Enhancing Mental Health Disorder Detection: A Hybrid Classifier System Using Soft Voting and Ensemble Methods

Bhavvya Jain[1], Harsh Chitaliya[2], Miral Gopani[3], Nikki Mehta[4], Arya Gawde[5], Sudhir Dhekane[6]

[1,2,3,4,5]Student, Department. of Artificial Intelligence and Data Science Dwarkadas J. Sanghvi College of Engineering, Mumbai, India
[6]Assistant Professor, Department. of Artificial Intelligence and Data Science Dwarkadas J. Sanghvi College of Engineering, Mumbai, India

Abstract
Early detection and diagnosis of mental health disorders based on patient-reported symptoms is vital in mental health care. This research proposes an ensemble learning pipeline for predicting mental health disorders using symptoms and demographic data. The pipeline incorporates preprocessing techniques such as standardization, one-hot encoding, and Term Frequency - Inverse Document Frequency transformation, and addresses class imbalance with the Synthetic Minority Over-sampling Technique to enhance predictions of rare disorders. Multiple classifiers, including Random Forest, Gradient Boosting, XGBoost, CatBoost, and LightGBM, are combined in a voting classifier, with each model optimized using Grid Search. The pipeline's performance is evaluated on its ability to predict mental health disorders, showing potential for supporting clinical diagnosis. CatBoost proves effective in certain models, while LightGBM delivers strong performance across most. The models achieve around 95% accuracy, demonstrating strong discrimination between disorders and other conditions.

Keywords: Mental Health Disorder Prediction, Voting Classifier, SMOTE, Random Forest, Gradient Boosting, XGBoost, CatBoost, LightGBM, TF-IDF, Ensemble Learning.

1. Introduction

Mental health disorders constitute a huge global health challenge, impacting people of all walks of life and very significantly influencing daily living, interpersonal relations, and quality of life in general. According to the World Health Organization [1], one in four people will experience a mental health disorder at some point, with depression affecting over 264 million people alone. In fact, many individuals never get to be diagnosed or receive proper treatment due to barriers such as stigma, cultural beliefs, and limited access to mental health services.

This burden is especially severe in low- and middle-income countries, where treatment resources are meager. Mental health disorders often have complex etiologies that include genetic and neurodevelopmental factors, making conventional diagnosis less effective. Much of the symptoms are subjective, which makes diagnosis even more challenging, calling for innovative solutions.

Artificial Intelligence (AI) and Machine Learning (ML) provide new opportunities to address the problems, as machine learning models can perform massive data processing to reveal patterns that human clinicians cannot perceive. Ensemble classifiers can reduce the variance and biases found in single-model approaches by finding subtle correlations, thereby providing more accurate prediction.
This study aims to build accessible diagnosis tools focused on the need for early identification, to reduce the growing mental health burden. The ensemble models will be applied in predicting mental health disorders by employing class imbalance correction techniques like Synthetic Minority Over-sampling Technique (SMOTE) and Term Frequency- Inverse Document Frequency (TF-IDF) vectorization to transform the symptom descriptions into usable data.
Beyond diagnosis, ML contributes to treatment planning and personalization, improving the accuracy of treatment outcome predictions and aligning with precision medicine. However, ethical concerns such as patient privacy, informed consent, and bias must be carefully addressed. Ensuring that AI in Mental Healthcare is implemented equitably and responsibly is critical for developing fair, unbiased diagnostic tools. AI has the potential to make mental healthcare more efficient and accessible across diverse populations and settings.

2. Literature Review

The diagnosis of disorders from symptoms has become a significant focus in healthcare analytics, particularly with the advent of advanced machine learning techniques. Early diagnosis and appropriate treatment can significantly improve patient outcomes and optimize healthcare resource utilization. This review examines various methodologies for predicting disorders from symptoms, highlighting current state-of-the-art techniques, their accuracy, and potential avenues for future research.
Multiple studies have explored the application of machine learning algorithms in mental health prediction, with varying degrees of success. Gradient Boosting has emerged as a particularly effective method, as demonstrated by Chung and Teo (2020), who reported an accuracy of 88.80%, closely followed by Neural Networks at 88.00% [2]. Chekroud et al. (2016) further showcased the potential of Gradient Boosting in personalized treatment planning, predicting successful remission in patients treated with citalopram with 64.6% accuracy [3].
Other algorithms have also shown promise; Tate et al. (2020) utilized Random Forest and Support Vector Machines on twin data, achieving AUC values of 0.739 and 0.735, respectively [4]. Similarly, Sumathi et al. (2018) discusses five basic mental health disorders occurring among children described using kappa statistics, accuracy, and AUC-ROC values [5]. S. Mohamed et al. (2019) implemented Support Vector Machines, Multilayer Perceptron, and Random Forest, while Sahlan et al. (2021) reached 64% accuracy using Decision Trees in predicting mental health for university students [6, 7].
The source and nature of data used in these studies vary widely. Le Glaz A et al. (2021) also highlighted similar trends, emphasizing the integration of machine learning and natural language processing techniques in this domain [8]. Marquez et al. (2020), Bibo Hao et al. (2021), and M. Joshi et al. (2022) all discussed the impact of social media data, while latter ones focused on Machine Learning and Deep Learning achieving accuracy rates [9, 10, 11]. Deepali et al. (2019) and Wang et al. (2020) explored unsupervised and ensemble learning techniques respectively on social media data [12, 13].
However, challenges remain. Chancellor and De Choudhury (2020) highlighted the lack of standardized guidelines for validating mental health assessments on social media, leading to issues with reproducibility and real-world generalization [14]. Many researchers, including Sahlan et al. (2021) and

Q. Feng et al. (2022), emphasized the need for larger datasets, advanced preprocessing techniques, and the integration of genetic information and multimodal data to improve predictive accuracy [7, 15].

Some studies focused on specific demographics or time frames. Su et al. (2017) and Rothenberg et al. (2019) applied machine learning to early childhood data to predict adolescent mental health outcomes, emphasizing the importance of early intervention [16, 17]. Jeyabose et al. (2020) reviewed various mental health disorders among adolescents [18]. Madububambachu et al. (2021), Abdullah et al. (2022), and others have called for multi-dimensional studies and standardized evaluation procedures to enhance the robustness and generalizability of predictive models [19, 20].

As the field progresses, researchers like Jain et al. (2022) suggest that while machine learning techniques show great potential in improving current predictive models, more comprehensive studies are needed [21].

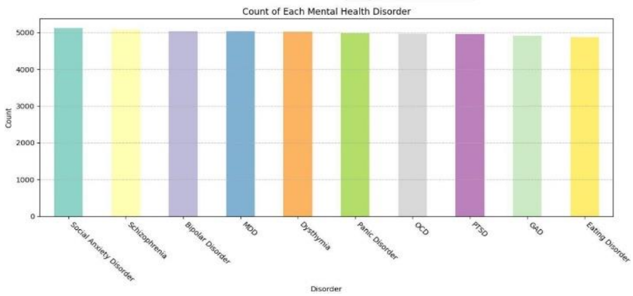
3. Dataset Description

The dataset provides detailed information about mental health disorders, their symptoms, and associated treatments. Below is an explanation of the disorders, their symptoms, and common treatments:

1. **Major Depressive Disorder (MDD):** It is diagnosed when an individual has a low or depressed mood, anhedonia or decreased interest in pleasurable activities, feelings of guilt or worthlessness, lack of energy, poor concentration, appetite changes etc. Treatments typically involve Cognitive Behavioral Therapy (CBT) and medications like Selective Serotonin Reuptake Inhibitors (SSRIs), Serotonin Norepinephrine Reuptake Inhibitors (SNRIs) [22].
2. **Persistent Depressive Disorder (PDD):** persistent depressive disorder is characterized by a depressed mood that occurs for most of the day, for more days than not, for at least 2 years, or at least 1 year for children and adolescents [23]. Treatments often combine long-term talk therapy, psychotherapy specifically CBT, with antidepressants.
3. **Post-Traumatic Stress Disorder (PTSD):** Post-Traumatic Stress Disorder (PTSD) develops after trauma, causing flashbacks, nightmares, and severe anxiety. Key symptoms include persistent intrusive recollections, avoidance of stimuli related to the trauma, negative alterations in cognitions and mood, and hyperarousal [24]. Treatment options include Trauma focused exposure therapy, CBT and Eye Movement Desensitisation and Reprocessing (EMDR) therapy to be effective [25].
4. **Eating Disorders:** This category includes disorders like Anorexia Nervosa and Bulimia Nervosa, characterized by disturbances in eating behaviors. Symptoms range from extreme food restrictions to binge eating with compensatory behaviors [26]. Treatment involves psychotherapy, particularly CBT, and nutritional counseling to promote healthy eating patterns.
5. **Social Anxiety Disorder (SAD):** SAD is characterized by intense fear in social situations, leading to avoidance and impairment in daily life. Symptoms include fear or anxiety in social situations in which the individual is exposed to possible scrutiny by others and a fear of acting in a way that will be negatively evaluated by others (either resulting from the individual’s own behavior or from showing anxiety symptoms such as blushing, trembling or sweating) [27]. Treatment typically includes CBT and medications like SSRIs.
6. **Obsessive-Compulsive Disorder (OCD):** OCD is characterized by persistent disturbing thoughts, images, or impulses (obsessions), or repetitive, ritualized behaviors that the person feels driven to perform (compulsions), or both. Effective treatments include Exposure and Response Prevention (ERP) therapy and SSRIs [28].

7. **Bipolar Disorder:** This disorder is characterized by extreme mood swings, including manic or hypomanic episodes and depressive episodes. Manic phases involve increased energy, while depressive phases resemble symptoms of MDD. Treatment typically includes mood stabilizers such as lithium or other antidepressants, along with psychotherapy like CBT [29].
8. **Schizophrenia:** Schizophrenia is a severe mental illness marked by distorted thinking and perception, with key symptoms being hallucinations and delusions. Treatment includes antipsychotic medications combined with supportive therapy [30].
9. **Generalized Anxiety Disorder (GAD):** Generalized anxiety disorder (GAD) is characterized by extreme and uncontrollable worries and is associated with other anxiety disorders, depression, and a range of physical health disorders. Treatments include Mindfulness-based Cognitive Therapy [31].
10. **Panic Disorder:** Panic attacks are sudden, sometimes unexpected paroxysmal bursts of severe anxiety, accompanied by several physical symptoms (eg, cardiorespiratory, otoneurological, gastrointestinal, or autonomic). Treatment often involves CBT, SSRIs and EMDR [32] .

Figure 1. Count of Each Mental Health Disorder in Dataset



The above Figure 1. depicts the distribution of the count of each mental health disorder in the dataset. The dataset records symptoms associated with each disorder, helping understand the symptomatic presentation and overlap among different mental health conditions. This comprehensive dataset aids in analyzing the prevalence, distribution, and symptomatology of mental health disorders across various demographic groups, providing valuable insights for mental health diagnosis and research.

4. METHODOLOGY

4.1. Preprocessing Data

Extracting an important feature by preprocessing the dataset, catering to missing values and data standardization in "Age", transformations applied here are differentiated with a consideration for the numeric requirement of the model in ML. Here, the strategy used is a median approach where missing values are replaced by the median value of that column without disturbing the distribution as no problem arises due to the presence of outliers. Standard Scaler-features standardized by removing the mean and scaling into unit variance; it puts these values onto the comparable scale with other features. In that way, performance will not be affected in the models sensitive towards scales of the features.

The column "Sex" needs another set of transformations among the categorical features. These are changes which involve replacing the missing values in the "Sex" column based on the strategy of using the most frequent value, known otherwise as the mode in statistics. In this case, this most frequent category fills in the missing value in that column such that no disruption is caused to the distribution for those categorical variables. The categorical data obtained is then one-hot encoded into binary variables, one for each category, so that the transformed data could now be used as the input to the ML models that require numerical input. Since the textual data in the column "Symptoms" needs to be converted into numerical format vectors, so the ML models may be trained over it

Figure 2. Mental Health Dashboard

This is made possible through the use of the Term Frequency-Inverse Document Frequency Vectorizer, commonly referred to as the TF-IDF Vectorizer. This technique in NLP preprocessing involves transforming text data into numerical features by looking at the relevance of a word in a document to a corpus that is a collection of documents. At its most simply, TF-IDF vectorization involves two parts: Term Frequency, which gives a measure of how commonly a term occurs in a given document, and Inverse Document Frequency, which gives a measure of how important a term is based on the count of the term in related documents or corpus of documents.

These preprocessing steps are to be placed inside a Column Transformer, which is a good way to efficiently and flexibly apply the proper transformations for the different kinds of features of a dataset. Column Transformer ensures all these preprocessing measures are consistently and systematically applied so that the data becomes ready for subsequent machine learning tasks.

4.2 Machine Learning Models

The authors use a combination of machine learning models and ensemble techniques in the prediction of mental health disorders. A Voting Classifier includes these optimized models by doing hyperparameter tuning and utilizing the strengths of each model.

1. Random Forest Classifier:

An ensemble has been added along with a classifier such as Random Forest. It is a model that produces a lot of decision trees and aggregates the prediction of each. The number of estimators in the trees was tuned with GridSearchCV, along with the values at 200. A fixed random state is ensured in order to get reproducibility.

2. Gradient Boosting Classifier:

Gradient Boosting is another model in the ensemble. It builds models sequentially, correcting errors from previous models. The number of estimators is tuned through GridSearchCV with options of 200.

That helps determine the right number of boosting stages for best performance.

3. XGBoost Classifier:

The ensemble consists of XGBoost, known for its speed and performance. Estimators are tuned by using GridSearchCV with estimators of 200. XGBoost is apt for handling large datasets due to its efficiency.

4. CatBoost Classifier:

CatBoost, which is especially good with categorical data, is also in the ensemble. GridSearchCV optimizes the number of iterations instead of the number of estimators by testing 200 iterations. This helps balance between speed and performance for CatBoost.

5. LightGBM Classifier:

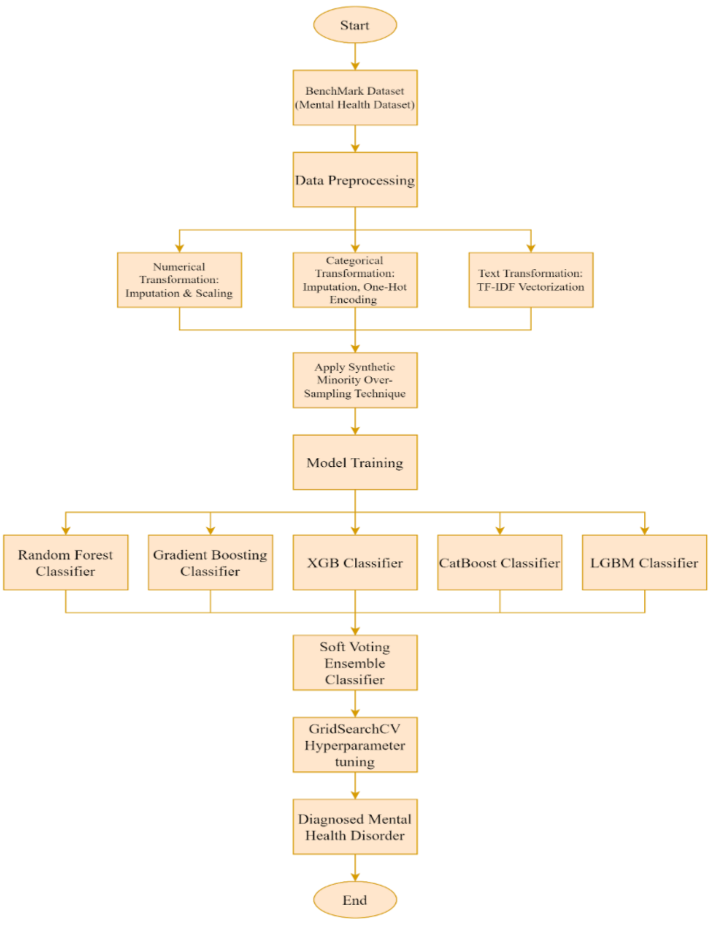
Quick training on large datasets using the LightGBM model is added to the ensemble. Again, like all the other models, the number of estimators in this model is tuned using GridSearchCV by testing 200 estimators.

All of the above models are then put together in a Voting Classifier that uses soft voting, which aggregates each classifier's predicted probabilities and makes the final prediction based on that. In other words, it enables the model to leverage the power of each individual algorithm.

The ensemble is optimized along hyperparameters, and the code uses GridSearchCV with 3-fold cross-validation focusing on the F1-score to evaluate performance. The model is trained on resampled data with SMOTE since it corrects for class imbalances that tend to be better predictors for rare disorders.

5. ARCHITECTURE

Figure 3. Architecture for Mental Health Disorder Detection



The architecture proposed includes lots of preprocessing and transformation techniques of the data combined with several ensemble learning models to attain the greatest achievable performance while diagnosing ten different unique mental health disorders according to the symptoms they display.
To prepare the dataset for the analysis, textual data is converted via TF-IDF vectorization that translates textual information into numerical features which quantifies word importance and overall context with the dataset and helps the model understand symptoms.
In order to balance the classes in the dataset, SMOTE is applied. SMOTE creates synthetic samples of the minority classes to ensure equal representation while training the model. This is an important step for better performance when the models have to predict disorders that are not so frequent.
After preprocessing, there are several ensemble models in use: Random Forest Classifier, XGBoost Classifier, Gradient Boosting Classifier, CatBoost Classifier, and LightGBM Classifier. The soft voting ensemble method is used for training each model uniquely and, in turn, the predictions obtained from them. Here, probabilities predicted by each model are averaged-that adds to the accuracy and strength of final predictions. It makes use of the strength of every model by reducing its own weaker feature.
The output obtained upon classifying mental disorders is then used to perform hyperparameter tuning and optimize the parameters of the ensemble model to have an ideal output. GridSearchCV checks all the possible combinations of the hyperparameters that are mentioned. Doing this ensures that the ensemble model it fits is highly configured for the best performance.
The final output of this structured approach provides insight into the diagnosed mental health condition based on the input features. Therefore, efficiently combining the preprocessing steps with ensemble learning and hyperparameter tuning, the pipeline gives its performance while handling complex data regarding mental health.
Algorithm- Symptom based Disorder Detection
Input: CSV file containing mental health data
Output: Trained models, performance metrics, and confusion matrices for each disorder
procedure Main
data ← LoadData()
X, y ← PreprocessData(data)
param_grids ← DefineParameterGrids() disorders ← DefineDisordersList()
for each disorder in disorders do
TrainAndEvaluateForDisorder(X, y, disorder, param_grids)
end for end procedure
function LoadData()
data ← ReadCSVFile() return data
end function
function PreprocessData(data)
numeric_features, categorical_features, text_features ←
DefineFeatureTypes()
preprocessor ← CreatePreprocessorPipeline()
X ← ApplyPreprocessor(preprocessor, data) y ← ExtractLabels(data)

return X, y
end function
function TrainAndEvaluateForDisorder(X, y, disorder, param_grids) X_train, X_test, y_train, y_test ← SplitData(X, y)
X_train_resampled, y_train_resampled ← ApplySMOTE(X_train, y_train) classifiers ← InitializeEnsembleClassifiers()
for each classifier in classifiers do
grid_search ← PerformGridSearchCV(classifier, param_grids) best_model ← FitModel(grid_search, X_train_resampled,
y_train_resampled)
predictions ← MakePredictions(best_model, X_test)
metrics ← CalculatePerformanceMetrics(y_test, predictions) PrintResults(metrics)
cm ← CalculateConfusionMatrix(y_test, predictions)
end for end function

The algorithm first initializes models and sets probability thresholds for a given diagnosis. The symptoms given by the user are preprocessed into a vector of numbers, then input into the models. The ensemble model provides the probability that it assigns to each disorder using the symptoms. If the predicted probability exceeds a threshold, a disorder is likely; otherwise, no disorder can be concluded with confidence because none of the probabilities surpass the threshold.
Thus, from time to time, updating and training with fresh data are important in keeping the system sound in terms of diagnostic accuracy and precision regarding positive cases, and thereby making the system sound in diagnosing mental disorders from their symptoms. The subsequent parts of the research paper will explain the experimentation process and the results obtained by applying these methods.

6. EXPERIMENTATION AND RESULTS

6.1. Stratification-Based Splitting Strategy

The dataset is split based on the stratification principle in such a way that keeps the representation about mental health disorders fair, that includes a number of classes the same for every class. This will ensure proportionate representation of each of the classes in both training and test datasets. Percentages will be 80% in relation to training and 20% in relation to testing.

6.2. Training and Tuning the Model

Class imbalance is addressed by using SMOTE on the train set in order to balance for each class. Machine learning models and ensemble methods are used in diagnosing mental health issues based on symptoms. Among the classifiers used are Random Forest, Gradient Boosting, XGBoost, CatBoost, and LightGBM. These are done within a Voting Classifier ensemble, where soft voting was used wherein average predicted probabilities given by each model will generate a final diagnosis.
We apply GridSearchCV to perform hyperparameter optimization. In the case of models, hyperparameters will be the number of estimators and iterations. With increased weights towards minority class examples, each model is trained a few times. At each iteration, models are scored by the number of how well they can classify it on a validation split. The best-performing balanced accuracy with minimal false positives selects the hyperparameters for the final model.

6.3. Performance Evaluation

The ensemble model is assessed based on accuracy, balanced accuracy, and classification report. However, predictions are done on the probability of the occurrence of a particular mental health disorder by a subject. Through inputting the symptoms of its sufferers, the model calculates the chances of disorder in people through machine learning to provide insights leading toward mental health diagnosis. The techniques used here offer a complete disorder analysis pertaining to early diagnosis with robust model selection and evaluation.

6.4. Results

Very encouraging results are shown by the produced research with accuracies over 94% for all disorders. The performance was significantly enhanced with a soft voting classifier on LightGBM, and in two cases, CatBoost showed better performance. Especially in the evaluation for Panic Disorder, the accuracy and outcomes from all models, including the ensemble, pointed out the efficiency of the approach implemented.

Table 1. Panic Disorder Accuracy Distribution

Sr. No.	Panic Disorder Accuracy Distribution	
	Classifier Name	**Accuracy**
1.	Random Forest	88.99%
2.	Gradient Boosting	92.47%
3.	XGBoost	93.80%
4.	CatBoost	94.89%
5.	LightGBM	96.03%
6.	Ensemble Results	94.56%

Figure 4. Confusion Matrix for Panic Disorder

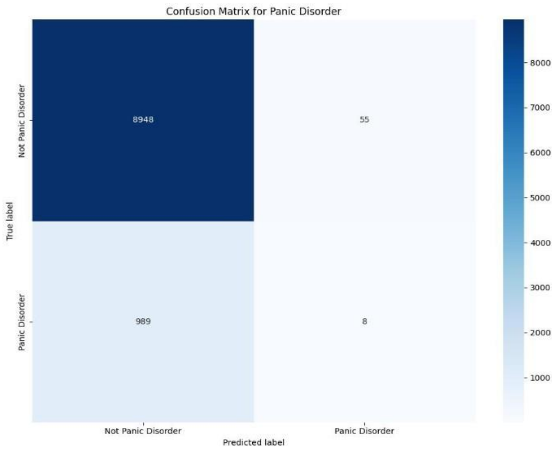
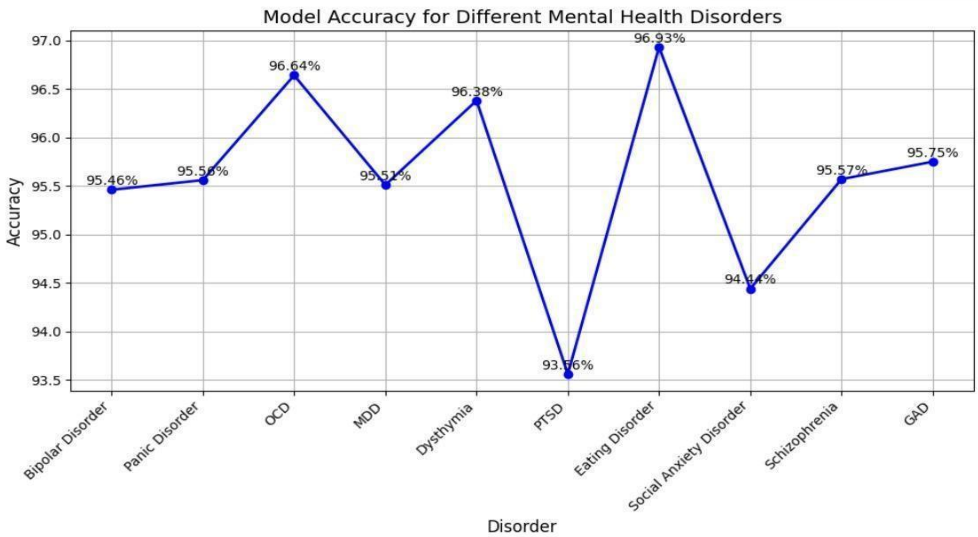


Table 2. Overall Results

Sr. No.	Overall Results		
	Disorder Name	**Classifier Selected**	**Accuracy**
1.	Bipolar Disorder	LGBM	95.46%

2.	Panic Disorder	LGBM	96.03%
3.	OCD	LGBM	96.64%
4.	MDD	LGBM	95.51%
5.	Dysthymia	LGBM	96.38%
6.	PTSD	CatBoost	93.56%
7.	Eating Disorder	LGBM	96.93%
8.	Social Anxiety Disorder	CatBoost	94.44%
9.	Schizophrenia	LGBM	95.57%
10.	GAD	LGBM	95.75%

Figure 5. Model Accuracy for different Mental Health Disorders



7. Future Scope

The data sources should be diversified, clinical data integrated, and more innovative machine learning techniques developed to make the prediction models of mental health more accurate and clinically applicable. Further, incorporating channel selection and detection using brain imaging techniques like EEG and fMRI can dramatically improve the precision and reliability of early diagnosis because it provides instantaneous knowledge about what's occurring in the neural activity and brain architecture. These techniques may be helpful in determining the neural correlates of mental health disorders hence paving a way for possible development of biomarkers which may help in early diagnosis and interventions.

8. Conclusion

The research proposed a machine learning-based pipeline for the identification of mental health disorders, treating complex data efficiently, such as preprocessing imputation, scaling, and TF-IDF vectorization. The integrated classifiers are built with Random Forest, Gradient Boosting, XGBoost, CatBoost, and LightGBM using SMOTE in handling class imbalance to have achieved accuracy between 93.56% and 96.93%. They gained their best performance in the model for the Eating Disorder at an accuracy of 96.93%. These results confirm the robustness of models under a variety of conditions, including Bipolar Disorder and GAD. Where one can see areas for improvement, this method provides valuable insights for early detection and personalized treatment of mental health disorders, facilitating timely diagnosis and intervention.

9. Author Contribution

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by all authors. The manuscript was written and revised by all authors on previous versions of the manuscript. All authors have read and approved the final manuscript.

References

1. World Health Organization, "Depression and Other Common Mental Disorders: Global Health Estimates", World Health Organization, 2017. https://iris.who.int/handle/10665/254610
2. Jetli C., Jason T., "Single classifier vs. ensemble machine learning approaches for mental health prediction", Brain informatics, 2023, 10 (1), 1. https://doi.org/10.1186/s40708-022-00180-6
3. A.M. Chekroud, et al., "Cross-trial prediction of treatment outcome in depression: a machine learning approach", The Lancet Psychiatry, 2016, 3 (3), 243-250. https://doi.org/10.1016/s2215-0366(15)00471-x
4. Ashley E.T., Ryan C.M., Henrik L., Sebastian L., Paul L., Ralf K.-H., "Predicting mental health problems in adolescence using machine learning techniques", PloS one, 2020, 15 (4), e0230389. https://doi.org/10.1371/journal.pone.0230389
5. M.R. Sumathi, B. Poorna, "Prediction of mental health problems among children using machine learning techniques", International Journal of Advanced Computer Science and Applications, 2016, 7 (1). http://dx.doi.org/10.14569/IJACSA.2016.070176
6. S. Mohamed, T. Naqishbandi, I. Bukhari, R. Rauf, V. Sawrikar, A. Hussain, "A hybrid mental health prediction model using Support Vector Machine, Multilayer Perceptron, and Random Forest algorithms", Healthcare Analytics, 2023, 3, 100185. https://doi.org/10.1016/j.health.2023.100185
7. Fadhluddin S., Faris H., Muhammad Z.M., Muhammad H.A., Sharyar W., Yonis G., "Prediction of mental health among university students", International Journal on Perceptive and Cognitive Computing, 2021, 7 (1), 85-91. https://journals.iium.edu.my/kict/index.php/IJPCC/article/view/225
8. A. Le Glaz, Y. Haralambous, D.-H. Kim-Dufor, P. Lenca, R. Billot, T.C. Ryan, J. Marsh, J. DeVylder, M. Walter, S. Berrouiguet, C. Lemey, "Machine Learning and Natural Language Processing in Mental Health: Systematic Review", J Med Internet Res, 2021, 23 (5), e15708. https://doi.org/10.2196/15708
9. M. Marquez, N. Karlin, "Impact of social media on mental health: A look at cohort differences", (Undergraduate honors thesis), University of Northern Colorado, 2022. https://digscholarship.unco.edu/honors/70/
10. Bibo H., Lin L., Ang L., Tingshao Z., "Predicting Mental Health Status on Social Media", 5th International Conference, CCD 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013, Proceedings, Part II. https://doi.org/10.1007/978-3-642-39137-8_12
11. M. Joshi, C. Mahajan, T. Korgaonkar, N. Raul, M. Naik, "Mental Health Analysis using Deep Learning of Social Media Data gathered using Chrome Extension", 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 2023, 1-8. https://ieeexplore.ieee.org/document/10170255
12. Deepali J., Manasi P., "An analysis of mental health of social media users using unsupervised approach", Computers in Human Behavior Reports, 2020, 2, 100036.

https://doi.org/10.1016/j.chbr.2020.100036
13. Xiaojun W., Yongsheng Z., "Ensemble Learning for Mental Health Prediction: A Case Study", Journal of Medical Systems, 2019, 43 (1), 1-9. https://doi.org/10.1007/s11517-019-01978-z
14. Stevie C., Munmun D.C., "Methods in predictive techniques for mental health status on social media: a critical review", NPJ Digital Medicine, 2018, 1 (1), 1-10. https://doi.org/10.1038/s41746-020-0233-7
15. Q. Feng, M. Du, N. Zou, X. Hu, "Fair Machine Learning in Healthcare: A Survey", IEEE Transactions on Artificial Intelligence, doi: 10.1109/TAI.2024.3361836. https://ieeexplore.ieee.org/document/10700762
16. J. Su, W. Yang, "Artificial intelligence in early childhood education: A scoping review", Computers and Education: Artificial Intelligence, 2022, 3, 100049. https://doi.org/10.1016/j.caeai.2022.100049
17. W.A. Rothenberg, A. Bizzego, G. Esposito, et al., "Predicting Adolescent Mental Health Outcomes Across Cultures: A Machine Learning Approach", J Youth Adolescence, 2023, 52, 1595–1619. https://doi.org/10.1007/s10964-023-01767-w
18. A. Jeyabose, M. Rudra, J. Andrew, R. Belfin, "Artificial intelligence in adolescents' mental health disorder diagnosis, prognosis, and treatment", Frontiers in Public Health, 2023, 11, Article 1110088. https://doi.org/10.3389/fpubh.2023.1110088
19. U. Madububambachu, A. Ukpebor, U. Ihezue, "Machine learning techniques to predict mental health diagnoses: A systematic literature review", Clinical Practice & Epidemiology in Mental Health, 2024, 20, Article 11. https://doi.org/10.2174/0117450179315688240607052117
20. M. Abdullah, N. Negied, "Detection and prediction of future mental disorder from social media data using machine learning, ensemble learning, and large language models", IEEE Access, 2024, 12, 120553–120569. https://doi.org/10.1109/ACCESS.2024.3406469
21. T. Jain, A. Jain, P.S. Hada, H. Kumar, V.K. Verma, A. Patni, "Machine learning techniques for prediction of mental health", 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), 2021, 1606-1613. https://doi.org/10.1109/ICIRCA51532.2021.9545061
22. N. Bains, S. Abdijadid, "Major Depressive Disorder", StatPearls, 2023 Apr 10. https://pubmed.ncbi.nlm.nih.gov/32644504/
23. R.K. Patel, S.P. Aslam, G.M. Rose, "Persistent Depressive Disorder", StatPearls, 2024 Aug 11. https://pubmed.ncbi.nlm.nih.gov/31082096/
24. World Health Organization, "The ICD-10 classification of mental and behavioural disorders: clinical descriptions and diagnostic guidelines", WHO, 1992. https://www.who.int/publications/i/item/9241544228
25. J.I. Bisson, S. Cosgrove, C. Lewis, N.P. Robert, "Post-traumatic stress disorder", BMJ, 2015 Nov 26, 351, h6161. https://doi.org/10.1136/bmj.h6161
26. J. Treasure, T.A. Duarte, U. Schmidt, "Eating disorders", Lancet, 2020 Mar 14, 395 (10227), 899-911. https://doi.org/10.1016/s0140-6736(20)30059-3
27. S.H. Spence, R.M. Rapee, "The etiology of social anxiety disorder: An evidence-based model", Behav Res Ther, 2016 Nov, 86, 50-67. https://doi.org/10.1016/j.brat.2016.06.007
28. W.K. Goodman, D.E. Grice, K.A. Lapidus, B.J. Coffey, "Obsessive-compulsive disorder", Psychiatr Clin North Am, 2014 Sep, 37 (3), 257-67. https://doi.org/10.1016/j.psc.2014.06.004
29. D.J. Smith, E.A. Whitham, S.N. Ghaemi, "Bipolar disorder", Handb Clin Neurol, 2012, 106, 251-63.

https://doi.org/10.1016/b978-0-444-52002-9.00015-2

30. G. Perrotta, "Psychotic spectrum disorders: definitions, classifications, neural correlates and clinical profiles", Annals of Psychiatry and Treatment, 2020, 4 (1), 070-084. https://doi.org/10.17352/APT.000023
31. S. Ghahari, K. Mohammadi-Hasel, S.K. Malakouti, M. Roshanpajouh, "Mindfulness-based Cognitive Therapy for Generalised Anxiety Disorder: a Systematic Review and Meta-analysis", East Asian Arch Psychiatry, 2020 Jun, 30 (2), 52-56. http://dx.doi.org/10.12809/eaap1885
32. P.P. Roy-Byrne, M.G. Craske, M.B. Stein, "Panic disorder", Lancet, 2006 Sep 16, 368 (9540), 1023-32. https://doi.org/10.1016/S0140-6736(06)69418-X