosting framework offers greater depth. By sequentially constructing trees that prioritize correcting prior errors, LightGBM excels at detecting subtle relationships within noisy PSD values.

3) **Robust Handling of Large, Noisy Datasets**
LightGBM's error-driven methodology actively adapts to such irregularities, enhancing resilience. Additionally, its capacity to manage high-dimensional PSD data outperforms Random Forest, which may struggle under similar complexity.

4) **Elevated Performance on Complex Tasks**
LightGBM is engineered for advanced performance. Its leaf-wise tree growth strategy maximizes accuracy by focusing on the most impactful splits. This makes LightGBM particularly effective for intricate PSD datasets with overlapping or challenging patterns.

### C. Best Candidate

After assessing the Random Forest and LightGBM Classifiers for psychiatric disease detection with PSD values, LightGBM stands out as the better choice. Random Forest offers ease of use, compatibility with PSD features, and noise robustness but falters with slower training and limited scalability for larger datasets, lacking precision for subtle EEG patterns. LightGBM, with its histogram-based learning and leaf-wise growth, provides superior speed, scalability, and pattern recognition, adeptly handling noisy, high-dimensional PSD data. Its optimized multi-class performance and advanced accuracy outshine Random Forest, making it the ideal model for reliable, insightful results despite modest tuning needs.

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