Enhancing the Diagnosis of Depression and Anxiety Through Explainable Machine Learning Methods

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***Abstract*—Diagnosing depression and anxiety involves various methods, including referenda-based approaches that may lack accuracy. However, machine learning has emerged as a promising approach to address these limitations and improve diagnostic accuracy. In this scientific paper, we present a study that utilizes a digital dataset to apply machine learning techniques for diagnosing psychological disorders. The study employs numerical, striatum, and mathematical analytic methodologies to extract dataset features. The Recursive Feature Elimination (RFE) algorithm is used for feature selection, and several classification algorithms, including SVM, decision tree, random forest, logistic regression, and XGBoost, are evaluated to identify the most effective technique for the proposed methodology. The dataset consists of 783 samples from patients with depression and anxiety, which are used to test the proposed strategies. The classification results are evaluated using performance metrics such as accuracy (AC), precision (PR), recall (RE), and F1-score (F1). The objective of this study is to identify the best algorithm based on these metrics, aiming to achieve optimal classification of depression and anxiety disorders. The results obtained will be further enhanced by modifying the dataset and exploring additional machine learning algorithms. This research significantly contributes to the field of mental health diagnosis by leveraging machine learning techniques to enhance the accuracy and effectiveness of diagnosing depression and anxiety disorders.**

***Keywords*—Mental health; Recursive Feature Elimination (RFE); machine learning; XGboost**

I. Introduction

Ongoing research, in the field of disorders is focused on creating effective diagnostic approaches using advanced artificial intelligence (AI) methods [1]. The involvement of individuals with health conditions in studies investigating the origins of these disorders is rapidly growing [2], [3]. While mental disorders are rooted in brain abnormalities, psychologists and psychiatrists often make evaluations based on their insights and experiences. This dependence on assessments can lead to diagnoses for many people suffering from depression causing delays, in receiving appropriate care [4], [5]. Hence it is essential to identify trustworthy ways to comprehend and diagnose health issues highlighting the importance of integrating AI technologies into this process [6].

Diagnosing mental illnesses such as depression, anxiety, and suicide attempts can be challenging due to potential overlap and variations in manifestations among patients [7]. This difficulty arises because symptoms sometimes blur and vary amongst those impacted. Acting to address these issues early can significantly shorten the duration of symptoms and lessen their impact. It's crucial to remember that mental health disorders range widely, encompassing conditions like-schizophrenia, bipolar disorder, depression, intellectual disabilities, and Alzheimer's disease [8], [9]. It's also well-documented that problems such as depression and anxiety are closely associated with poorer sleep quality and various sleep issues, which can significantly impact a person's day-to-day functioning [10].

Depression, a serious health condition is acknowledged by the World Health Organization as the fourth leading cause of disability globally [11] [12]. One-fifth of the population grapples with anxiety or depression disorders. The conventional healthcare system faces challenges, in catering to the number of patients leading to access to specialized care and extended waiting periods, for therapy commencement [13] [14]. Anxiety, ranked as the prevalent mental health issue after depression is characterized by physical manifestations of worry and persistent irrational stress that necessitates continuous and affirmative therapeutic interventions [15] [16].

Depressive disorders often show up as long-term conditions linked to feelings of boredom, guilt, and difficulty focusing [16]. The level of symptoms determines how severe the depression is, in individuals. Treating depression directly can be tough causing some patients to turn to methods making diagnosis complicated [16] [17]. Studies have found that the neurons in people with disorders operate differently from those in individuals leading to disrupted neurotransmitter movement and decreased focus [18]. Current approaches to treating disorder (DD) rely on trial and error resulting in challenges and delays in patient recovery. Choosing the antidepressant for optimal clinical response remains a difficult task even though it is the main form of treatment for patients, with depressive disorder [19] [20].

The rise of AI technology has made diagnosing disorders efficient emphasizing the importance of mainstream AI applications being familiar, with how to detect them. Magnetic resonance imaging (MRI) electroencephalography (EEG) and kinesics diagnosis are three methods used in health research [21].

II. Related Work

Despite the variety of integration techniques, the field of psychiatric disorders still encounters numerous obstacles. This challenge is particularly noteworthy, due to the prevalence of health conditions with rates of depression and anxiety reaching 26% and 28% respectively during the 2022 COVID-19 pandemic [22]. Disparities between the demand for and access, to health treatment are stark when compared to physical ailments. Bridging this treatment gap can be achieved through interventions; however, it's crucial to recognize that individuals may respond differently to interventions. While some may benefit positively others may still require forms of care [13].

Several previous studies have employed machine learning techniques to predict diagnoses using digital therapy. Table I presents the findings of these studies indicating results, in treating depression (N = 283) with an improvement of 8.0% (95% CI 0.8–15; total R2 pred = 0.25) reducing disability by 5.0% (95% CI -0.3 to 10; total R2 pred = 0.25) and enhancing well-being by 11.6% (95% CI 4.9–19; total R2 pred = 0.29) [18]. Additionally, machine learning methods have been utilized to predict anxiety with an accuracy rate of ninety-two percent based on a dataset involving just twenty-six individuals [23] and to forecast obsessive-compulsive disorder with an accuracy of eighty-three percent from sixty-one cases [24]. Furthermore, other research has demonstrated accuracy, in diagnosing anxiety and depression through this methodology [13].

Computer-assisted detection (CAD) systems have been used in Electroencephalograph (EEG) studies to diagnose conditions. Examples include the use of the network (ANN) classifiers, for diagnosing depression with a 98.11% accuracy rate [25] Enhanced Probabilistic Neural Network (PNN) classifier with 91.30% accuracy [26] logistic regression classifier achieving 90.05% accuracy [27] Support Vector Machine (SVM) classifier with an accuracy of 98.40% [28] another SVM classifier with an accuracy of 81.23% [29] and Convolutional Neural Network (CNN) classifiers attaining accuracies of 93.54 and 95.96 respectively [30]. Accurate diagnostic processes are crucial for treatment, in the realm of health given the challenges associated with precise psychiatric diagnoses owing to the overlapping symptoms of various mental illnesses making it difficult to differentiate or diagnose them accurately. This is to get the right psychiatric diagnosis before starting any treatment plan [31-49].

Traditional diagnosis for depression and anxiety relies on clinician expertise, which can be subjective and time-consuming. Machine learning (ML) offers an alternative approach, but previous methods often lacked transparency:

Black Box Problem: Traditional ML models are often like black boxes - they produce results but don't explain how they arrived at those conclusions. This makes it difficult for clinicians to trust the recommendations or understand why a patient is flagged for depression or anxiety.

- Limited Data Integration: Prior models might have focused on analyzing a single data source, like surveys. However, mental health is complex and can manifest in various ways.
- The proposed work with "Explainable Machine Learning Methods" suggests it addresses these issues by:
- Making ML interpretable: The approach might involve using specific algorithms or techniques that help explain the model's reasoning behind its diagnosis. This would increase trust and allow clinicians to understand the model's decision-making process.
- Utilizing Multimodal Data: The method might incorporate a wider range of data sources beyond just surveys. This could include speech patterns, facial expressions, or physiological data to create a more comprehensive picture of the patient's condition.

By overcoming limitations in explainability and data integration, this approach has the potential to improve the accuracy and effectiveness of diagnosing depression and anxiety compared to previous methods.

TABLE I. A List of Previously Published work in the Diagnosis of Mental Illnesses

Authors	Year	Factors of Dataset	Techniques	Accuracy
Pearson et al. [18**]**	2019	(N = 283) from across the USA	Random Forest & Elastic net regression	95%
Månsson et al. [23**]**	2015	(N = 26)-Fmri	SVM	91.7%
Lenhard et al. [24**]**	2018	(N = 61)	logistic regression	83%
Jacobson et al. [13**]**	2021	(N=632)	base learner	95%
Subha et al. **[**25**]**	2012	16 females and 14 male-EEG	ANN	98.11%
Ahmadlou et al. [26**]**	2012	12 normal and 12 depressed subjects	Enhanced-PNN	91.30%
Hosseinifard et al. [27**]**	2013	11 male and 11 female depressed subjects	Logistic regression	90.05%
Mumtaz et al. [28**]**	2017	30 normal and 33 depressed subjects	SVM	98.40%
Liao et al. [29**]**	2017	20 normal and 20 depressed subjects	SVM	81.23%
U. Rajendra Acharya.[30**]**	2018	15 normal and 15 depressed subjects	CNN	93.54%, 95.96%
Present work	2023	403 female and 380 male depressed and anxious subjects	SVM, Decision Tree, Logistic Regression, Random Forest and xgboost	91%, 92%, 93%,94%, 95%,96%,98%

III. Materials and Methods

A. Dataset Description

This dataset is based on 19 features and 783 samples of 403 females and 380 males, aged between 18 and 31 years old. This dataset collection was gathered from University of Lahore undergrads and was created using the Depression and Anxiety inventories as a model, as shown in Table II.

TABLE II. This is a Table of Dataset Description

Features Name	Abbreviations	Rang of Features	Description
ID	-	783 Samples	Identify the patients
school_year	-	(1-4)	-
Age	-	(18-31)	Age of patients
Gender	-	(Male-Female)	types of patients
Body mass index	BMI	(0-54)	It is an indicator of the scale of body mass
Patient Health Questionnaire	PHQ_Score	(0-24)	is the depression module
Depression_Severity	-	(Mild-Moderate- None-minimal- Severe)	Is the severity of depression in patients
Depressiveness	-	(TRUE-False)	-
Suicidal	-	(TRUE-False)	-
Depression_diagnosis	-	(TRUE-False)	Diagnosis of depression in the patient
Depression_treatment	-	(TRUE-False)	-
Generalized Anxiety Disorder	GAD_score	(0-21)	The measure of anxiety intensity
Anxiety_severity	-	(Mild-Moderate- None-minimal- Severe)	Is the severity of anxiety in patients
Anxiety_diagnosis	-	(TRUE-False)	Is the severity of anxiety in patients
Anxiety_treatment	-	(TRUE-False)	-
Epworth score	-	(0-32)	Measures the general level of daytime sleepiness.
Sleepiness	-	(TRUE-False)	-

B. Data Visualization

- Box Plot for Depression and Anxiety Data (Fig. 1)

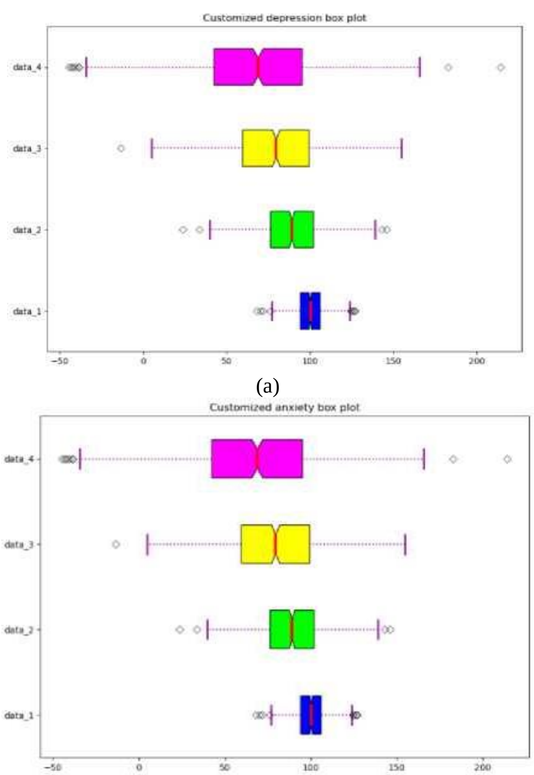


Fig. 1. Figure of Box Plot for Depression and Anxiety Data, (a) Customized depression box plot; (b) Customized anxiety box plot.

- Heatmap for Depression and Anxiety Data (Fig. 2)

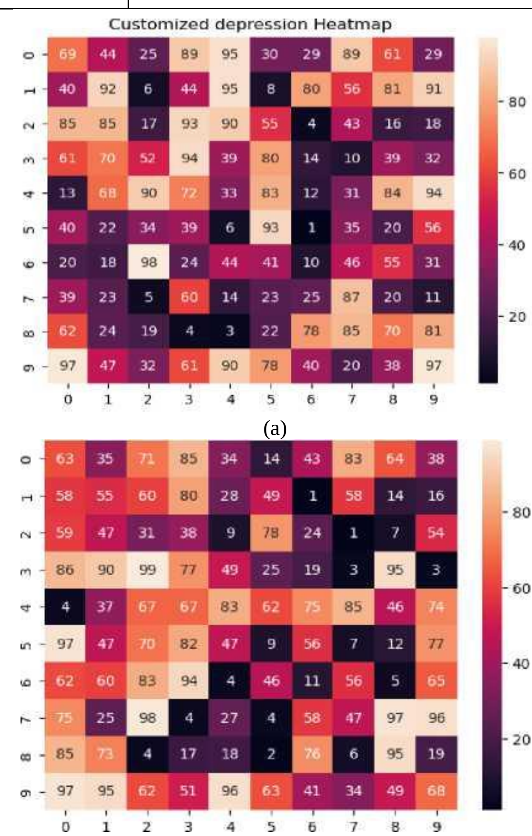


Fig. 2. Figure of Heatmap for Depression and Anxiety Data, (a) Customized depression heatmap; (b) Customized anxiety heatmap.

C. Proposed Work

This section presents a machine learning framework proposed for the diagnosis of depression and anxiety using a digital dataset. The framework, illustrated in Fig. 3, encompasses a series of essential procedures including digital data preprocessing, feature extraction, feature selection, classification, and validation processes, all of which are crucial for the success of the approach. In the initial step, the preprocessing method is employed to remove extraneous noises and handle missing data. This critical stage involves selecting representative samples, ensuring data balance, normalizing the data, removing outliers, and addressing the issue of missing data. By performing these preprocessing steps, the dataset is prepared for further analysis.

During the feature extraction process, we randomly split the feature matrix into training and test sets. To improve classification accuracy and reduce the dimensionality of the feature matrix we employ the Recursive Feature Elimination (RFE) approach, for feature selection. At this point, an RFE algorithm is utilized on the training set to identify the subset of features. It is important to note that each iteration of the proposed procedure using RFE results in a specific subset of features. The next step is to use the training and testing sets of RFE-derived features to train and validate the classification model appropriately. The selected attributes act as an input for the machine learning algorithm so that it can learn patterns and make predictions accurately. Finally, the classification performance of the proposed approach is assessed based on the outcomes obtained from classifying the testing set during each repetition of the process. The analysis shows that the technique works well in diagnosing anxiety and depression. In summary, if this detailed methodology is followed, which includes processes of data pre-processing, feature extraction, feature selection, classification, and validation, the machine-learning system proposed has the potential to diagnose depression and anxiety accurately using digital data.

[Please note that Fig. 3 is not included in the response as it is not visible to the AI model.]

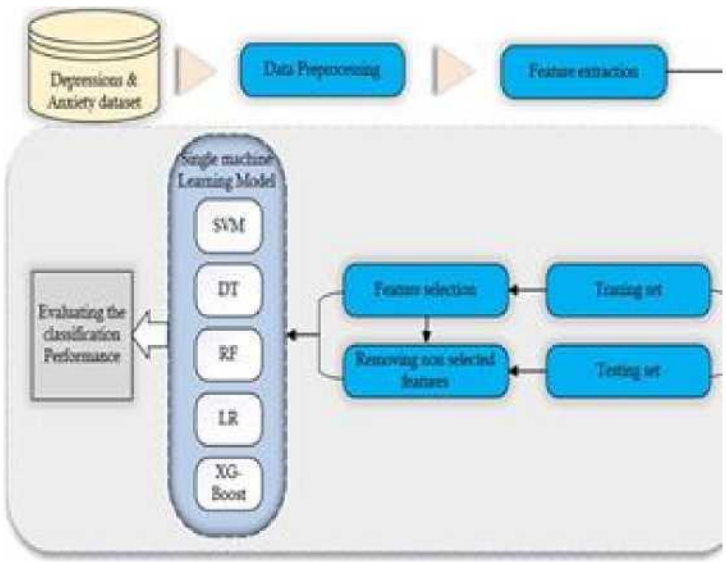


Fig. 3. Figure of the scheme for the proposed framework.

D. Methods

The present study is founded on an ample dataset of 783 individuals, where machine learning algorithms have been employed to prognosticate diagnoses with digital therapy. The outcomes have shown promising results, especially for depression and anxiety. The following algorithms, namely SVM, decision tree, logistic regression, random forest, and xgboost have been applied to both depressive and anxiety samples, and their corresponding results have been meticulously documented, as illustrated below in Table II and Table III.

Diagnosing depression and anxiety can be a complex process. Traditional methods rely on clinical interviews and standardized tests, but these can be time-consuming and subjective. Machine learning (ML) offers a promising alternative, but its "black box" nature often raises concerns. Here's a breakdown of how explainable ML methods can be used to improve the diagnosis of depression and anxiety:

TABLE III. THIS IS A TABLE OF RESULTS FOR DEPRESSION PREDICTIONS

Algorithms Performance (%)	Accuracy	precision	recall	f1-score
SVM	0.91%	0.91%	1.00%	0.95%
Decision tree	0.91%	0.95%	0.94%	0.95%
Random Forest	0.93%	0.94%	0.98%	0.96%
Logistic Regression	0.94%	0.95%	0.98%	0.96%
XGBOOST	0.92%	0.95%	0.97%	0.96%

1) Data Collection and Preprocessing:

- Gather relevant data: This could include survey responses, electronic health records (EHRs), speech patterns, or physiological measurements.
- Clean and prepare the data: Ensure data quality by addressing missing values, inconsistencies, and outliers.

2) Model Selection and Training:

- Choose an explainable ML algorithm: Options include decision trees, rule-based models, or LIME (Local Interpretable Model-agnostic Explanations). These provide insights into how the model arrives at its conclusions.

- Train the model: Split your data into training and testing sets. Train the model on the training data, allowing it to learn the patterns associated with depression and anxiety.

3) Model Evaluation and Explanation:

- Evaluate performance: Use metrics like accuracy, precision, and recall to assess the model's effectiveness in identifying depression and anxiety.

- Generate explanations: Analyze the model's predictions to understand what factors contribute most to the diagnosis. This could involve highlighting specific survey responses, keywords from speech, or patterns in physiological data.

4) Clinical Integration and Refinement:

- Integrate the model into clinical workflow: Present the model's prediction alongside explanations to support the clinician's diagnosis.

- Refine the model: Continuously monitor and improve the model based on new data and feedback from clinicians.

5) Benefits of this Approach:

- Improved diagnostic accuracy: Explainable ML can identify subtle patterns missed by traditional methods.

- Enhanced patient engagement: Explanations can empower patients to understand their diagnosis and treatment options.

- Increased clinician confidence: Explainable models provide additional information to support clinical judgment.

By following these steps, healthcare professionals can leverage the power of ML for mental health diagnosis while maintaining transparency and building trust with patients.

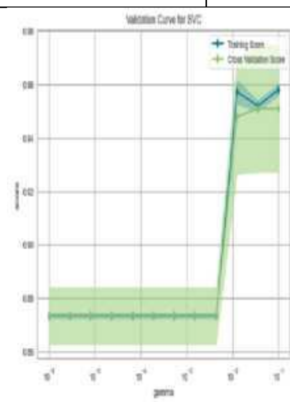
IV. Results

A. Results without Feature Selection

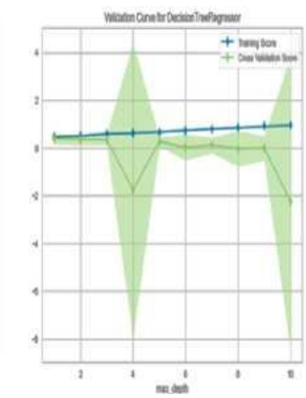
Next Stage the model used five classifiers; Support Vector Machine (SVM) Decision Tree (DT) Random Forest (RF) Logistic Regression (LR) and XGBoost to train a dataset having suicide, depression, and anxiety person. The system performs an algorithm of classification and documents its result for performance measurement. Below are stored classification performance metrics for each of the classifiers; SVM (0.91/0.91/1.00/0.95) DT (0.91/0.95/0.94/0.95) RF (0.93/0.94/0.98/0.96) LR (0.94 / 0.95 / 098 / 096) XGBoost (92%). This is shown in Table III as for the case it is summarized by accuracy=87% precision=87%, recall-1%and f1-score =93%. Further analysis also indicated that other classifiers such as decision trees gave better results than SVM with an accuracy level of up to 99% and an f1 score=96%, recall=0.98, and f1- score=0.98) in Table IV. After analyzing the results, it was found that the logistic regression algorithm performed the best with the dataset. In contrast, the random forest algorithm showed effectiveness, with the anxiety dataset as, per the data provided.

TABLE IV. This is a Table of Results for Anxiety Predictions

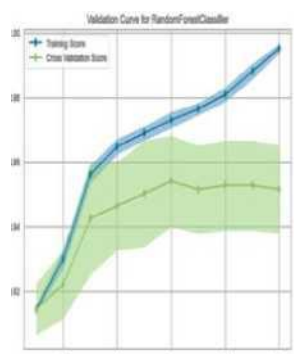
Algorithms Performance (%)	Accuracy	precision	recall	f1-score
SVM	0.87%	0.87%	1.00%	0.93%
Decision tree	0.93%	0.94%	0.99%	0.96%
Random Forest	0.94%	0.94%	1.00%	0.97%
Logistic Regression	0.91%	0.91%	1.00%	0.95%
XGBOOST	0.96%	0.98%	0.98%	0.98%



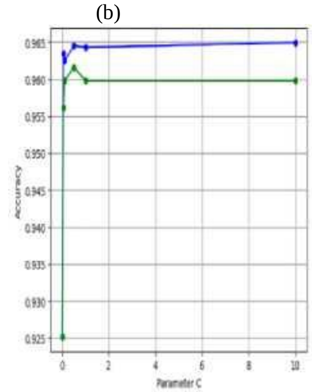
(a)



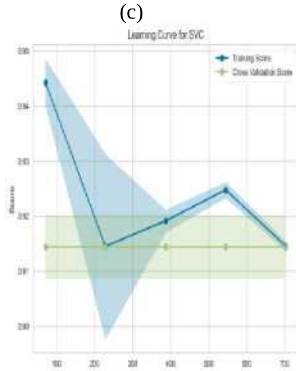
(b)



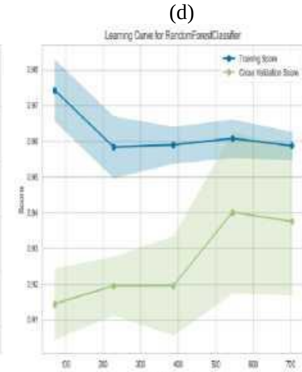
(c)



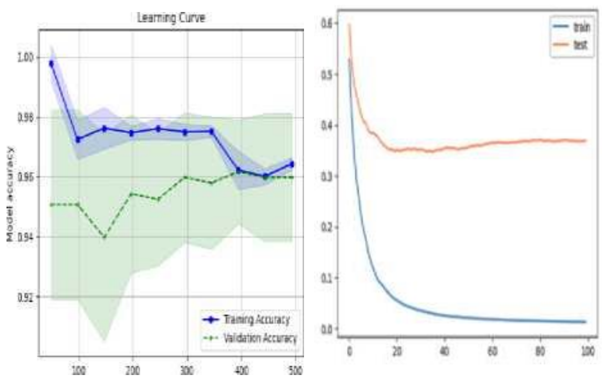
(d)



(e)



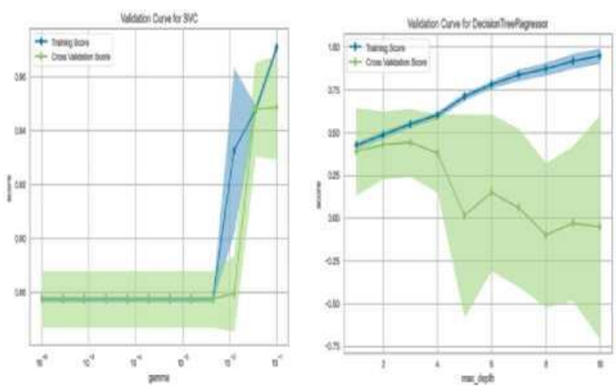
(f)



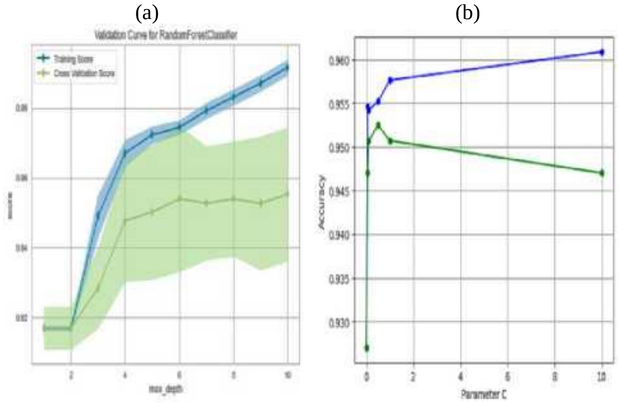
(g) (h)

Fig. 4. This is a figure of the Validation and learning Curve for the depression data set, (a) Validation Curve for SVM; (b) Validation Curve for DT; (c) Validation Curve for RF; (d) Validation Curve for LR; (e) Learning Curve for SVM; (f) Learning Curve for RF; (g)Learning Curve for LR; (h)Learning Curve for XGboost.

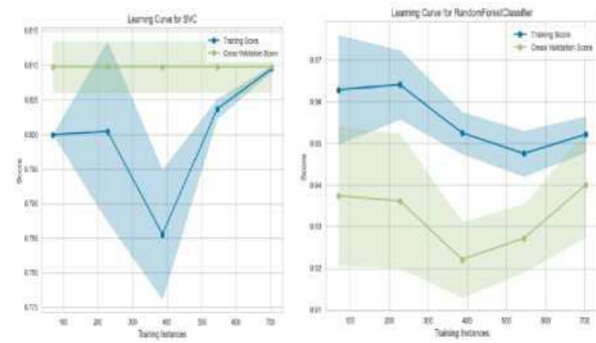
Through the Yellow brick analyses, we incorporated the validation curve and learning curve techniques to assess the efficacy of all models for both the depression and anxiety datasets. As shown in Fig. 4 and Fig. 5. Furthermore, we utilized the SHAP Interaction Value and force plot techniques to explicate the predictions and customize them according to the requirements. As shown in Fig. 6 and Fig. 7.



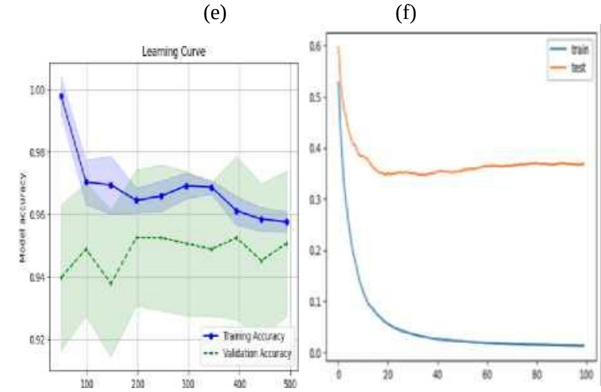
(a) (b)



(b) (d)



(e) (f)



(g) (h)

Fig. 5. This is a figure of the Validation and learning Curve for the anxiety data set, (a) Validation Curve for SVM; (b) Validation Curve for DT; (c) Validation Curve for RF; (d) Validation Curve for LR; (e) Learning Curve for SVM; (f) Learning Curve for RF; (g) Learning Curve for LR; (h) Learning Curve for XGboost.

B. Results with Feature Selection

In this part we identify the feature using the data set for all algorithms and use the feature selection method also called as feature elimination (RFE) it can point out those effective features decrease the fuzzy set and help algorithms and feature improvement performance the process of feature selection as shown in these result column were suiting of RFE make the inform of data novice in target value The result of RFE for depression data: SVM (accuracy = 0.92) precision = 0.92 recall = 1.00, f1 score = 0.97) DT (accuracy = 0.94) precision=0.96, recall=0.98, f1 score=0.97) RF (accuracy = 0.94) precision=0.94, recall=0.99, f1 score=0.96) LR (accuracy = 0.94) precision=0.96, recall=0.98, f1-score=0.97) RF (accuracy = 0.94) precision=0.94, recall=0.99, f1score=0.96) LR (accuracy=0.95) precision=0.97, recall=0.98, f1-score=0.97) XGboost (accuracy = 0.95) precision=0.96, recall=0.99, f1-score=0.97) depression for anxiety data: SVM (accuracy = 0.92) precision=0.92, recall=1.00, f1 score=0.97) DT (accuracy = 0.96) precision=0.97, recall=0.98, f1 score=0.98) RF (accuracy = 0.94) precision=0.93, recall=1.00, f1 score=0.97) LR (accuracy = 0.95) precision=0.96, recall=0.99, f1-score=0.97) XGboost (accuracy = 0.98) precision=0.98, recall=1.00, f1-score=0.99)in anxiety The result of performance of our algorithms after feature selection as shown in this Table VI of our the algorithm decrease and increase performance after use feature of selection.

TABLE V. THIS IS A TABLE OF RESULTS FOR DEPRESSION PREDICTIONS WITH FEATURE SELECTION

Algorithms Performance (%)	Accuracy	precision	recall	f1-score
SVM	0.94%	0.94%	1.00%	0.97%
Decision tree	0.94%	0.96%	0.98%	0.97%
Random Forest	0.94%	0.94%	0.99%	0.96%
Logistic Regression	0.95%	0.97%	0.98%	0.97%
XGBOOST	0.95%	0.96%	0.99%	0.97%

TABLE VI. THIS IS A TABLE OF RESULTS FOR ANXIETY PREDICTIONS WITH FEATURE SELECTION

Algorithms Performance (%)	Accuracy	precision	recall	f1-score
SVM	0.92%	0.92%	1.00%	0.96%
Decision tree	0.96%	0.97%	0.98%	0.98%
Random Forest	0.94%	0.93%	1.00%	0.97%
Logistic Regression	0.95%	0.96%	0.99%	0.97%
XGBOOST	0.98%	0.98%	1.00%	0.99%

C. Results with Optimized Models

In this part of our study, we focused on enhancing the effectiveness of five machine learning models: SVM, DT, RF, LR, and XGboost. We used grid search methods to adjust the parameters of each model and determine which one performed best for both depression and anxiety data sets.

TABLE VII. THIS IS A TABLE OF RESULTS FOR DEPRESSION PREDICTIONS WITH THE OPTIMIZED MODEL

Algorithms Performance (%)	best score
SVM	0.94%
Decision tree	0.96%
Random Forest	0.96%
Logistic Regression	0.96%
XGBOOST	Nan

TABLE VIII. THIS IS A TABLE OF RESULTS FOR ANXIETY PREDICTIONS WITH THE OPTIMIZED MODEL

Algorithms Performance (%)	best score
SVM	0.92%
Decision tree	0.95%
Random Forest	0.95%
Logistic Regression	0.93%
XGBOOST	Nan

Table VII and Table VIII provide a comprehensive overview of the results obtained through this optimization process. These tables showcase the performance metrics and corresponding scores achieved by each algorithm across different evaluation measures. We have used grid search, where we compared different algorithms and chose the one with the best performance. This helped us to improve our diagnostic framework for anxiety and depression. During the phase of our study, we refined our machine learning algorithms by utilizing grid search methods. We also gathered information on parameter configurations that enhanced their effectiveness. These findings have the potential to enhance approaches in health studies and showcase the advancements in using machine learning to diagnose anxiety and depression with greater accuracy and speed, than ever before.

D. Discussion

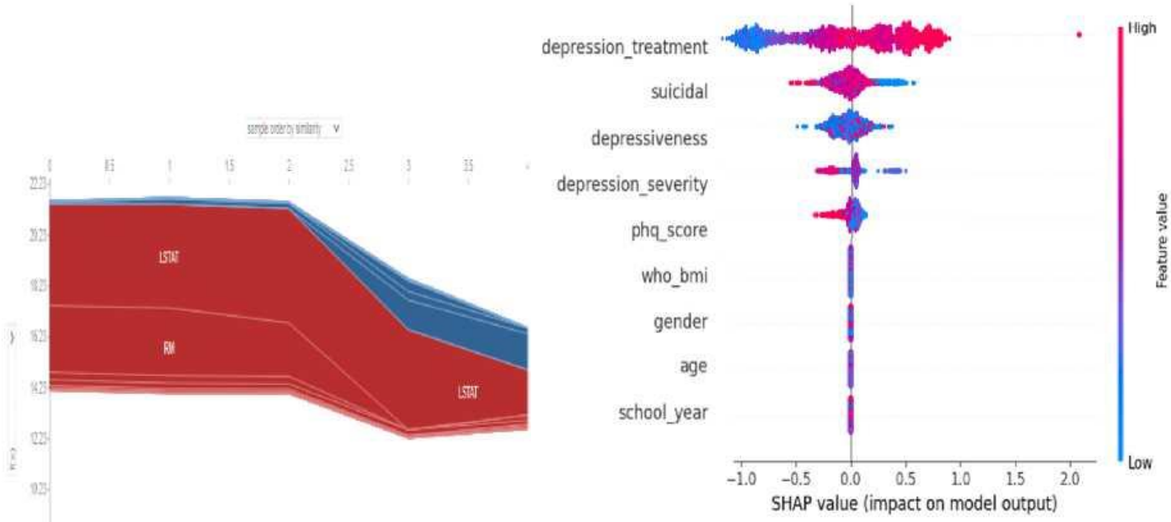
The current research offers insights by suggesting a range of machine-learning techniques that can effectively be used to compare different mental illnesses, including anxiety and depression. This proposed framework utilizes characteristics to improve the accuracy of diagnosing these disorders. The study's results are presented in three phases; a phase, without selecting features a subsequent phase with feature selection, and a final phase comparing the outcomes of both approaches. Importantly the results from feature selection showed performance compared to those without feature selection as shown in Tables III, IV, V and VI along, with the phase incorporating the optimized model, as illustrated in Tables VII and VIII [10].

Besides, as Table I above reveals, I studied more successfully with our findings compared to the health paper that talks about the diagnosis of his issues. I later state how we are definite that the methods that I am proposing will work also well and pass the exam. Finally, we are confident after comparing our results they are more successful in our study. Also, we have to pay attention to the problems that are raised on "Discriminant between psychosis and Major Depression". We can notice from Table I how the problem of different disorders rather our results which based on civil form.

V. EXPLANATION OF THE DEVELOPED MODEL

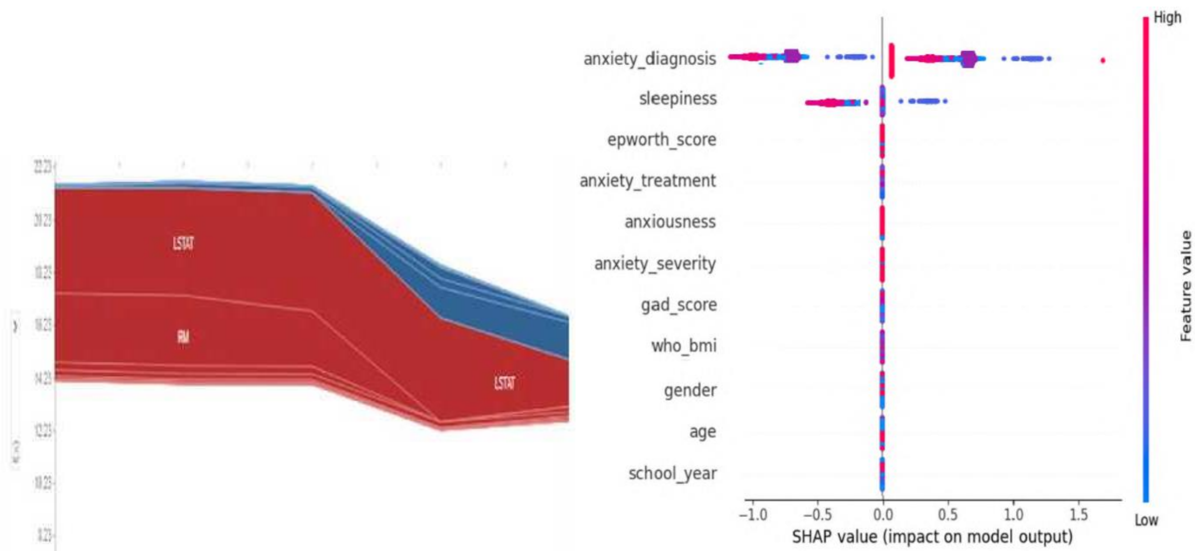
Our main focus is, on tackling the issue with two classes. To give an overview of how each feature influences the model's decisions as a whole we've created a summary visualization. This visual representation showcases the importance of features through a bar graph with the x-axis showing the key features and the y-axis indicating their significance. The length of each bar reflects its importance in the model. In this visualization blue signifies the impact on class AD while red represents its influence on class CN. The summary plot, in Fig. 6 depicts this for the scenario involving three classes (AD=0, CN=1, sMCI=2).

Based on Fig. 6, we observe that the CDMemory, Q7, and Q4 forms are considered the most important features. To further explore the importance of each feature on an instance level, we utilized SHAP explainers to generate a waterfall plot. The waterfall plot presents all the features contributing to the decision-making process, sorted according to their SHAP values. Fig. 7(A, B, C, D) demonstrates the waterfall plots, where each plot displays the Base_value, representing the value according to the entire dataset, and the predict_proba_value, representing the probability for the specific instance. The left side of the plot shows the feature values for that instance, while the arrows indicate the feature contributions towards the prediction. Each row in the plot represents negative and positive contributions, depicted by blue and red bars, respectively. These explanations assist medical experts in understanding and placing trust in the decisions made by the model.



(a) (b)

Fig. 6. This is a figure of SHAP Interaction Value and force plot for the depression data set, (a) SHAP value impact for XGboost; (b) Force plot for XGboost.



(a) (b)

Fig. 7. This is a figure of SHAP Interaction Value and force plot for anxiety data set, (a) SHAP value impact for XGboost; (b) Force plot for XGboost.

VI. CONCLUSION

According to the results of this study, it is possible to deduce that using treatment information alone can help accurately forecast treatment results by examining shifts, in anxiety and depression indicators. Cutting-edge machine learning algorithms showed accuracy in these forecasts providing guidance, for doctors when deciding on low-resource online therapies and conventional medical interventions. The strong precision of these models indicates their ability to identify the suitable level of traditional or digital care before starting treatment. It is a matter of great concern to the patients as this can save them time, energy, and money and just point them promptly toward appropriate healthcare resources. In addition to this, these results might guide healthcare providers toward identifying those patients likely not to benefit from online therapies to properly allocate their limited time and resources. By making use of these complicated machine learning algorithms, clinicians will enhance their decision-making regarding treatment that is evidence-based and patient-specific which ultimately leads to better outcomes for patients seeking mental health care by these models could alter its course through efficient guidance to suitable treatment options for those affected. However, more research is required before it can be determined if this knowledge applies or scales up across different populations of patients and within diverse healthcare contexts. Further studies in this area will promote the development of strategies for treating mental illnesses thereby enhancing care for anxiety and depression disorders thus improving the quality of life among individuals with such conditions.

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