Decoding Psychiatric Disorders with EEG Signals: A Machine Learning Perspective

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***Abstract*—Psychiatric disorders affect millions of individuals worldwide, yet their diagnosis remains challenging due to the complexity of mental health assessments. Electroencephalography (EEG) has shown promise as a non-invasive tool for analyzing brain activity and identifying patterns associated with various psychiatric conditions. This study aims to classify psychiatric disorders using EEG signals, leveraging data-driven techniques to uncover distinguishing features among different conditions. By analyzing EEG recordings, this research seeks to explore the potential of computational methods in assisting clinical diagnosis and improving the understanding of neurological patterns underlying psychiatric disorders. The findings of this study could contribute to the development of automated diagnostic support systems, offering a more objective and accessible approach to mental health assessment.**

***Keywords*—EEG Signals, Psychiatric Disorder Classification, Machine Learning, Data Visualization, Deep Learning, Pattern Recognition, Feature Extraction, Predictive Modelling, Computational Psychiatry.**

I. Introduction

Psychiatric disorders, such as depression, schizophrenia, and bipolar disorder, affect millions of people worldwide and pose significant challenges in diagnosis and treatment. Traditionally, the diagnosis of these disorders relies on clinical evaluations, self-reported symptoms, and psychological assessments, which can be subjective and vary between practitioners. As a result, there is a growing interest in developing objective, data-driven approaches to assist in the identification and classification of psychiatric conditions. Electroencephalography (EEG) has emerged as a promising tool in this domain, offering a non-invasive method to record brain activity and analyze neural patterns associated with mental health disorders.

EEG signals capture electrical activity in the brain through multiple electrodes placed on the scalp, providing valuable insights into cognitive and neurological functions. Studies have shown that different psychiatric disorders exhibit distinct EEG signal patterns, making it possible to use computational techniques to classify these conditions. With advances in data science and machine learning, analyzing EEG data has become more feasible, allowing researchers to extract meaningful patterns that can aid in psychiatric diagnosis. This study aims to explore the classification of psychiatric disorders using EEG signals, leveraging computational methods to identify distinguishing features among different conditions.

Machine learning has revolutionized many fields, including healthcare, by enabling the automatic identification of patterns in complex datasets. In the context of EEG-based psychiatric disorder classification, machine learning techniques can learn from existing patient data to differentiate between various conditions. By employing data-driven models, this approach seeks to provide an objective and scalable method for assisting mental health professionals in diagnosing psychiatric disorders more accurately and efficiently. A key aspect of this research is understanding how different psychiatric disorders manifest in EEG signals and whether computational models can effectively capture these distinctions. The study will involve analyzing EEG data to uncover trends and variations linked to different psychiatric conditions. The insights gained from this research could contribute to the development of automated diagnostic support systems, reducing reliance on subjective evaluations and enhancing early detection of mental health disorders.

Furthermore, visualizing EEG data is crucial for interpreting brain activity patterns and understanding how different disorders impact neural functions. Data visualization techniques will be used to explore EEG signal characteristics, highlight key differences between psychiatric conditions, and assess model performance in classification tasks. Effective visual representation of EEG signals can improve the interpretability of results and provide valuable insights for clinicians and researchers.

In summary, this research aims to bridge the gap between neuroscience and machine learning by leveraging EEG signals for psychiatric disorder classification. By analyzing brainwave data and applying computational techniques, this study seeks to advance the field of mental health diagnostics and contribute to the development of objective, data-driven tools for psychiatric assessment.

II. Dataset Description

The dataset used in this study consists of EEG recordings aimed at identifying psychiatric disorders. It contains 1,149 columns, representing various attributes extracted from EEG signals. These attributes capture statistical, temporal, and frequency-domain features that help in understanding the brainwave activity associated with different mental health conditions. The dataset includes EEG data from individuals diagnosed with a range of psychiatric disorders, including depression, personality disorders, anxiety disorders, schizophrenia, eating disorders, and addictive behaviours. The diverse nature of the data makes it a valuable resource for studying variations in brain activity linked to different psychiatric conditions.

The dataset provides a detailed view of EEG signal characteristics by including a wide array of features that reflect brainwave fluctuations across different frequency bands. These features help in identifying patterns that may distinguish one psychiatric disorder from another. The presence of a large number of attributes allows for an in-depth analysis, offering opportunities for feature selection and dimensionality reduction techniques to enhance classification performance. The target variable in this dataset corresponds to the psychiatric disorder classification assigned to each individual. This study aims to explore distinct neural patterns associated with various mental health conditions.

III. RELATED WORKS

The use of machine learning techniques for classifying psychiatric disorders using EEG data, demonstrating the potential of ML-based approaches in objective diagnostics. Their study employed models such as Support Vector Machine (SVM), Random Forest (RF), and Elastic Net (EN), with the Elastic Net model performing best due to its ability to handle high-dimensional, correlated features through regularization. EEG signals were pre-processed to remove artifacts, and key features such as power spectral density (PSD) and functional connectivity (FC) were extracted across multiple frequency bands. The study also incorporated covariates like IQ, age, sex, and education to improve model robustness, ensuring reliable classification results. However, a limitation of this research is its reliance on predefined feature extraction techniques, which may restrict the discovery of novel patterns in EEG data. From this study, we gain valuable insights into the dataset and EEG feature engineering, which will guide our approach to preprocessing and feature selection in our research. [1]

The reviewed studies provide a comprehensive analysis of EEG signal processing in psychiatric and BCI systems, utilizing preprocessing methods such as ICA, PCA, CSP, and wavelet transforms to reduce noise and enhance feature extraction. Machine learning models like SVM, k-NN, LDA, and CNNs are widely applied for classification tasks. However, the papers generally lack standardized preprocessing protocols and robust comparative evaluations of model performance across datasets. There is also limited focus on adaptive artifact removal, real-time data handling, and cross-study validation. Future work should emphasize standardized benchmarking, integrate hybrid preprocessing pipelines, explore ensemble/transfer learning approaches, and focus on generalizable models for broader clinical application. [2]

A comprehensive review of EEG-based BCI systems, highlighting preprocessing techniques such as ICA, PCA, CSP, and wavelet transforms for enhancing signal quality. Machine learning approaches like SVM, k-NN, LDA, and deep learning models (CNN, DNN) are extensively applied for EEG signal classification. [7] While both papers successfully explore key methods, they lack in-depth comparative analysis of classifier performance across datasets and insufficiently address real-time adaptive preprocessing and artifact removal. [10] The integration of hybrid feature extraction techniques and ensemble classifiers is underexplored. Our work from this focuses on standardized benchmarking, and cross-domain transfer learning to improve system accuracy and robustness.

Electroencephalogram (EEG)-based analysis has emerged as a promising approach for diagnosing psychiatric disorders due to its ability to capture neural activity non-invasively. EEG provides high temporal resolution, making it valuable for studying neural abnormalities associated with conditions such as schizophrenia, bipolar disorder, obsessive-compulsive disorder, and depression. Machine learning techniques have significantly enhanced EEG-based diagnostics by automating classification tasks and improving diagnostic accuracy. Prior research has demonstrated the effectiveness of various models, including artificial neural networks (ANN), long short-term memory (LSTM), and convolutional neural networks (CNN-LSTM), in distinguishing psychiatric disorders from healthy controls [3,4]. Furthermore, EEG-based biomarkers, such as power spectral density (PSD) and functional connectivity (FC), have been identified as key indicators of psychiatric conditions, enabling machine learning models to detect subtle neural variations [5]. Despite these advancements, challenges such as low spatial resolution, high inter-subject variability, and EEG susceptibility to artifacts like muscle movements and eye blinks remain significant limitations in clinical applications [4,6].

Feature engineering plays a critical role in optimizing classification performance, as effective feature selection enhances model interpretability and diagnostic precision. Previous studies have explored various spectral, temporal, and connectivity-based attributes to refine psychiatric disorder classification [5]. However, the lack of standardized EEG recording protocols has been identified as a key limitation, as variations in methodology across studies may lead to inconsistencies in model performance [4]. Additionally, while deep learning models such as CNN-LSTM have demonstrated accuracy rates exceeding 96% in some cases, the interpretability of these models remains a challenge, limiting their adoption in real-world clinical settings [3,6]. Despite these concerns, EEG-based psychiatric disorder classification holds promise for automating diagnoses, reducing subjectivity in clinical evaluations, and advancing computational psychiatry.

Building upon these findings, our study aims to develop a machine learning pipeline for multi-class classification of psychiatric disorders using EEG data. We will employ deep learning models, including CNN, LSTM, and hybrid CNN-LSTM architectures, to extract disorder-specific EEG biomarkers and improve predictive accuracy [3,5]. Additionally, we will implement feature engineering techniques to optimize spectral and functional connectivity features, ensuring the selection of the most informative attributes for classification [4,6]. To address generalization concerns, model validation will be a key focus, as we aim to assess performance across different EEG datasets and mitigate inter-subject variability challenges [5]. By integrating insights from prior research, our study seeks to develop robust, interpretable AI-driven diagnostic tools that can enhance clinical decision-making and advance the field of computational psychiatry.

Recent studies emphasize the importance of integrating hybrid ML-DL models and explainable AI techniques to improve the clinical applicability of EEG-based psychiatric disorder classification. While deep learning models, including CNNs and LSTMs, have shown high accuracy, their black-box nature limits clinical trust and interpretability [p8, p11]. Research has also highlighted the need for adaptive preprocessing methods that dynamically adjust to subject-specific EEG variations, reducing dependency on fixed feature extraction techniques [p12]. Additionally, ensemble learning approaches combining multiple classifiers have demonstrated potential for improving robustness across datasets [p9]. However, most studies lack cross-dataset validation, which is essential for assessing model generalization [p8]. Furthermore, the computational efficiency of deep learning models remains a challenge, as high-dimensional EEG data requires extensive processing power, making real-time applications difficult [p11]. Future advancements should also focus on transfer learning techniques, leveraging pre-trained models to improve classification performance on new EEG datasets [p12]. Our study will incorporate insights from these works by exploring ensemble models, explainable AI frameworks, and cross-validation strategies to enhance model reliability and practical usability in psychiatric diagnostics.

IV. Project Objectives and Roadmap

Our project aims to develop a robust machine learning pipeline for the classification of psychiatric disorders using EEG data. The initial phase will focus on comprehensive data preprocessing, which includes artifact removal, signal enhancement, and transformation of EEG signals into meaningful features. We will employ preprocessing techniques such as Independent Component Analysis (ICA) and wavelet transforms to filter noise from muscle movements and eye blinks while normalizing the signals to a uniform scale. Feature extraction will play a crucial role in this stage, where we will analyze power spectral density and functional connectivity to identify relevant patterns associated with psychiatric disorders. This step will ensure that the input data is optimized for effective learning by machine learning models.

Once the data is pre-processed, we will conduct an in-depth exploratory data analysis (EDA) to visualize EEG signal trends, detect outliers, and understand class distributions. Statistical and graphical techniques such as histograms, correlation matrices, and t-SNE plots will be utilized to interpret the dataset structure and identify potential challenges. Through EDA, we will also explore the relationship between EEG biomarkers and different psychiatric conditions, ensuring that our feature engineering strategy aligns with domain knowledge. Additionally, we will generate heatmaps and spectral representations of EEG data to observe variations in frequency bands that may be indicative of specific disorders.

Following EDA, we will move to the model-building phase, where we will train and compare various machine learning and deep learning models for psychiatric disorder classification. Traditional classifiers such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbours (k-NN) will be tested for baseline performance, while advanced deep learning architectures—including CNN, LSTM, and CNN-LSTM hybrids—will be explored for capturing complex spatiotemporal patterns in EEG signals. Model evaluation will be conducted using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC) to ensure robustness. Additionally, hyperparameter tuning and cross-validation will be implemented to optimize performance and prevent overfitting.

To enhance the practical application of our research, we will develop an interactive dashboard that provides a user-friendly interface for visualizing EEG data, classification results, and model insights. The dashboard will display EEG waveforms, highlight key biomarkers, and allow users to interact with predictive outputs. This component will be valuable for clinicians, researchers, and stakeholders in computational psychiatry. The final phase of the project will focus on result analysis, identifying critical EEG biomarkers, and refining our models for improved clinical relevance. By integrating insights from previous studies and employing state-of-the-art techniques, our work aims to contribute to the advancement of EEG-based psychiatric disorder diagnostics, making them more reliable, interpretable, and applicable in real-world scenarios.

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