

Machine Learning-Based Anxiety and Depression Prediction Among College Students Using GAD-7 And PHQ-9 Questionnaires

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Abstract—In recent years, rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent healthcare systems capable of continuously monitoring an individual's psychological health.

These technologies have made mental health assessment more accessible, cost-effective, and user-friendly by facilitating real-time data collection and automated analysis. Anxiety and depression are among the most prevalent mental health disorders affecting college students, often leading to reduced academic performance, emotional distress, and diminished quality of life.

Therefore, early identification of these conditions is essential for timely intervention and effective treatment. This study presents a framework for predicting anxiety and depression by integrating standardized psychological assessment tools—the Generalized Anxiety Disorder-7 (GAD-7), the Patient Health Questionnaire-9 (PHQ-9).

The acquired data are preprocessed and used to train and evaluate multiple supervised machine learning algorithms to identify the most effective predictive model. Model performance is assessed using standard evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Experimental findings indicate that psychological questionnaire responses significantly improve prediction performance compared with previous works. The proposed framework demonstrates the potential of machine learning to support continuous mental health monitoring, facilitate early detection, and enable timely intervention for anxiety and depression among college students.

Index Terms—Anxiety Prediction, College Students, Depression Detection, GAD-7, Mental Health, PHQ-9, Predictive Analytics, Psychological Assessment.

I. INTRODUCTION

A. Problem Statement:

Mental health disorders, particularly anxiety and depression, have emerged as significant public health challenges worldwide, affecting people across all age groups and socioeconomic backgrounds. Among college students, these disorders are increasingly prevalent due to academic pressure, social expectations, financial concerns, and lifestyle changes[1], [2], [3]. Persistent symptoms of anxiety and depression can adversely affect emotional well-being, cognitive functioning, academic achievement, interpersonal relationships, and overall quality of life. Reports from international health organizations indicate that millions of individuals experience symptoms of these disorders each year; however, many cases remain undiagnosed or untreated because of limited mental healthcare resources, social stigma, and delayed clinical consultation[4], [5], [6]. Consequently, the development of effective technologies for the early detection and continuous monitoring of mental health conditions has become an important research priority[7], [8], [9].

Machine Learning (ML) has become an effective computational approach for analysing large volumes of multidimensional healthcare data and identifying complex patterns that are difficult to detect using traditional statistical techniques. Supervised learning algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Naive Bayes, Gradient Boosting, and Extreme Gradient Boosting

(XGBoost), have demonstrated considerable success in disease prediction and medical decision-support applications. These algorithms can learn nonlinear relationships among psychological variables, enabling accurate classification and prediction of mental health conditions[5], [10], [11].

This study proposes a machine learning framework for the prediction of anxiety and depression by integrating responses from the Generalized Anxiety Disorder-7 (GAD-7) and Patient Health Questionnaire-9 (PHQ-9). Standardized self-report questionnaires such as the Generalized Anxiety Disorder-7 (GAD-7) and the Patient Health Questionnaire-9 (PHQ-9) are clinically validated and widely accepted for screening anxiety and depressive symptoms. Moreover, these assessments provide periodic evaluations of mental health status[8], [12], [13].

The collected data are subjected to preprocessing, feature engineering, and model training before being evaluated using multiple supervised machine learning algorithms. The predictive performance of each model is assessed using widely accepted evaluation metrics, including accuracy, precision, recall, F1-score, Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), and confusion matrix analysis[14], [15], [16].

The primary objective of this research is to identify the most accurate and reliable machine learning model for the early prediction of anxiety and depression while demonstrating the effectiveness of integrating with standardized psychological assessment instruments. The proposed framework aims to provide a scalable, cost-effective, and intelligent solution for continuous mental health monitoring, enabling timely identification of individuals at risk and supporting proactive intervention by healthcare professionals and educational institutions. This research contributes to the development of next-generation intelligent mental healthcare systems capable of improving screening accuracy, enhancing clinical decision-making, and promoting overall psychological well-being[17], [18].

B. Motivation

Mental health has emerged as one of the most critical global healthcare challenges of the twenty-first century. Among various psychological disorders, anxiety and depression are the most prevalent, affecting millions of individuals across different age groups, occupations, and socioeconomic

backgrounds[2]. These conditions have a profound impact on emotional well-being, cognitive functioning, academic performance, workplace productivity, interpersonal relationships, and overall quality of life. When left undiagnosed or untreated, they may lead to severe psychological distress, social isolation, reduced educational and professional outcomes, and an increased burden on healthcare systems. Consequently, the development of effective approaches for the early identification and continuous monitoring of these disorders has become an important research priority [3], [4].

Anxiety Disorder-7 (GAD-7) and Questionnaire-9 (PHQ-9) questionnaires are widely accepted and clinically validated; they rely on self-reported responses and are typically administered at discrete time intervals. As a result, they provide periodic assessments of an individual's mental health[3], [5].

Simultaneously, Machine Learning (ML) has become a powerful computational approach for analysing complex healthcare datasets and identifying hidden relationships among psychological variables. Supervised learning algorithms, including Decision Tree, Random Forest, Extra Trees, Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Extreme Gradient Boosting (XGBoost), have demonstrated strong predictive capabilities in disease diagnosis and clinical decision-support systems. Their ability to learn from historical data, model nonlinear relationships, and generate accurate predictions makes them particularly suitable for mental health applications, where multiple interconnected factors influence psychological outcomes[4], [12], [14].

This research is motivated by the growing need for an intelligent, automated, and scalable framework capable of accurately predicting anxiety and depression using standardized psychological assessment tools[16], [19]. The increasing adoption of artificial intelligence in healthcare provides an opportunity to develop predictive systems that support early diagnosis, continuous monitoring, and personalized intervention. Furthermore, conducting a comprehensive comparative evaluation of multiple machine learning algorithms can identify the most effective predictive model for anxiety and depression classification, thereby improving the reliability and clinical applicability of intelligent mental health systems[20], [21].

The proposed research uses standardized mental health questionnaires and advanced machine learning algorithms in a unified prediction framework. The outcomes of this study are expected to contribute to the development of cost-effective, scalable, and data-driven mental healthcare systems that facilitate early detection, continuous monitoring, and timely clinical intervention. Ultimately, the proposed framework aims to enhance decision-making for healthcare professionals, support preventive mental healthcare strategies, and improve the overall quality of life of individuals experiencing anxiety and depression[22], [25], [38].

C. Research Objectives

- To develop a machine learning framework for predicting psychological data such as anxiety and depression using GAD-7 and PHQ-9.
- To preprocess and analyze questionnaires for improving prediction quality.
- To implement and evaluate Decision Tree, Random Forest, Extra Trees, K-Nearest Neighbors, Naïve Bayes, LightGBM, Support Vector Machine, and XGBoost algorithms.
- To compare the predictive performance of these algorithms using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix.
- To identify the most effective machine learning model for early prediction of anxiety and depression using GAD-7 and PHQ-9 questionnaires.
- To demonstrate the feasibility of machine learning for continuous mental health monitoring.

II. LITERATURE REVIEW

The following researchers made contributions to predicting anxiety and depression, along with the research outcomes from their respective publications.

Agrawal et al.[1] Presents a predictive system that uses GAD and SWL to collect the players' data to check if a player suffers from psychological illnesses by combining game and player information. Four different ML algorithms were tested using a 10-fold cross-validation approach on gamer datasets. Among the four algorithms, the Decision Tree (DT) classifier achieved the highest accuracy across all predicted parameters. For the GAD and SWL questionnaires, the

Decision Tree (DT) achieved accuracies of 100% and 84.71%, respectively.

Malik et al.[2] This system, which uses DASS21, was used to collect data from 400 students to check the severity levels of anxiety, stress, and depression in college students. Support Vector Machine (SVM), KNN, Logistic Regression (LR), Decision Tree, and Naive Bayes (NB) were applied to compute metrics such as accuracy, precision, and specificity, which were used to compare the models. After implementing all the algorithms, it was found that K-Nearest Neighbour performed best.

Chandra et al. [3] This study developed a model that can assist healthcare providers in identifying patients' mental issues and enable early intervention and prevention. It makes people aware that they may be suffering from mental health disorders like Anxiety, Depression, and Stress. Establishing such a system could help us avoid future Mental health issues and make diagnoses easier for people.

Jo et al.[4] The study evaluates the performance of various machine learning algorithms, with the Random Forest algorithm demonstrating the highest accuracy rate of 99.30%. On mental health conditions such as schizophrenia, bipolar disorder, eating disorders, anxiety disorders, drug use disorders, and alcohol use disorders, and their correlations with depression.

Priya et al. [5] In this paper, the Depression, Anxiety and Stress Scale questionnaire (DASS 21) was used to collect data from employed and unemployed individuals across different cultures and communities. Predictions of depression, anxiety, and stress were made using ML algorithms. After applying the different methods, it was found that classes were imbalanced in the confusion matrix. Therefore, the F1 score measure was added, which shows that the Random Forest classifier was the best accuracy model among the five applied algorithms.

Ahmad et al.[6] The proposed model used two datasets of anxiety and depression. Comparing the results on the basis of different measurement metrics like accuracy, recall, and precision, the CNN algorithm achieves the highest accuracy of 96% and 96.8% for anxiety and depression, respectively.

Tuan et al.[7] This system used COVID-19 patients' data. The experimental results show that SVM is the most suitable model for accurately predicting mental health with an accuracy ≥ 0.984 . Furthermore, the ET method is more effective than the RFE method for feature selection in the anxiety and stress datasets.

Sulak et al. [8] This study used the DASS-42 questionnaire as a psychological assessment tool. Administered to 680 students at Necmettin Erbakan University. The ANN method achieved remarkable distinctiveness scores for depression (99.26%), anxiety (98.67%), and stress (97.35%). The study highlights the potential of data mining in enhancing psychological assessment.

Vitoria et al. [9] This work proposes the PROMIS questionnaire to predict the scores of anxiety and depression, and to perform a comparative study between supervised learning models to estimate the scores of anxiety and depression. The proposed model achieved an average MAPE of 6.31%, R2 of 0.76, and a Spearman coefficient of 88.86.

Almutairi et al. [10] The dataset used in the methodology consists of text questions asked by young users on the online platform. The experimental outcomes show that the proposed approach achieves an accuracy of 97.23%, a precision of 98.57%, a recall of 97.13%, an F1-score of 97.84%, and a specificity of 97.93%, respectively. These results highlight the efficiency of the developed methodology that accurately predicts depression.

Qasrawi et al. [11] The study collected fifth to ninth grades, aged 10-15 years, for a total of 3984 students. The results indicated that the Support Vector Machine (SVM) and Random Forest (RF) models had the highest accuracy levels for depression, SVM: 92.5% and RF: 76.4%, and anxiety, SVM: 92.4% and RF: 78.6%. Thus, the SVM and RF models had the best performance in classifying and predicting the students' depression and anxiety.

Nayan et al. [12] A structured questionnaire-based online survey using PHQ 9 and GAD-7 was collected from 2121 university students to predict mental illness among university students from Dhaka city in Bangladesh. The results showed that RF outperformed

other models for the prediction of depression (89% accuracy), while SVM provided the best result among other models for the prediction of anxiety (91.49% accuracy).

III. RESEARCH METHODOLOGY

A. Data Collection

A survey was performed to collect data from college students of different age groups. A 24-question questionnaire was designed. The first 6 questions were designed to gather socio-demographic information such as age group, gender, current living status, occupation status, and economic status; the next 16 questions were related to psychosocial information, such as the GAD-7 and PHQ-9 scores used to assess the actual anxiety and depression level of each student. The survey was conducted between July 2025 and January 2026. The dataset consists of the responses of 1052 individuals.

Table I: Input Relative Contribution for Anxiety Scores

GAD-7 (Generalized Anxiety Disorder) - Assessment of Anxiety: (Features)				
Over the last 15 days, how often have you been bothered by any of the following problems?	Not at all	Several days	More than half the days	Nearly every day
Felt nervous, anxious, or on edge due to any pressure?	0	1	2	3
Unable to stop or control worrying?	0	1	2	3
How often have you had trouble relaxing?	0	1	2	3
Easily annoyed or irritated?	0	1	2	3
Worried too much about different things?	0	1	2	3
Restless that it is hard to sit still?	0	1	2	3
Felt afraid, as if something awful might happen?	0	1	2	3

Source: <https://www.apa.org/depression-guideline/patient-health-questionnaire.pdf>

Table II: Input Relative Contribution for Depression Scores

PHQ-9 (Patient Health Questionnaire) Assessment of Depression (Features)				
Over the last 15 days, how often have you been bothered by any of the following problems?	Not at all	Several days	More than half the days	Nearly every day
Had little interest or pleasure in doing things?	0	1	2	3
Feeling down, depressed or hopeless?	0	1	2	3
Trouble falling, staying asleep, or sleeping too much?	0	1	2	3
Felt tired or had little energy?	0	1	2	3
Poor appetite or overeating?	0	1	2	3
Failure, or have let yourself or your family down?	0	1	2	3
Trouble concentrating on things, such as reading books or watching television?	0	1	2	3
Moving or speaking so slowly that other people could have noticed. Or the opposite: being so fidgety or Restless that you have been moving around a lot more than usual?	0	1	2	3
Had thoughts that you would be hurting yourself?	0	1	2	3

Source: <https://www.apa.org/depression-guideline/patient-health-questionnaire.pdf>

B. Data Processing:

Preprocessing is necessary to guarantee that the diverse input data can be properly analysed and

modelled. In this phase, it systematically cleans the data, transforms it, and prepares it for a correct predictive model[5], [7], [8].

Preprocessing ensures that the raw questionnaire responses are clean, consistent, and ML-ready.

a. Normalization and Scaling:

Numerical features are normalized using:

- StandardScaler
- MinMaxScaler

b. Feature Engineering

Feature engineering is performed to derive meaningful insights from raw sensor data.

c. Outlier Detection

Outliers are unlikely because questionnaire scores are bounded (0–3 per question).

Data validation ensures all values are within valid ranges.

- Outliers are identified and handled using: Interquartile Range (IQR)
- Z-Score Method

C. Data Description:

Table III: Features Category and Example

Feature Category	Example
Demographic	Age, Gender, Education Year
PHQ-9	PHQ 1-PHQ9
GAD-7	GAD1- GAD7
Target Variable	Anxiety Label, Depression Label

a. Demographic Information

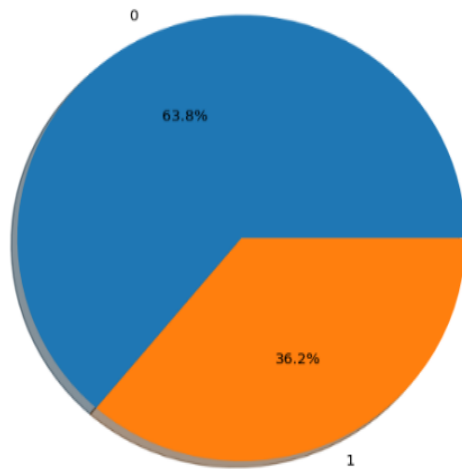
The following socio-demographic details are collected through a questionnaire

- Age Group
- Gender
- Current Living Status
- Occupation Status
- Economic Status
- Education Year

b. Psychological Data

Psychological assessments are conducted using standardized questionnaires, including PHQ-7 and GAD-7.

Gender Distribution



c. PHQ-9 Assessment

The Patient Health Questionnaire PHQ-9 (Patient Health Questionnaire-9) – for depression assessment consists of nine questions that evaluate depressive symptoms over the previous 15 days. [2], [3], [8].

d. GAD-7 Assessment

The Generalized Anxiety Disorder Scale GAD-7 (Generalized Anxiety Disorder-7) – for anxiety assessment consists of seven questions designed to assess anxiety symptoms. [2], [3], [8].

Table IV: Severity Level of Depression and Anxiety Measuring Scale

Score Range	Depression Severity	Score Range	Anxiety Severity
0–5	Normal	0–5	Normal
6–10	Mild	6–10	Mild
11–15	Moderate	11–15	Moderate
16–20	Moderately Severe	16–21	Severe
21–27	Severe		

The total PHQ-9 and GAD-7 scores are used as significant predictive features.

IV. EXPERIMENT SETUP

A. Overview

This section describes the experimental environment, dataset preparation, implementation details, Machine Learning models, and evaluation procedures used to assess the performance of the proposed framework for

predicting anxiety and depression among college students. The experiments were conducted using demographic and psychological data collected from standardized mental health assessment tools (GAD-7 and PHQ-9).

B. Experimental Environment

The implementation and evaluation of the proposed framework were performed using Python in the Jupyter Notebook environment.

Table V: Software Configuration

Component	Specification
Programming Language	Python 3.11
Development Environment	Jupyter Notebook
Operating System	Windows 11
Data Analysis Library	Pandas
Numerical Computing Library	NumPy
Visualization Libraries	Matplotlib, Seaborn
Machine Learning Library	Scikit-Learn
Advanced Boosting Library	XGBoost

C. Dataset Preparation

The proposed system dataset consists of demographic and psychological attributes collected from college students. This database comprises around 22 attributes. In the prediction of anxiety and depression, 22 attributes are used, while the last two attributes act as the output or predicted attribute for the presence of anxiety or depression in a student. The first stage is to collect data. The questionnaire was taken from <https://www.apa.org/depression-guideline/patient-health-questionnaire.pdf> and collected using online questionnaires. In total, 1052 students' data were collected [6]. Questions were objective. There are no right or wrong responses in it. There are a total of 22 questions from the standard form (PHQ-9 and GAD-7) based on the dataset. The students' responses are transformed using numeric values ranging from 0 to 4 in PHQ-9 and 0 to 3 in GAD-7. Once data gathering is complete for these 22 questions. The data for pre-processing is moved to feature extraction, thenceforth, prediction of mental illness. The numbers corresponding to the responses to every question in the specific class were added to determine the scores for anxiety and depression. After calculating the final scores, they were categorized according to severity (TABLE VI).

Table VI: Parameters & Values

Parameter	Value
Total Records	1052
Individual Features	6
Psychological Features	16
Target Variables	2
Total Features	24

V. MODEL BUILDING

A. Machine Learning Model Implementations:

The final dataset contains approximately 1052 students' records with multiple features representing demographic and psychological characteristics.

B. Model Training and Validation

The dataset is divided into training and testing subsets.

C. Dataset Splitting

The dataset was divided into training and testing subsets.

Table VII: Training & Testing %

Dataset Portion	Percentage
Training Set	80%
Testing Set	20%

The train-test split was performed using a random state of 42 to ensure reproducibility of experimental results.

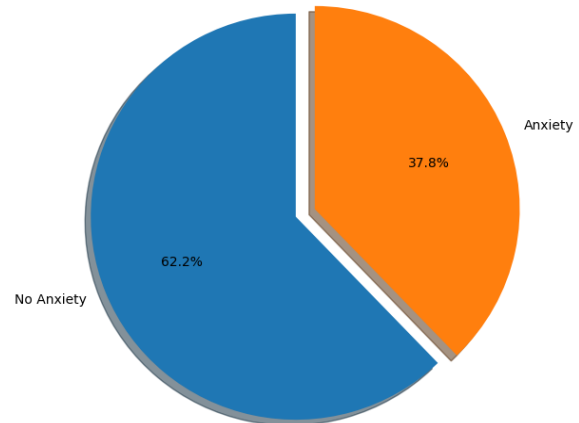
VI. EVALUATION

A total of 1052 students' records with multiple features representing demographic and psychological characteristics were collected and processed. The following percentage of students have anxiety and depression symptoms.

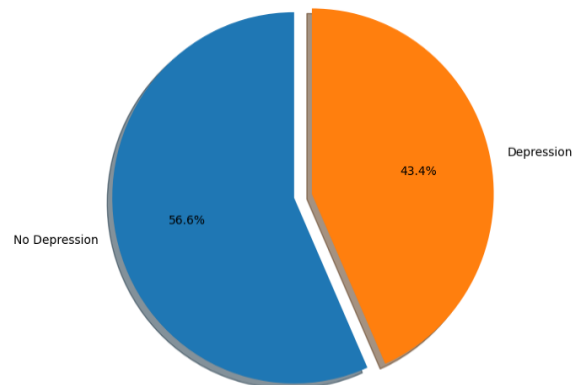
The below pie chart (Anxiety Distribution) illustrates the distribution of anxiety among the students. The results show that 62.2% of participants were classified as No Anxiety, while 37.8% were identified as experiencing Anxiety based on the GAD-7 assessment.

This indicates that the majority of students did not exhibit significant anxiety symptoms; however, more than one-third of the study population demonstrated anxiety, highlighting a notable prevalence of mental health concerns.

Anxiety Distribution



Depression Distribution



The observed class distribution reflects a moderately imbalanced dataset, which remains appropriate for machine learning classification while warranting the use of evaluation metrics such as precision, recall, F1-score, and ROC-AUC to ensure robust performance. Overall, the findings support the development of machine learning-based models for early anxiety detection systems.

(Depression Distribution) illustrates the distribution of depression among the study participants based on the PHQ-9 questionnaire. The results indicate that 56.6% of students belong to the No Depression category, while 43.4% of students are classified as experiencing Depression. This distribution suggests a moderately imbalanced dataset, with a higher proportion of non-depressed individuals. Despite this imbalance, the depression class represents a significant segment of the population, emphasizing the need for reliable predictive models for early identification of depressive

symptoms. The class distribution is appropriate for supervised machine learning and supports the use of evaluation metrics such as precision, recall, F1-score, and ROC-AUC to ensure accurate and clinically meaningful predictions. These findings highlight the importance of integrating machine learning techniques with PHQ-9 assessments in mental health monitoring systems.

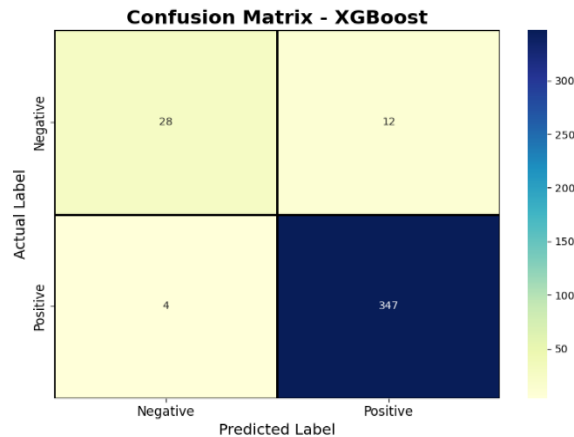


Fig 1: Confusion Matrix of Results

1. True Negatives (TN = 28):

The model correctly predicted 28 negative cases as negative. These are correctly classified depression/non-depression and anxiety/non-anxiety cases (depending on your target variable). The model successfully identified 28 actual negative instances.

2. False Positives (FP = 12):

There were 12 negative samples that the model predicted as positive. These are called Type-I Errors. The model incorrectly classified 12 negative anxiety and depression individuals as positive.

3. False Negatives (FN = 4):

There were 4 positive samples that the model predicted as negative. These are called Type-II Errors. Only 4 actual positive cases were missed by the model

4. True Positives (TP = 347):

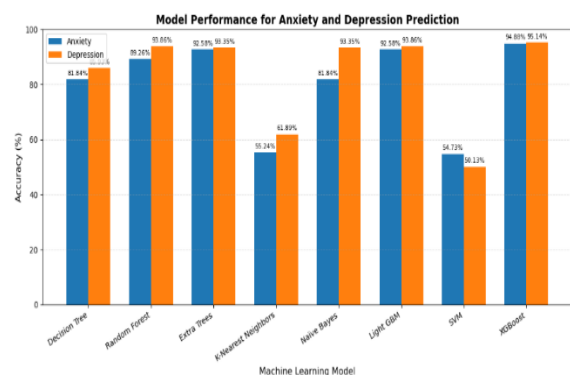
The model correctly predicted 347 positive cases. Most positive cases were correctly identified. The XGBoost classifier demonstrated excellent classification performance with an overall accuracy of 95.91%. Out of 391 test samples, the model correctly classified 347 positive and 28 negative instances while misclassifying only 16 samples (12 false positives and

4 false negatives). The model achieved a precision of 96.66%, indicating that most predicted positive cases were correctly identified, and a recall of 98.86%, demonstrating a very high capability to detect actual positive cases. The resulting F1-score of 97.76% confirms a strong balance between precision and recall. However, the specificity of 70% suggests comparatively weaker performance in identifying negative cases, likely due to the class imbalance in the dataset (351 positive vs. 40 negative samples). Overall, the confusion matrix indicates that the XGBoost model is highly effective for identifying positive instances while maintaining a low false-negative rate, making it well suited for healthcare applications where missing true positive cases should be minimized.

A. Evaluation of Models

Table VIII: Model Accuracy of Anxiety and Depression

Model	Anxiety (%)	Depression (%)
Decision Tree	0.818414	0.859335
Random Forest	0.892583	0.938619
Extra Trees	0.925831	0.933504
K-Nearest Neighbors	0.552430	0.618926
Naïve Bayes	0.818414	0.933504
Light GBM	0.925831	0.938619
SVM	0.547315	0.501279
XGBoost	0.948849	0.951407



XGBoost and LightGBM maintained high accuracy, indicating strong generalization and minimal overfitting.

B. Anxiety Prediction Results:

The performance of the implemented Machine Learning models for anxiety prediction is presented in

Table IX: Performance Comparison of ML Models for Anxiety Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC
DT	0.8184	0.8441	0.8809	0.8621	0.7929
RF	0.8925	0.8776	0.9682	0.9207	0.9822
ET	0.9258	0.9054	0.9880	0.9449	0.9889
KNN	0.5524	0.6859	0.5634	0.6187	0.5606
NB	0.8184	0.8197	0.9206	0.8672	0.9224
LGBM	0.9258	0.9207	0.9682	0.9439	0.9861
SVM	0.5473	0.6903	0.5396	0.605791	0.535686
XGB	0.9488	0.9531	0.962	0.9063	0.9927

The results indicate that XGBoost achieved the highest prediction accuracy of 0.948849, followed closely by LightGBM and Extra Trees with 0.925831 respectively. Ensemble learning techniques outperformed traditional classification algorithms by capturing complex feature interactions and reducing overfitting. SVM exhibited the lowest performance.

C. Depression Prediction Results

The performance metrics obtained for depression prediction are shown in Table X.

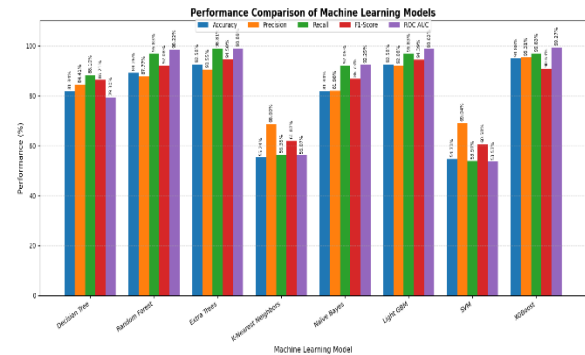
Table X: Performance Comparison of ML Models for Depression Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC
DT	0.8593	0.9277	0.914	0.921	0.644
RF	0.9386	0.9360	1.000	0.966	0.983
ET	0.9335	0.9333	0.997	0.964	0.984
KNN	0.6189	0.9139	0.635	0.749	0.585
NB	0.9335	0.9333	0.997	0.964	0.974
LGM	0.9386	0.9407	0.994	0.966	0.982
SVM	0.5012	0.9148	0.490	0.638	0.549
XGB	0.9514	0.9560	0.991	0.973	0.984

Table X shows that similar trends were observed in depression prediction. XGBoost achieved the highest accuracy of 0.951407, followed by Light GBM with 0.938619. The superior performance of ensemble learning algorithms demonstrates their effectiveness in handling high-dimensional depression datasets and identifying complex patterns associated with depression symptoms.

D. Comparison of different Machine Learning Models based on Performance Metrics (Anxiety):

The above graph compares the performance of eight machine learning algorithms for anxiety prediction using five evaluation metrics:

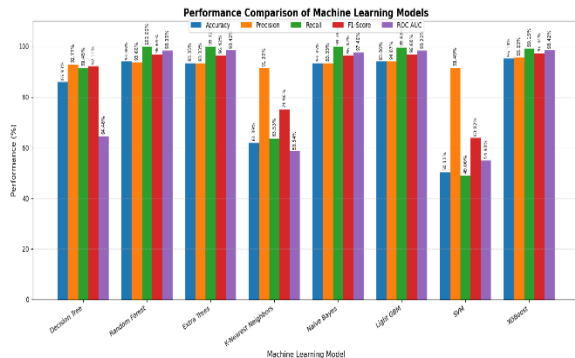


Accuracy, Precision, Recall, F1-score, and ROC-AUC. Among all the evaluated models, XGBoost achieved the highest overall performance, with approximately 95% accuracy, 96% precision, 97% recall, 97% F1-score, and an ROC-AUC close to 1.00, demonstrating excellent classification capability. Extra Trees, Logistic Regression, and Random Forest also produced strong and balanced results, with accuracy exceeding 90% and ROC-AUC values above 0.95, indicating high predictive reliability. In contrast, K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) recorded substantially lower performance across all metrics, with accuracy around 55% and ROC-AUC values below 0.60, suggesting limited suitability for anxiety prediction on the given dataset. Overall, the results indicate that ensemble learning techniques, particularly XGBoost and Extra Trees, outperform traditional classifiers, making them more appropriate for accurate anxiety prediction using questionnaire-based data.

E. Comparison of different Machine Learning Models based on Performance Metrics (Depression):

The above graph presents a comparative evaluation of eight machine learning algorithms for depression prediction using five performance metrics: Accuracy, Precision, Recall, F1-score, and ROC-AUC. The results demonstrate that XGBoost achieved the highest

overall performance, with approximately 95% accuracy, 96% precision, 98% recall, 97% F1-score, and an ROC-AUC close to 1.00, indicating excellent predictive capability and class discrimination. Random Forest,



Extra Trees, Logistic Regression, and Naïve Bayes also exhibited strong and consistent performance, achieving accuracy values above 90% and ROC-AUC values approaching 1.00. In contrast, Decision Tree showed acceptable predictive accuracy but comparatively lower ROC-AUC, while K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) produced the weakest results, primarily due to lower recall and reduced discriminatory ability.

These findings suggest that ensemble learning approaches are more effective than traditional classifiers for questionnaire-based depression prediction for mental health monitoring systems.

VII. RESULTS

This study shows that machine learning can effectively predict anxiety and depression using different demographic and psychological factors. Several machine learning models were tested and XGBoost achieved the best performance. These models consistently outperformed traditional Machine Learning algorithms such as Logistic Regression, Naive Bayes, K-Nearest Neighbors, Support Vector Machines, and Decision Trees.

Overall, the proposed model is accurate, reliable, and can be useful for the early detection of anxiety and depression. This suggests that the proposed framework can effectively classify unseen data and may be applicable in real-world mental health monitoring scenarios.

VIII. DISCUSSION & CONCLUSION

The experimental results demonstrate that ensemble learning techniques, particularly XGBoost and LightGBM, are highly effective for predicting anxiety and depression among college students. Combining demographic and psychological factors significantly enhances prediction accuracy by capturing continuous psychological information. These findings align with previous research highlighting the strong relationship between psychological well-being.

Furthermore, the proposed framework provides a scalable, non-invasive approach to continuous mental health monitoring. Educational institutions can leverage such systems to identify at-risk students early and implement timely intervention strategies.

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