

A Comparative analysis of predictive machine learning models on student mental health impact on academic outcomes

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Abstract

Mental health (MH) profoundly influences emotional, psychological, and social well-being throughout all life stages, impacting how individuals think, feel, and cope with stress. This study explores the relationship between academic life and MH among college students via a survey comprising 15 targeted questions addressing depressive symptoms. Most responses were binary, with some scaled to reflect symptom frequency. The analysis assessed question-wise response accuracy, revealing differences between boys' and girls' students "Yes" and "No" answers. Using five machine learning classifiers – Logistic Regression (LR), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees (DT), and Naïve Bayes (NB) – the study achieved notable prediction accuracies, with Logistic Regression attaining 92.4% accuracy for depression detection and SVM achieving 94.1% accuracy for anxiety recognition. These results underscore the feasibility of employing predictive models for early identification of MH issues in academic settings. This work highlights the importance of gender-specific insights in MH assessment, contributing to the development of targeted interventions aimed at improving student well-being and academic success.

Keywords:Anxiety, College Students, Depression, Gender Differences, Mental Health, Machine Learning, Predictive Patterns

1. Introduction

Human beings are becoming more ambitious and eager to seize employment opportunities in today's fast-paced and competitive society. As a result, mental health (MH) conditions – including anxiety, depression, stress, irritability, and dissatisfaction – are increasingly recognized and prevalent. Depression is the most common MH condition worldwide, affecting approximately 300 million people. The World Health Organization (WHO) emphasizes the importance of overall well-being – both physical and mental – and highlights the need for effective learning algorithms to support accurate diagnosis.

The identification of mental health (MH) disorders remains a significant challenge, particularly among college students who frequently encounter psychological difficulties during their academic pursuits. Upon obtaining essential qualifications and seeking future career opportunities, students often face monitoring financial pressures, which are further exacerbated by unpredictable economic conditions and global crises such as COVID-19 pandemic. These compounding factors significantly complicate the detection and effective management of MH issues.

The Mental Health Questionnaire (MHQ) is an invaluable tool for diagnosing depression and related disorders. Comprising 15 items, the MHQ evaluates symptoms of depression, anxiety, and stress. Common manifestations included impaired concentration, restlessness, indecision, weight loss, feelings of worthlessness, decreased appetite, diminished interest in activities, guilt, irritability, helplessness, and suicidal ideation. Such symptoms profoundly impact academic performance and participation in extracurricular activities, underscoring the MHQ's critical role in clinical assessment and support.

Generally, college life presents numerous challenges that contribute to increased vulnerability to anxiety among students. A sample of 917 students participated in a study that employed anxiety screening instruments and looked at a variety of stressors. With a rate of 74%, the neural network showed the highest accuracy among the various machine learning (ML) techniques used[1]

In [2], the authors analysed depression, anxiety, and stress among first-year university students through a cross-sectional survey of approximately 9,479 participants using DASS-21 and academic records, employing non-parametric and correlational analyses to derive subgroup insights; however, the findings are constrained by potential response bias and the inability to establish causal relationships.

The significant investigation was covered in [3], which utilized information from MH surveys and library records to examine the connection among university students' reading habits and their propensity for depression. The study examined many text classification algorithms, which comprise KNN, SVM, and Naïve Bayes, comparing their processing times and accuracy over a range of sample sizes. Employing a polynomial model and the Naïve Bayes technique, a book classifier was created with an accuracy of 0.82.

The scientists employed both logistic regression and linear regression to create a psychological prediction model; under different error situations, logistic regression performed better. Ten students' stress levels during tests were monitored and measured using wearable sensors in [4]. Applying several classification methods with Electro Cardio Gram (ECG) and Electro Dermal Activity (EDA) data as inputs, such as SVM, linear discriminant analysis, and KNN. The results showed a recognition accuracy ranging from 86% to 91% for distinguishing among three states: relaxed, written exam, as well as oral exam.

The research work in [5] aimed at identifying depression among Bangladesh under graduate students to refer those who were at risk to a psychiatrist. The researchers created a poll after consulting with academics, counselors, and psychologists to collect pertinent data. With accuracy and F-measure scores of around 75% and 60%, respectively, Random Forest outperformed the other algorithms under evaluation. Support Vector Machine (SVM) came in second. Interestingly, Random Forest scored better than the others in terms of recall, accuracy, and reducing false negatives.

In [6], the authors predicted anxiety and depression among elderly patients using a 510-case OPD dataset assessed with HADS and WEKA-based feature selection with ten machine-learning classifiers and external validation on 110 cases, achieving high accuracy (Random Forest $\approx 91\%$) but being limited by an elderly-specific sample, reliance on demographic predictors, and the absence of multicentric data.

The study on the impact of COVID-19 on MSMEs in Pakistan [7] integrated an exploratory literature review with an online survey of 184 firms and descriptive statistical analysis to provide sector-specific policy insights, but was limited by a small convenience sample, lack of student focus, and restricted generalizability.

In [8], the authors examined the mental health status of school-going adolescents in Northeast India through a cross-sectional, school-based survey, identifying the prevalence and patterns of psychological problems in this group.

In [9], the authors carried out a systematic review of artificial intelligence applications in mental health using social media data, synthesizing the methodologies, use cases, and key challenges associated with detecting and addressing mental health issues online.

In [10], the authors explored the association between smartphone addiction, stress, and depression among university students, finding that excessive smartphone use is significantly linked to higher stress levels and increased depressive symptoms.

In [11], the authors analysed the prevalence and effects of depression, anxiety, and stress among first-year undergraduate students, highlighting the substantial mental health burden and the need for early detection and timely intervention strategies.

In [12], the authors conducted a systematic review of the Patient Health Questionnaire-9 (PHQ-9) as a depression screening tool in primary care, evaluating its reliability, validity, and effectiveness in accurately identifying depressive symptoms across diverse patient populations.

In [13], the authors examined the prevalence of emotional and behavioral problems among Bangladeshi adolescents, reporting a high burden of psychological difficulties and emphasizing the need for targeted mental health interventions.

In [14], the authors assessed mental health, suicidality, and associated health and social indicators among college students across nine Indian states, uncovering widespread psychological distress and identifying key risk factors that underscore the need for comprehensive student mental health interventions.

This paper's structure is set up as follows: The research approach used for this study is described in depth in Section 2. The outcomes of using different categorization algorithms are shown in Section 3. Lastly, Section 4 provides the conclusion, offering a comprehensive summary of the research findings.

2. Materials and Methods

The research work was conducted in the Kamrup (Metro) district of Assam, India – one of the 35 districts in the state, located in North-Eastern India and administered by the Guwahati Metropolitan Development Authority. Three colleges within this district participated in the research. The main goal of present investigation was to access knowledge, attitudes, as well as MH concerns of college students. These institutions represent a diverse range of academic disciplines.

Data for the study were collected through targeted group discussions with students and the development of questionnaires aimed at understanding their belief systems and mental well-being. A total of 156 student representatives from three different colleges were involved. Information was gathered on various aspects which might comprise MH care, family background, efforts for improving MH, and related factors. Objective of the investigations is to identify signs of depression and anxiety using five ML classifiers: DT, KNN, Logistic Regression, NB, and SVM, which are discussed here later in 2.1.3.

The research was conducted on data collected through questionnaires from $N=156$ college students. The dataset is denoted as:

$$D = \{(x_i, y_i) \mid i = 1, 2, \dots, N\} \{1\}$$

where $x_i \in \mathbb{R}^m$ is the feature vector representing answers to 15 questionnaire items for student i , encoded numerically (e.g., values 0, 1, or 2), and y_i is the target outcome (e.g., indicators of depression or anxiety).

Before training, the data was preprocessed to handle missing values and scale features. The dataset was then split into training and test sets, with proportions 80% and 20%, respectively.

Five machine learning classifiers $\{M_j\}_{j=1}^5$ are applied for prediction: Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naive Bayes (NB), and Support Vector Machine (SVM). Each model M_j learns a mapping:

$$h\theta_j: \mathbb{R}^m \rightarrow \{0,1\} \quad (2)$$

parameterized by θ_j , such that for input x_i the predicted label is:

$$\hat{y}_i^{(j)} = h\theta_j(x_i) \quad (3)$$

The models optimize parameters θ_j by minimizing a loss function $J_j(\theta)$, e.g., logistic loss for LR or hinge loss for SVM:

$$J_j(\theta_j) = \frac{1}{|D_{train}|} \sum_{(x_i, y_i) \in D_{train}} \mathcal{L}(y_i, h\theta_j(x_i)) + \lambda \mathcal{R}(\theta_j) \quad (4)$$

where $\mathcal{L}(\cdot)$ is the loss function and $\mathcal{R}(\cdot)$ is a regularizer with regularization parameter λ .

Hyperparameter tuning is conducted through cross-validation to prevent overfitting and improve generalization.

2.1 Proposed Model

The proposed model follows the pipeline shown in Figure 1, comprising the following stages:

1. *Data Collection*: Gathering questionnaire responses from students, forming dataset D.
2. *Preprocessing*: Handling missing data, encoding categorical responses into numerical features $\{x_i\}$.
3. *Feature Encoding*: Mapping discrete responses into feature space $\mathbb{R}^m$, using one-hot encoding.
4. *Model Training*: Training classifiers M_j by minimizing $J_j(\theta_j)$ over training data.
5. *Model Prediction*: For new student input x , the model outputs predicted mental health outcome $\hat{y}$.
6. *Evaluation*: Using metrics such as accuracy, precision, recall, and F1-score on test set predictions.

The evaluation metrics used are:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

where TP, TN, FP , and FN denote counts of true positives, true negatives, false positives, and false negatives. The optimal model is selected based on these metrics, balancing predictive accuracy and reliability.

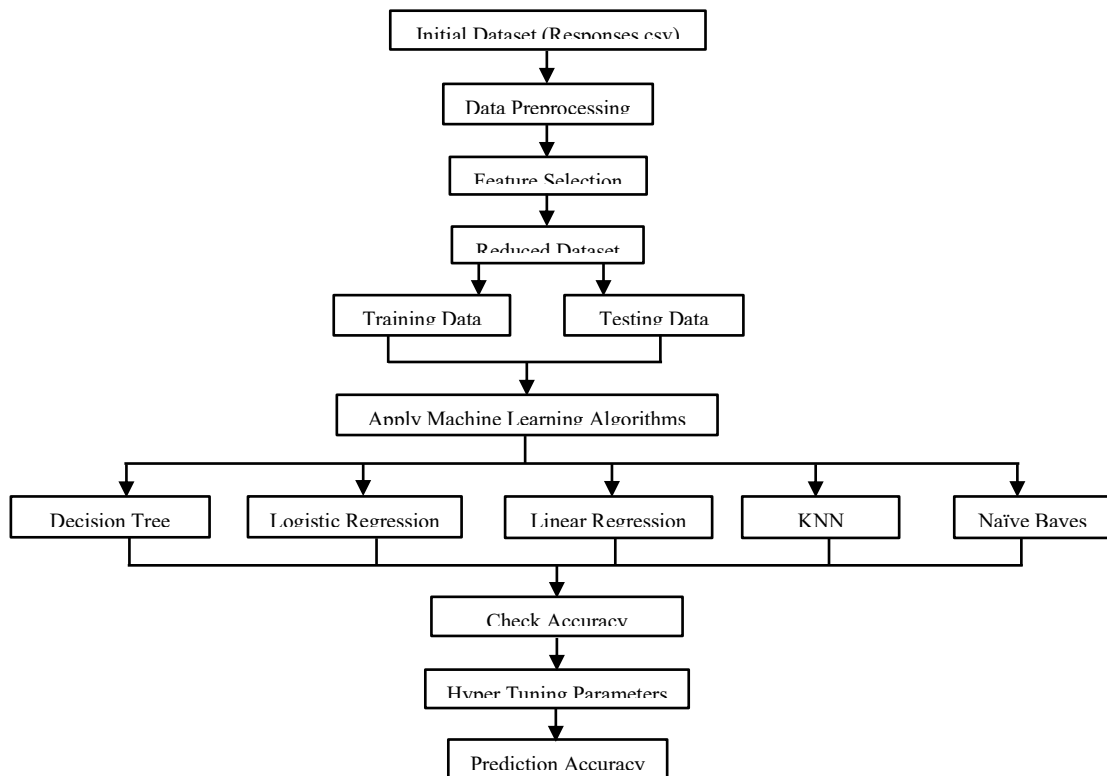


Figure1Block diagram of the proposed model.

2.1.1 Participation

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2.1.2 Questionnaire

A total of 156 college students participated in research by completing a 150-item questionnaire administered through Google Forms. After preprocessing data, it had been divided into training as well as testing sets for further analysis, with responses typically assigned numerical values ranging from 0 to 2.

2.1.3 Machine Learning (ML) Algorithms

The present work focuses on enhancing accuracy of ML algorithms by fine-tuning key parameters. Parameter tuning is essential, as different data types and tasks demand tailored model configurations. The research involves applying ML techniques to a dataset divided into 80% training and 20% testing portions, with the goal of minimizing overfitting. The selection of algorithms was based on thorough research into their performance and accuracy. Once the optimal parameters are determined, the models will be applied to the dataset to ensure maximum effectiveness.

A) Decision Tree (DT)

A DT is a supervised learning method made up of decision nodes and leaves that divide data based on predetermined standards. Data is separated at decision nodes, and each branch leads to terminal nodes, also known as leaves, which provide the ultimate results [15].

B) K-Nearest Neighbor (KNN)

Nonparametric algorithms, also known as feature similarity methods, make predictions based on the proximity of data points. Since these algorithms retain all training data, working with large datasets can lead to increased computational costs [16].

C) Logistic Regression (LR)

An efficient supervised learning technique for handling binary classification issues is LR, which makes use of a sophisticated cost function derived from the sigmoid, or logistic, function [17].

D) Naïve Bayes (NB)

Study uses a classifier based on conditional probability models called Gaussian NB, as well as a collection of classification algorithms based on Bayes' theorem, all of which are based on the same fundamental idea [18].

E) Support Vector Machines (SVM)

An approach that is frequently used for both classification and regression problems is SVM. Creating an ideal decision boundary, or hyperplane, in an n-dimensional space is how it effectively classifies fresh data points. The most important data points, called support vectors, are identified and used by SVM to form this hyperplane, which makes it a well-liked and successful option for predictive modeling [19].

2.2 Concept Analysis

The term "Mental Health" (MH) describes our social, psychological, as well as emotional health, which affects our thoughts, feelings, and actions. MH conditions affect mood, thought, and behavior. These include eating disorders, anxiety, schizophrenia, depression, and toxic behavioral patterns. A healthy mental state is marked by stable, efficient, and well-regulated emotions, reflecting a balanced interaction between the mind and body. Maintaining good MH is vital for preventing mental illnesses.

The WHO defines MH as a condition of well-being in which people are aware of their potential, effectively handle daily stress, work efficiently, and make significant contributions to their communities. The rights of people with mental diseases are outlined in United Nations Convention on the Rights of Persons with Disabilities (UNCRPD), which also draws attention to the stigma that these people frequently face. UNCRPD's approval by India presents a significant chance to update mental health legislation and better serve the needs of those with psychosocial disability.

A person with a long-term physical, mental, intellectual, or sensory impairment that substantially limits their capacity to fully and effectively participate in society is considered to have a disability, according to the Rights of Persons with Disabilities Act of 2016. According to the MH care Act of 2017, mental illness is defined as a significant disease that affects thinking, emotion, perception, orientation, or memory and hinders behavior, judgement, reality recognition, and the ability to handle daily tasks.

This Act guarantees that everyone has right to get government-funded MH therapy and medical care. Additionally, it protects the rights of those with mental illness, shielding them from cruel and humiliating treatment. Crucially, the Act decriminalizes attempted suicide and prioritizes recovery over penance.

By substituting "mental illness" for "mentally unsound", the Bhartiya Nagarik Suraksha Sanhita (BNSS) brings its definition into line with the MH care Act of 2017 [20]. The care of people with mental illness is governed by laws in majority of nations, including India. Furthermore, no one's life or personal freedom may be taken away from them unless a legally mandated procedure is followed, as guaranteed by Article 21 of the Indian Constitution [21].

2.3 Data Analysis

MH is a critical concern for college students, as conditions such as mental illness, anxiety, stress, and related challenges can significantly impact their early lives. These issues often arise from a range of contributing factors. According to the data, out of 156 respondents, 99 reported experiencing worry or stress due to past traumatic experiences, and 49 admitted to self-harming or having suicidal thoughts. Such mental states can

lead to serious antisocial behavior, often rooted in relationship difficulties, family problems, or unresolved past experiences.

More severe MH conditions, particularly those involving suicidal ideation or self harm, typically require professional intervention and treatment. These cases are diagnosed by certified medical professionals and, if left untreated, may develop into chronic mental illnesses. Early identification and intervention are essential to prevent such escalation.

Substance abuse is another major concern among college students and is often closely tied to MH struggles. Among the 156 respondents, 31 indicated that they use substances as a way to relax or feel happy. Although this represents a minority, even a small number of substance users can face serious long-term consequences and pose risks to themselves or others. Therefore, addressing these underlying issues is vital for promoting overall mental well-being in student populations.

Social media sites like Facebook, Instagram, Twitter, and WhatsApp have a big impact on how teenagers and young people develop. These platforms often feature alcohol-related content that includes attractive visuals and persuasive messaging. While many students initially turn to substances like alcohol for relaxation, continued use can lead to harmful behavioral changes that extend into adulthood. These effects may include poor academic performance, unemployment, substance dependence, criminal behavior, heightened risk of MH disorders, and even suicide.

A student's academic performance, interpersonal connections, as well as general well-being are just a few of areas of their life that can be adversely affected by alcoholism. It often results in feelings of guilt, inadequacy, and dissatisfaction when personal or societal expectations are not met. Substance addiction can also strain family resources and contribute to MH challenges such as depression, developmental delays, emotional withdrawal, apathy, and other psychological issues. As such, addiction continues to be a major concern in the modern era.

According to the study, 96 out of 156 respondents expressed concerns about family-related issues, with 60 specifically worried about problems at home. These concerns are frequently linked to disrupted family dynamics, low income, domestic violence, traumatic life events, which might comprise death of loved one or divorce, and broader social challenges like poverty and unemployment. Additionally, 72 respondents believe that their family's income affects their academic performance, and 47 reported concerns about financial instability—particularly stemming from inadequate family involvement—which may significantly influence the MH of young individuals.

MH counselors support individuals dealing with fatigue, confusion, sadness, and other MH challenges by identifying the root causes of their distress, guiding them in addressing these issues, and developing a long-term, personalized treatment plan. The study indicates that 51 respondents are interested in counseling, while 105 have not engaged with such services. Similarly, 51 respondents participate in yoga, meditation, or gym classes, suggesting limited integration between physical wellness practices and MHcare efforts.

MH is fundamental human right, essential for overall well-being. Every individual, regardless of their geographic location, is entitled to highest attainable standard of MH. Recognizing it as universal right enables people to advocate for themselves and others in pursuit of mental wellness. Unfortunately, mental illness is often stigmatized as a sign of weakness, leading to the neglect of critical MH issues.

Common signs of MH struggles encompass avoiding certain situations, self-harm, aggression toward others, or feeling persistently anxious or uneasy. MH goes beyond emotional and psychological stability—it involves the ability to employ one's cognitive as well as emotional capacities to attain demands of daily life, moreover, contribute to society effectively. Table 2 presents the statistical analysis of responses, categorized by question-wise accuracy. To analyze the relationships between the response variables in our study, we applied the Karl Spearman rank correlation coefficient. This non-parametric measure evaluates the strength and direction of association between two ranked variables, making it appropriate for ordinal data collected from survey responses.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (9)$$

where d_i represents the difference between the ranks of each pair of observations, and n is the total number of paired ranks [22].

This coefficient helped quantify correlations among various mental health indicators across participant groups. The methodology ensured a robust, scale-independent assessment of monotonic relationships in the dataset, supporting accurate interpretation of symptom cooccurrences.

Table 2 Accuracy rate based on question-wise.

Question	Options	Male	Female
Do you often feel worry or stress out?	Yes	58.73	66.67
	No	41.27	33.33
Do you often remember or think about unpleasant experience that happened in the past?	Yes	57.14	67.74
	No	42.86	32.26
Have you ever harmed yourself in the past?	Yes	50.79	26.88

	No	61.90	73.12
Have you used substances (alcohol, drugs, marijuana) to make yourself feel better?	Yes	36.51	8.60
	No	63.49	91.40
Would you like to get counselling about something that is bothering you?	Yes	25.40	37.63
	No	74.60	62.37
Are you worried about problems at home or your family?	Yes	68.25	56.99
	No	31.75	43.01
Have you ever seriously thought about killing yourself, made a plan or tried to kill yourself?	Yes	17.46	21.51
	No	82.54	78.49
How often do you get irritable, restless or anxious when you cannot play games as much as you want?	Yes	15.87	15.05
	No	84.13	84.95
Did you have any gap in your academic career?	Yes	44.44	22.58
	No	55.56	77.42
Do you ever feel that insufficient family income will effect on your academic performance?	Yes	50.79	0.43
	No	49.21	0.57
How often you felt anxious that many members in your family will affect your study?	Yes	34.92	31.18
	No	65.08	68.82
Are you engaged with any yoga or meditation or gym class?	Yes	17.46	20.43
	No	82.54	79.57
What type of device you are used in your mobile phone?	Yes	80.95	73.12
	No	19.05	26.88
How much time do you spend on social media per day?	0-2 hours	30.16	32.26
	2-4 hours	26.98	33.33
	4-6 hours	22.22	21.51
	> 6 hours	20.63	12.90
What situations or interactions make you feel anxious?	Financial problem	42.86	21.51
	Not enough sleep	17.46	11.83
	Social gatherings	19.05	22.58
	Arguments with people	12.70	34.41
	A messy home	7.94	9.68

3. Results and Discussion

From Table 2, the responses to the first 13 questions by boys' and girls' participants have been considered for analysis. Using the Karl Spearman Correlation Coefficient method as shown in equation 9, separate analyses were conducted for the "Yes" and "No" responses of boys' and girls' participants, with the corresponding correlation graphs presented in Figure 2 and 3 respectively.

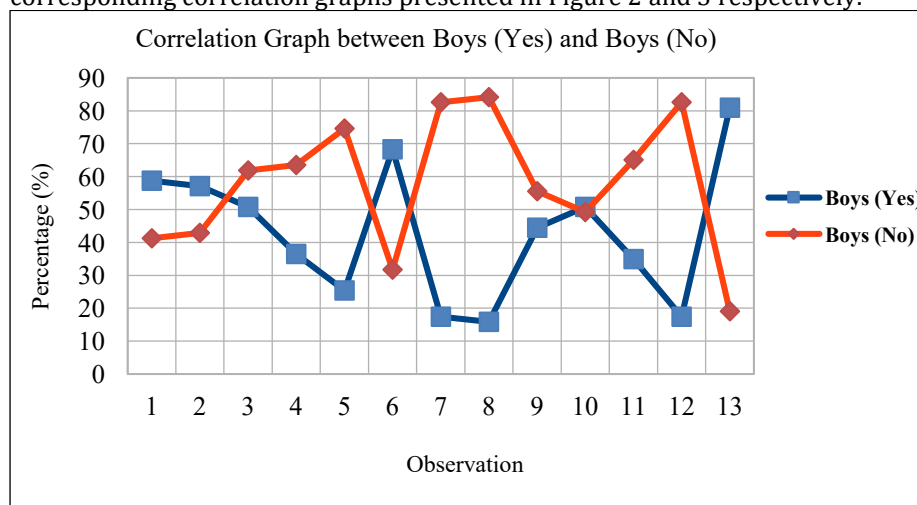


Figure2Correlation of Boys respondents.

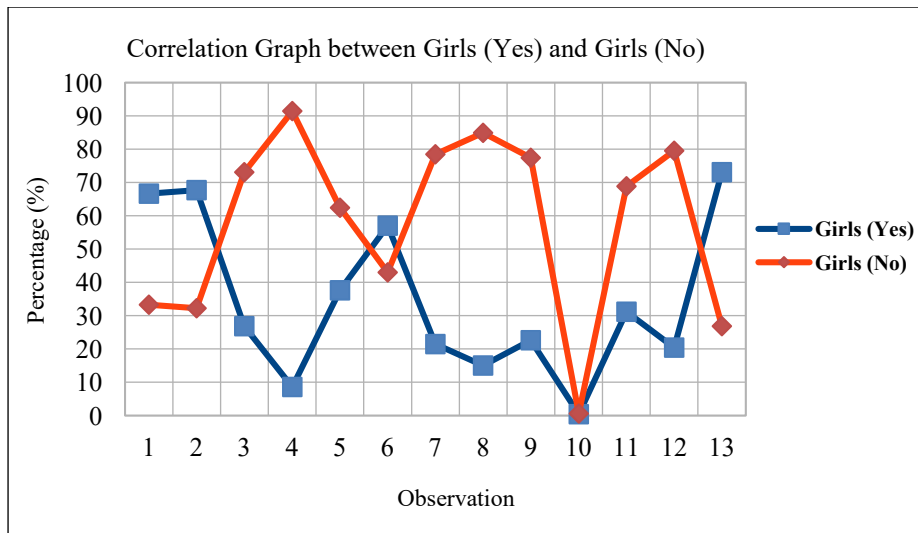


Figure3Correlation of Girls respondents.

The correlation graph illustrates the distribution or responses, with Boys (Yes) and Girls (Yes) represented in blue, and Boys (No) and Girls (No) shown in red. Each point on the line represents an observation, enabling a visual comparison of the variation in responses throughout the dataset. For boys' respondents, the correlation coefficient is $r = -0.99$, indicating a strong negative correlation between "Yes" and "No" responses. Similarly, for girls' respondents, $r = -0.44$, reflecting a moderate negative correlation between the two response types.

We thoroughly cleaned and preprocessed the dataset employing Python libraries encompassing NumPy, Pandas, and Matplotlib for enhancing model accuracy. Several ML algorithms were applied, encompassing LR, SVM, KNN, DT, as well as NB. LR model achieved a 92.4% accuracy rate in diagnosing depression, while the SVM model reached a 94.1% accuracy rate in detecting anxiety. Hyperparameter tuning was also implemented to further optimize performance. Tables 3 and 4 present the model accuracy results categorized by parameters for depression and anxiety, respectively.

Table 3Model with highest accuracy for depression

Disease	Algorithms	Accuracy
Depression	Logistic Regression	92.4%
	KNN	90.12%
	SVM	89.78%
	Decision Tree	86%
	Naïve Bayes	84.23%

Table 4Model with highest accuracy for anxiety

Disease	Algorithms	Accuracy
Anxiety	SVM	94.1%
	KNN	92.41%
	Logistic Regression	91.81%
	Decision Tree	90%
	Naïve Bayes	88%

Figures 4 and 5 respectively illustrate the highest accuracy rates achieved by the selected models in detecting depression and anxiety, as detailed in Tables 3 and 4.

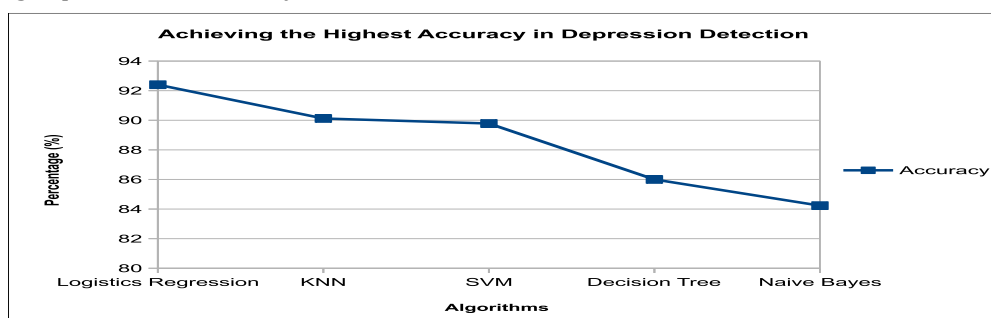
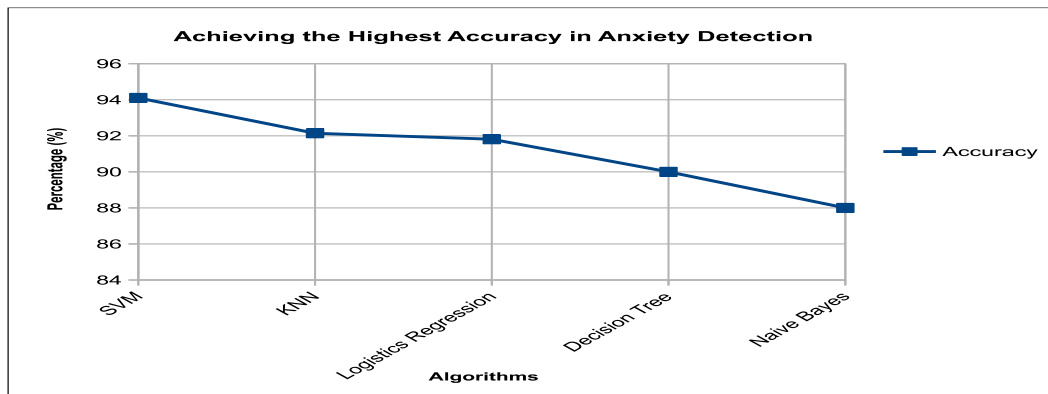


Figure4 Model achieving the highest accuracy in depression detection.**Figure5** Model achieving the highest accuracy in anxiety detection.

4. Conclusion

It is believed that both diseases were accurately identified in this study. In the near future, this process can be expanded by incorporating a wider range of diseases and integrating multiple methods alongside questionnaire-based approaches. All classifiers used in the study achieved an accuracy rate of 84% or higher. To increase accuracy and dependability, future studies should make use of bigger and more complete datasets because the current one is so small. Although the dataset size has increased, it has been noted that the accuracy trend in the graph shows a negative trajectory, which may be a sign of issues like overfitting, a restricted model capacity, or the existence of noise and class imbalance in the supplemented data.

5. Ethical Approval

Not Applicable

6. Declaration of Generative Ai and Ai-assisted Technologies

Not Applicable

7. Acknowledgement

The authors gratefully acknowledge the participants who shared their data for the purpose of this research.

7. Conflict of Interest

The authors declare that they have no conflict of interest.

8. Authors Contribution

All authors have contributed significantly to the work and approved the final manuscript.

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