Application of Machine Learning Models for Mental Health Classification - Revised

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***Abstract*— There is immense potential in the ability to apply machine learning (ML) models for the prediction of mental health outcomes. This paper, therefore, aims to develop an ML model that can effectively categorize major mental health conditions from structured data. An extensive review of the literature was conducted for assessing current ML models in classification tasks, focusing on mental health prediction. After this, Decision Tree, XGBoost, SVM, and TabNet classifiers were developed with measures of predictive accuracy. The results indicated that XGBoost and TabNet most accurately classified the data in a variety of training scenarios, demonstrating potential for optimizing predictive performance across many diverse datasets and applications. These two models were then combined to create a model that combined the benefits of an artificial neural network and the power of gradient boosting. These findings would recommend that the field of mental health could adopt ML tools in general, especially an XGBoost and/or TabNet model, to enable individuals to check their mental health status and appropriate intervention. This approach could help reduce the workload on mental health professionals and support people who do not have access to therapeutic services.**

Keywords*— *Mental Health Classification, Machine Learning, Decision Tree, XGBoost, Support Vector Machine (SVM), Support Vector Classification (SVC) TabNet, Supervised Learning, Hyperparameter Tuning, Grid Search, Random Search, Confusion Matrix, Data Privacy, Ethical Implications, Diagnostic Accuracy

I. Introduction

Mental health significantly impacts emotional, psychological, and social well-being, adversely affecting cognitive functions, emotions, and relationships [1]. Timely assessment is crucial for diagnosing and mitigating these conditions, but often individuals cannot get access to a mental health professional or are unable to recognize that what they are experiencing are symptoms of a mental health condition.

Machine learning (ML), a subfield of artificial intelligence (AI), offers innovative solutions for early identification and intervention in mental health by addressing classification, regression, and clustering problems through data-driven algorithms [2]. By focusing on the correlation between specific symptoms and overall mental health diagnoses, this paper aims to contribute to the development of more efficient, accurate, and accessible mental health diagnostic tools, improving patient care and outcomes.

The effectiveness of ML algorithms, specifically Support Vector Machines (SVM), Decision Trees, XGBoost, and TabNet are assessed in classifying mental health conditions from structured symptom data. The dataset includes responses from 120 patients regarding various symptoms used to diagnose mental health conditions, which include Bipolar Type-1 (Mania), Bipolar Type-2 (Depressive), and Major Depressive Disorder, or indicate that the patient does not have a mental health condition (Normal). Subsequent sections include a literature review, data review, model explanations, initial results, model fine-tuning, future applications and development, and ethical implications.

II. Literature Review

A. *Mental Health Overview*

Mental health conditions are a significant global health concern affecting millions of people worldwide. According to the World Health Organization (WHO), about 1 in 4 people will be affected by a mental or neurological condition in their lives, with depression, anxiety, bipolar disorder, and schizophrenia among the most prevalent conditions [3], [4]. The impact of mental health issues extends beyond the individual, affecting families, communities, and even economies through lost productivity and increased healthcare costs [5].

Despite the widespread prevalence of mental health conditions, diagnosing them can be a challenge. Access to mental health services is often limited, especially in rural or underserved areas [6]. Services can be prohibitively expensive and long waitlists delay critical treatment and support. Additionally, the stigma surrounding mental health discourages many from seeking help due to fear of judgment or discrimination [7]. Consequently, there is a growing need for innovative solutions which can enhance early detection, improve diagnostic accuracy, and provide more accessible and cost-effective mental health assessments.

B. Introduction to Machine Learning

ML involves the development of algorithms that can learn from and make predictions based on data. In recent years, ML has shown great promise in various fields, including healthcare [8]. By analyzing large datasets, ML algorithms can identify patterns and make predictions with a level of accuracy that often surpasses traditional methods.

In the context of mental health, ML models can analyze diverse data sources, such as electronic health records (EHRs), genetic information, and even social media activity, to predict the likelihood of mental health issues and suggest appropriate interventions [9]. This approach can enhance diagnostic accuracy and enable early detection and personalized treatment plans [10].

C. Existing Applications of Machine Learning in Mental Health

ML has been increasingly applied to diagnose and predict mental health conditions. For instance, the utilization of EHRs to predict the onset of depression with ML algorithms demonstrated that these models could achieve high accuracy, surpassing traditional diagnostic methods [11].

Another study employed natural language processing (NLP) techniques to analyze unstructured clinical notes and identify patients at risk of suicide. It incorporated demographic data, medical history, and textual data to achieve significant predictive performance [12].

Additionally, the analysis of social media posts to detect signs of depression successfully identified markers of depression in digital activity [13]. These studies collectively illustrate how ML can enhance diagnostic accuracy, enable early intervention, and leverage diverse data sources to improve mental health outcomes.

III. Methodology

A. Mental Health Condition Classification Dataset

The dataset comprises 120 samples, 17 features, and 4 classes. The samples are responses from psychology patients rating their experience with the 17 features, which are symptoms used to diagnose the 4 classes, which are mental health conditions. The symptoms include Sadness, Exhaustion, Euphoria, Sleep disorder, Mood swings, Suicidal thoughts, Anorexia, Anxiety, Try-explaining, Nervous breakdown, Ignore & Move-on, Admitting mistakes, Overthinking, Aggressive response, Optimism, Sexual activity, and Concentration. The mental health conditions are Bipolar Type-1 (Mania), Bipolar Type-2 (Depressive), Major Depressive Disorder, and Normal individuals. The data is almost perfectly evenly split between the 4 classes, with each class comprising ~25% of total instances. The data is presented in a Comma Separated Value (CSV) format. The data was sourced from the public domain and is available on Kaggle [14].

B. Software and Libraries

This paper utilizes Python 3 for all aspects, including data preprocessing, model development, and evaluation. Key libraries include pandas for data manipulation, NumPy for numerical operations, and scikit-learn for model development and evaluation. Specific tools from scikit-learn include train_test_split, LabelEncoder, DecisionTreeClassifier, SVC, XGBoost's XGBClassifier, TabNet, GridSearchCV, RandomizedSearchCV and classification_report. Matplotlib, seaborn, and LaTex are used for data visualization. Jupyter Notebooks are used for the integrated development environment (IDE).

C. Initial Model Selection

SVM, Decision Trees, XGBoost, and TabNet were selected for their proven effectiveness in similar mental health diagnostic studies [2], [15], [16], [17], [18], [19]. SVMs are ideal for binary classification tasks and handle high-dimensional data well, making them suitable for datasets with complex, non-linear relationships. Though the specific classifier used for this study is Support Vector Classification (SVC), a specific implementation of the SVM algorithm designed specifically for classification tasks. Decision Trees are chosen for their interpretability and ability to manage categorical data, providing clear decision rules crucial in clinical settings. XGBoost, known for its high performance and robustness, efficiently handles complex feature interactions and prevents overfitting through advanced regularization techniques. TabNet combines the interpretability and efficiency of decision trees with the flexibility and power of deep learning. It uses attention mechanisms to select which features to reason about at each decision step, making it particularly effective for tabular data.

First, the performance of SVC, Decision Trees, and XGBoost were compared. The training set and test set were fixed as 75:25 respectively. Each model was trained and evaluated on the dataset. Classification reports were generated for all three models to assess their accuracy, precision, recall, and F1 scores, providing a comprehensive evaluation of each model's ability to correctly classify mental health conditions. The Decision Tree and XGBoost model performed equally with a 75:25 data split, so further split ratios were tested. XGBoost consistently performed better across all ratios so was selected for further optimization and deployment.

D. Initial Model Tuning and Deployment

After selection, the XGBoost model underwent hyperparameter tuning to optimize its performance. A grid search with 5-fold cross-validation was performed to evaluate hyperparameters. In this process, the dataset was divided into five parts, the model was trained on four parts and validated on one part. The combination of hyperparameters yielding the highest cross-validation score was selected for the final model. The model was then retrained on the general dataset and deployed to the data. The resulting performance was measured to achieve the aspect of consistency and reliability.

E. TabNet Model Development, Tuning, and Deployment

After optimization, to continue increasing the effectiveness of the XGBoost model it was compared to and combined with a TabNet artificial neural network to create a multimodal learning framework. The TabNet model was developed utilizing the same data and 75:25 split as the XGBoost model, though the data was scaled as it can help the model converge faster and perform better. Scaling is not usually necessary for models like XGBoost because it is a tree-based model, which is not sensitive to the scale of the data, and therefore the difference in data scaling should not affect performance.

TabNet performance was evaluated using both training and validation datasets, with the accuracy metric being used to monitor the model. The training was configured to run for up to 100 epochs, with early stopping if there was no improvement after 10 epochs.

The TabNet model then underwent hyperparameter tuning using a random search with 5-fold cross validation. Both a grid search and random search were conducted, with the random search yielding better performance. While random search only evaluates a random sample of points on the grid whereas grid search searches over the entire grid, a study found that if the near-optimal region of hyperparameters covers at least 5% of the grid surface then conducting 60 random search trials will likely identify that region [20].

F. Ensemble Model Development, Tuning, and Deployment

After tuning, the TabNet model was combined with the optimized XGBoost model using a stacking technique.

A meta-model was then trained to test the performance of the new combined model. The classifiers for the meta-model tested were XGBoost, Logistic Regression, and Gaussian Naive-Bayes. These were selected simply because they all represent a different algorithm, each with unique strengths: XGBoost for its boosting capabilities and complex relationship handling, logistic regression for simplicity and interpretability, and Gaussian Naive-Bayes for its probabilistic approach and efficiency on small datasets. All models performed similarly, but XGBoost was selected as the highest performing meta-model for deployment.

The combined XGBoost and TabNet model was then optimized using a random search. A more rigorous 10-fold cross-validation was utilized to achieve better performance. A parameter grid was defined for the XGBoost meta-model, specifying options for hyperparameters such as the number of estimators, maximum depth, learning rate, subsample ratio, column sample by tree ratio, gamma, and minimum child weight. A random search was initialized to sample 100 different combinations from this grid, optimizing for accuracy. Upon completion, the best hyperparameters were selected for deployment of the ensemble model.

IV. Results

A. Initial Model Comparison

The performance of classifiers measures the decision-making capability of the classifier. The measures used to determine the performance are accuracy, precision, recall, and F1 score.

Accuracy gives an overall effectiveness of a classifier. The accuracy scores obtained for the initial three classifiers (SVC, Decision Tree, and XGBoost) are given in Table 1. Decision Tree and XGBoost performed the highest with a score of 0.73, in that they correctly classified 73% of instances.

	SVC	**Decision Tree**	**XGBoost**
Accuracy	0.67	0.73	0.73

Table 1: Accuracy

Precision is a measure of the class agreement of the data labels with the positive labels given by the classifier. Table 2 shows the values for precision score for each classifier and label. Decision Tree and XGBoost scored highest with a 0.76 macro average for both, indicating that 76% of positive identifications were correct.

	SVC	**Decision Tree**	**XGBoost**
Bipolar Type-1	0.45	0.50	0.50
Bipolar Type-2	0.50	1.00	1.00
Depression	1.00	0.78	0.78
Normal	1.00	0.75	0.75

Table 2: Precision

Recall represents the classifier's effectiveness to identify class labels. The recall scores for 3 class labels and the classifiers are shown in Table 3. Decision Tree and XGBoost again scored highest at 0.75 macro average, indicating that the model correctly identified the instances of the target class 75% of the time.

	SVC	**Decision Tree**	**XGBoost**
Bipolar Type-1	1.00	0.80	0.80
Bipolar Type-2	0.67	0.83	0.83
Depression	0.56	0.78	0.78
Normal	0.60	0.60	0.60

Table 3: Recall

Lastly, F1 Score gives the relationship between positive labels and those given by the classifier. It is computed by taking the harmonic mean of precision and recall for all the 3 labels across all the classifiers. The F1 scores for the class labels are shown in Table 4. Again. the classifiers Decision Tree and XGBoost scored highest at 0.75 macro average

	SVC	**Decision Tree**	**XGBoost**
Bipolar Type-1	0.62	0.62	0.62
Bipolar Type-2	0.57	0.91	0.91
Depression	0.71	0.78	0.78
Normal	0.75	0.67	0.67

Table 4: F1-Score

Since both models performed equally for all metrics, the ratio by which the train and test data was split was modified to assess performance of both models with more and less training and testing data. A split of 80:20 yielded the same results, while splits of 85:15 and 70:30 showed significant differences, with XGBoost outperforming Decision Tree by an average of 0.1 and 0.05 for all metrics, respectively.

	70:30	85:15
Decision Tree	0.79	0.66
XGBoost	0.84	0.75
Difference	0.05	0.10

Table 5: Average of all classification report values

XGBoost was therefore chosen for further tuning and deployment as it performed better on multiple data splits, has generally better performance due to advanced techniques, and is not as prone to overfitting as Decision Tree. This is especially important as the model utilizes medical data and provides a diagnosis, where accuracy and reliability are crucial for patient outcomes.

B. XGBoost Tuning and Deployment

To tune the XGBoost model, a grid search with 5-fold cross-validation was performed to evaluate hyperparameters.
The hyperparameters evaluated were n_estimators, max_depth, learning_rate, subsample, colsample_bytree, gamma, reg_alpha, reg_lambda, booster, tree_method, n_jobs, and random_state. The highest cross-validation score achieved was 0.91, but upon application of the optimized hyperparameters, the model did not improve. There was an attempt to test more hyperparameters but there was not sufficient computing power. Manual adjustment of certain hyperparameters achieved an improved model, indicating that further analysis of hyperparameters may achieve a better performing model.

The normalized confusion matrix in Fig. 1 displays the classification performance of a model across the four classes. The values in the matrix represent the proportion of correct and incorrect predictions normalized by the actual class counts. For Bipolar Type-1, 80% of cases were correctly classified, while 20% were misclassified as Normal. In the case of Bipolar Type-2, 83% were correctly identified, with 17% of cases being classified as Bipolar Type-1. For Depression, 78% of cases were correctly classified, with 11% of cases misclassified as Bipolar Type-1 and another 11% as Normal. As for the Normal category, 60% of cases were correctly classified, with 20% being classified as Bipolar Type-1 and another 20% as Depression. Overall, the model shows reasonable performance in classifying the given categories, though there are some notable misclassifications, particularly between Bipolar Type-2 and Bipolar Type-1, and between Normal and the other conditions.

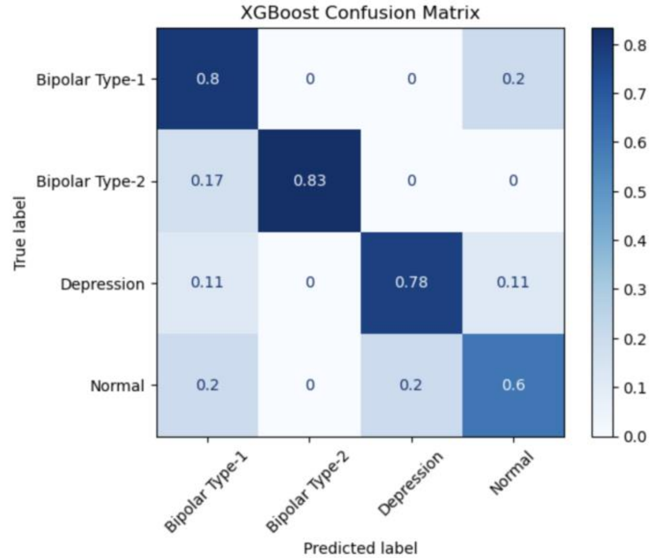

Fig. 1

C. TabNet Development, Tuning, and Deployment

The TabNet model was trained on the data using the same 75/25 split as the initial models. Performance was lower across all macro averages compared to the initial XGBoost model as shown in Table 6. It also showed greater variability between classes as shown in the classification report Table 7.

The model was then tuned using a random search with 5-fold cross-validation, similar to the tuning of the XGBoost model. A grid search and random search were performed but performance was better using the random search, so the resulting hyper-parameters were used in the final model.

The deployment of the tuned model showed a significant increase in performance across all macro averages by about 23% as well as greater congruence among classes. Macro averages for the preliminary and tuned models can be seen in Table 8.

A confusion matrix was generated for this model to assess classification by showing the distribution of predicted vs. actual class labels. As seen in Figure 2, the normalized confusion matrix shows perfect performance for Bipolar Type-1 with a correct classification rate of 100%. The model also exhibits high accuracy for the Normal class, with a correct classification rate of 90%. However, the model struggles with Bipolar Type-2 and Depression, misclassifying them into each other at rates of 33% and 22%, respectively. Additionally, the Depression class has a 22% misclassification rate into Bipolar Type-2 and an 11% misclassification rate into Bipolar Type-1.

	Accuracy	Precision	Recall	F1
XGBoost	0.73	0.75	0.75	0.74
TabNet	0.47	0.70	0.44	0.40

Table 6: Macro average of all classification report values

	Accuracy	Precision	Recall	F1
Bipolar Type-1	0.47	0.40	0.40	0.40
Bipolar Type-2	0.47	1.00	0.29	0.83
Depression	0.47	0.41	1.00	0.58
Normal	0.47	1.00	0.20	0.33

Table 7: Initial TabNet performance

	Accuracy	Precision	Recall	F1
Initial	0.47	0.70	0.44	0.40
Optimized	0.70	0.70	0.81	0.79

Table 8: Macro averages for initial vs optimized TabNet

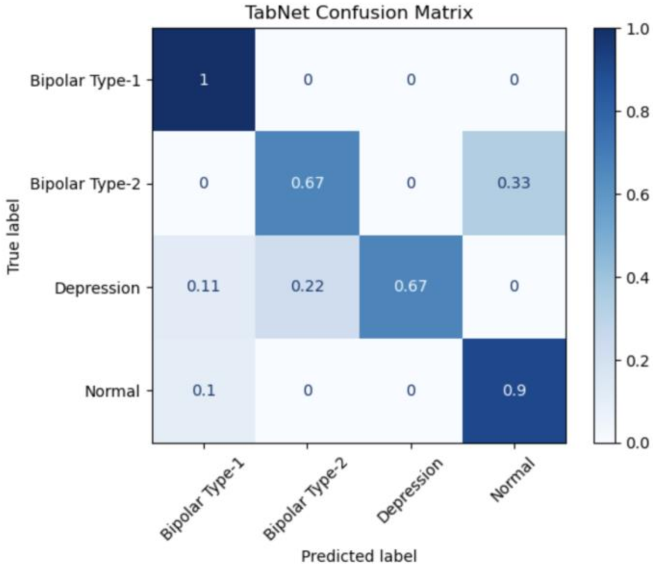

Fig. 2

D. Combined model development, tuning, and deployment

The optimized XGBoost and TabNet models were then combined using a stacking technique, creating a meta-model that leverages their individual predictive capabilities for improved overall performance.

Three meta-models were used to determine how to best combine the predictions of the stacking ensemble to produce optimal results. The three models – Naive Bayes, Logistic Regression, and XGBoost all performed very similarly. Ultimately, XGBoost was chosen for the final model due to its balance of overall performance and class-level precision and recall.

This model was then tuned utilizing a random search with 5-fold cross validation. However, neither resulted in increased performance. The random search was then run again with 10 folds instead of 5. This resulted in a ~2% increase for accuracy and all macro averages as shown in Table 9.

A confusion matrix was then generated for this model to assess classification by showing the distribution of predicted vs. actual class label. As seen in Figure 3, the normalized confusion matrix shows perfect performance for Bipolar Type-1 and high accuracy for the Normal class, with misclassification rates of 0% and 10%, respectively. However, the model struggles with Bipolar Type-2 and Depression, misclassifying them into each other at rates of 33% and 22%, respectively.

	Accuracy	Precision	Recall	F1
Initial	0.80	0.80	0.81	0.79
Optimized	0.83	0.83	0.84	0.82

Table 9: Macro averages for initial vs optimized ensemble model

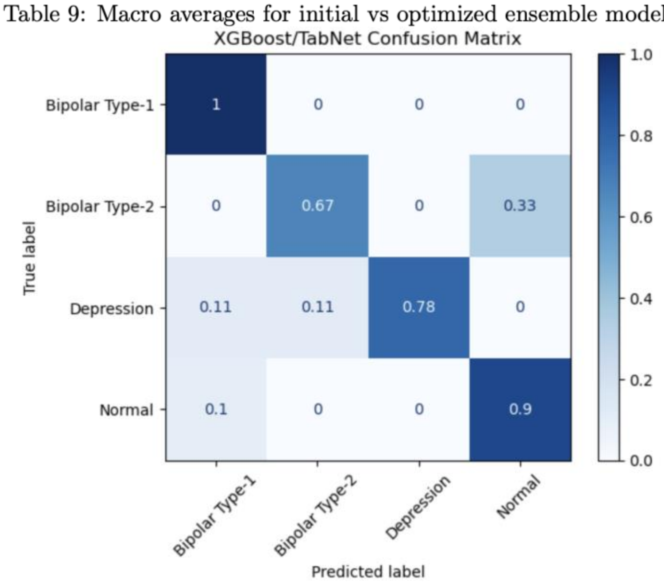

Fig. 3

E. Comparison of all three models

Overall between the XGBoost model, the TabNet model, and the combined XGBoost/TabNet model, the optimized ensemble model showed the highest performance. However, the optimized TabNet model performed exactly the same as the initial ensemble model. This shows that the TabNet model was already highly effective on its own, and further combination with XGBoost did not significantly enhance its performance until hyperparameter tuning was applied.

This highlights the robustness and superior baseline performance of the TabNet architecture, suggesting that its design and features are particularly well-suited to the problem at hand. Future research could focus on further optimizing the TabNet model through more advanced hyperparameter tuning and exploring various regularization techniques. Additionally, identifying and integrating models that better complement TabNet could lead to the development of more powerful ensemble methods, potentially unlocking higher levels of predictive accuracy.

F. Drawbacks and Further Analysis

While this model performs well, significant improvement is needed before considering its use in a clinical setting. Firstly, a much larger dataset is required to give ample training data to the model. Currently there are only 120 samples, which are further split into the training and test sets. It was attempted to split this further to allow for the model to be deployed on 5% of unlabeled data, but this resulted in a significant decrease with model performance and skewed results as it left only 6 samples with which to predict on. This limited sample size restricts the model's ability to accurately predict diagnoses.

During optimization of the initial XGBoost model as well as the first random search for the combined model, the searches did not yield any significant improvement to the model. More hyperparameters were attempted to be tested for XGBoost, but there was not sufficient computing power. Though the ensemble model did increase performance with the increased number of folds. Running the model through a more powerful machine may yield more options.

There were some steps taken to mitigate overfitting such as early stopping, sparse regularization, and cross-validation, but further examination for potential overfitting or underfitting is warranted fully ensure the model's performance and generalization on unseen data. This could be done by through such techniques as comparing training and validation scores and using tools like regularization or model simplification if needed.

With medical diagnosis, models must perform well to not misdiagnose patients, since this could lead to patients not receiving proper treatment or being treated for a condition they don't have. Both a standalone TabNet model and combined XGBoost/TabNet model have been shown to be viable option for this application among models that utilize supervised learning, and with sufficient data, computing power, and further analysis could be an efficient tool for diagnosing mental health conditions. The main drawback in the effectiveness of this model is the lack of data. The fact of the matter is that 120 samples are not nearly enough to generate viable predictions that could significantly affect health and wellbeing. To truly harness the potential of these models, a larger and more diverse dataset is essential to improve their accuracy and reliability.

V. Ethical Considerations

The development of ML algorithms for diagnosing mental health conditions offers significant potential for improving patient care and outcomes. However, ethical considerations must be addressed to ensure responsible use. Data privacy is paramount; although the dataset that was utilized is anonymized, there is no information as to the original anonymization process, which raises concerns about the adequacy and effectiveness of the methods used.

In a healthcare application such as this, mitigating risks like misdiagnosis is essential. One of the most crucial aspects of this is ensuring there is sufficient training data. As mentioned in the previous section, not only is more data required to improve accuracy and reliability, but it is paramount to ensure the ethical deployment of such a model. Having a large and well-rounded dataset is necessary as it ensures that the model can learn from a variety of cases and scenarios. This reduces the likelihood of biased or inaccurate predictions, ensuring fair and equitable treatment for all patient groups.

Continuous validation of algorithm accuracy is necessary in ensuring that these tools supplement professional diagnoses rather than replace them. The impact on stakeholders includes providing patients with easier access to diagnostic services, which may lead to reliance on the tool and avoidance of professional help. For healthcare providers, these tools can enhance diagnostic accuracy but must support, not substitute, professional judgment.

Accessibility is a concern, as this technology requires devices like smartphones or computers to be utilized.

Compliance with regulations such as HIPAA and GDPR is vital. This includes regular audits, data protection impact assessments, and obtaining informed consent where applicable. Ensuring fairness and reducing bias in algorithms is crucial. This also involves conducting regular audits, using diverse training data, and maintaining transparency in development.

Addressing these ethical considerations is critical for the successful integration of ML in mental health diagnostics. This assures that the technology provides an accurate and reliable assessment and upholds principles of fairness, privacy, and transparency that foster trust and acceptance among users and practitioners.

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