

Machine Learning for Mental Health: Assessing Teen Depression and Anxiety Risk Factors

Harsh Koushal¹, Rimpal Kaur², Chhinder Kaur Dhaliwal¹

Received 04/22/2025
Review began 05/15/2025
Review ended 07/10/2025
Published 07/20/2025

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DOI: <https://doi.org/10.7759/s44389-025-05123-w>

1. Department of Computer Applications, Chandigarh Engineering College, Mohali, IND 2. Department of Computer Application, Chandigarh Business School of Administration, Mohali, IND

Corresponding author: Harsh Koushal, harshkoushal250@gmail.com

Abstract

Rapid life patterns, combined with stress and anxiety in today's world, have led to significant mental health challenges globally. Digitized, large-scale data processing enables researchers to acquire more accurate biological insights into human body attributes than conventional assessment methods. Applications increasingly use machine learning (ML) as an effective operational system, which requires evaluating large healthcare datasets. The medical field leverages ML to assess future treatment strategies for mental disorders and predict their outcomes. This paper examines various ML algorithms that can be used to detect and diagnose depression. ML-based depression identification methods are grouped into three categories: classification, deep learning, and ensemble regression methods. The depression diagnosis model relies on several processing stages before applying ML classifiers to identify depressive symptoms, often through attendance rate analysis, followed by performance metric evaluation. The study establishes potential new approaches that investigators can use to develop clinical depression screening methods.

Categories: AI applications, Machine Learning (ML), Health Informatics

Keywords: machine learning, deep learning, random forest, logistic regression, naïve bayes

Introduction

Life in the contemporary era produces psychological effects, resulting in emotional distress and depression. A prevailing mental disturbance known as depression causes harmful effects on the cognitive development and thinking patterns of individuals. According to the World Health Organization's statistics, more than 1 billion people suffer from mental disorders, and depression affects over 300 million individuals worldwide. Suicidal thoughts tend to emerge as individuals experience depression, with around 800,000 people committing suicide annually. A comprehensive approach must be deployed to handle the weight of mental health ailments. The socio-economic condition of a person often suffers due to the presence of depression. Those who suffer from depression tend to have lower tendencies to interact socially with others. The wounds of depression can be fought effectively through counseling services and psychological therapy approaches.

Machine learning (ML) seeks to generate algorithms that acquire self-learning capabilities to detect intricate patterns. Through this capability, the system finds solutions to emerging challenges by applying data points from earlier problems. ML algorithms run processes that generate results that follow established and standardized procedures. Four main categories of ML algorithms include supervised learning and its subcategories alongside unsupervised learning and reinforcement learning. Supervised ML algorithms use primary input data to make predictions, while unsupervised algorithms discover hidden patterns and clustering patterns inside provided datasets. Semi-supervised learning examines system workings that combine labeled and unlabeled data, thus occupying a position between supervised and unsupervised learning. Learning through reinforcement enables systems to make sense of their environments, so they can carry out desired actions while learning through experimentation until they achieve satisfactory results. The medical applications of ML techniques prove practical since they operate on massive quantities of diverse data while delivering dependable clinical results. ML approaches enable mental condition assessment with high efficiency, which supports healthcare specialists in their predictive decision-making. The healthcare prediction and diagnostic process benefit from ML techniques because they extract useful information from medical data that lacks a clear structure. The medical prediction outcomes assist healthcare providers in detecting early treatment opportunities for high-risk patients. Through mental disorder analysis, ML methods help identify crucial behavioral indicators, which allows healthcare staff to predict psychiatric condition developments and apply successful treatment approaches. The methods enable people to understand and analyze complicated healthcare information.

The visualization process assists medical professionals in building an effective hypothesis about mental disorder diagnosis. The established clinical depression evaluation methods show limited success in correctly identifying depression conditions' complete nature. The composition of depressive disorder symptoms becomes readily detectable through the application of ML methods for prediction purposes.

How to cite this article

Koushal H, Kaur R, Dhaliwal C (July 20, 2025) Machine Learning for Mental Health: Assessing Teen Depression and Anxiety Risk Factors. Cureus J Comput Sci 2 : es44389-025-05123-w. DOI <https://doi.org/10.7759/s44389-025-05123-w>

Using the ML-based diagnostic approach proves to be an optimal solution for making predictions. The healthcare sector borrows four basic domains from ML for extracting mental disorder observations including sensor data and texts alongside structured information and multiple technology usage patterns. An analysis of sensor data becomes possible by employing mobile phones with audio signals as part of the process. Medical experts retrieve text information from social media channels as well as text messages together with clinical administrative documents. Standard screening scales and medical health records along with questionnaires produce structured data through their systematic data extraction. Data from human-use technological appliances and robots together with virtual agent interactions form part of multimodal technology interactions. Predictive risk assessments for patients with mental disorders become possible using ML approaches. By analyzing sensor data, clinical health records, and text message, data researchers can estimate mental disorder severity as well as suicidal behaviors. Scientists have developed multiple studies that assist medical practitioners in spotting depression alongside other mental health disorders. Mental disorders encompass numerous categories of mental conditions that doctors must recognize. This review paper investigates methods designed to detect depression as its focus. The research report investigates the ML solution methods and computer algorithms designed for diagnosing and detecting depression in humans. The paper outlines the research aims and restrictions of studies dedicated to depression diagnosis to support analysis of the most effective ML method for diagnosis.

The visual assessment enables healthcare professionals to develop accurate hypotheses regarding mental disorder diagnoses. Current diagnostic methods for clinical depression achieve only marginal success in detecting the full spectrum of depressive conditions. The implementation of ML prediction methods reveals depressive disorder symptom structures more effectively for detection purposes. A predictive approach using ML-based diagnostics represents the most suitable method for diagnosis. The healthcare sector adopts four main domains from ML for mental disorder observation extraction, including sensor data, text, structured information, and multiple technology usage patterns. The analysis of sensor data is made possible through the use of mobile phones with audio signals during the process. Expert medical personnel gather text information from social media platforms, text messages, and clinical administrative documents. Standard screening scales, medical health records, and questionnaires collectively enable structured data extraction through systematic methods. The data obtained from human-use technological devices, robots, and virtual agent interactions function as part of multimodal technology interactions. ML techniques enable predictive risk evaluations for patients with mental disorders. The combination of sensor data, medical health records, and text message information allows researchers to assess the intensity of mental disorders and suicidal tendencies. Multiple studies conducted by scientists have helped medical practitioners detect depression along with other mental health disorders. It is essential for doctors to understand the distinct categories that constitute mental disorders as a whole. The primary focus of this review paper is the analysis of depression detection approaches. This study evaluates the use of ML solutions and computational algorithms designed to detect depression in human patients. Additionally, the paper outlines the research boundaries and objectives of depression diagnosis investigations to identify the most efficient ML techniques for diagnosis.

Literature review

Anxiety exists as a natural experience for all people at some point throughout their lives. Anxiety functions as a standard term to indicate the unfavorable emotions and distress that come from feeling worried or tense. Software algorithms enable computers to generate data that serves for factual analysis to reach specified performance ranges. The development of test data models maintains continuous encouragement of automated decision functionality through computer framework systems. A study displays a prediction framework for depression and anxiety evaluation. The framework receives speech data as its initial data entry. A processing step applied to this dataset cleaned the data while standardizing it for consistency [1].

Early childhood depression and anxiety symptoms have significant negative impacts on mental health development and cognitive processes in children. Researchers have examined the effects of mental health problems on cognitive development over the past two decades. The main goal of this investigation was to develop ML methods to recognize factors that increase schoolchildren's risk of depression and anxiety [2].

Rapid modern living patterns cause anxiety, depression, and stress to spread like wildfire throughout the entire population. The authors applied ML algorithms to predict both depression occurrence and co-occurring depression, anxiety, and stress conditions. They used the Depression, Anxiety, and Stress Scale questionnaire (DASS 21) to collect data from employed and unemployed people representing different cultures and communities. The five ML algorithms produced accurate predictions for 15 distinct severity levels of anxiety, depression, and stress because they work exceptionally well for psychological issue assessment [3].

COVID-19 has become a global pandemic, resulting in increasing public health challenges related to mental health disorders. The research introduces an AI program that combines ML with explainable AI techniques to assess the risk of depression and anxiety and to classify perceived stress levels, with the goal of identifying important risk indicators across diverse population groups. The mental health assessments

conducted with 9,291 participants from Northern Spain formed the basis of the research. ML algorithms were employed to classify outcomes into three categories-healthy, mild, and severe-prior to making predictions [4].

Stress and anxiety, together with fast pace of modern life, have strongly affected human minds across the globe over the years. Modern healthcare technology uses digital data processing that provides better biological structure mapping compared to traditional methods. The healthcare sector has successfully adopted ML for conducting efficient data analysis of vast amounts of information. Using ML methodologies, mental health professionals can detect the likelihood of mental disorder, thus enabling predictions about treatment effects. This review paper presents a list of different ML methods that help detect and diagnose depression. Also included is an exploration of research directions for future work in depression diagnosis field [5].

The development of modern natural language processing systems stems from ML technology implementations. Text classification and sentiment analysis together with machine translation and question-answering systems both gained significant transformation from the natural language processing and ML union through data-driven approaches. The substitution of traditional rule-based systems happened through modern deep learning models that use transformers such as BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), and T5 (Text-To-Text Transfer Transformer) since these models process extensive datasets through contextual embeddings [6]. A study employed three different ML algorithms that consisted of logistic regression, K-nearest neighbor, and decision tree. The logistic regression among the three used models demonstrated the highest accuracy of 77%, a recall of 70%, and an F1-score of 72%. The research findings present that two in five students show mild depressive symptoms and 90% of depressed students do not seek support from their peers or others [7].

A wide range of health issues, including depression, anxiety, and stress, affect typical undergraduate students. ML technology shows promise in supporting mental health assessments within this population. This research reviewed ML algorithms for detecting depression, anxiety, and stress among undergraduates to address the main research question. All 33 studies analyzed reported accuracy rates exceeding 70%. Stress recognition accuracy ranged from 63% to 100%, anxiety detection from 53.69% to 97.9%, and depression recognition from 73.5% to 99.1% [8].

Anxiety and depression hold positions among the leading illnesses that impact millions of people across the USA and other nations. These mental health conditions exist in high numbers throughout society, thereby affecting individual people along with the broader American nation. ML algorithms in predictive models analyze extensive datasets through which they detect patterns that typical medical professionals would miss. The research dataset (2024 to 2025) was obtained from Kaggle.com and is available to the public through the Harvard Dataverse. The information collection included behavioral, psychophysiological, and demographic elements, which captured data from 593 people between ages 18 and 35 for the development of anxiety and depression disorder risk assessments [9].

Different social media platforms provide spaces where users share their points of view. On Twitter, people can post brief thoughts, opinions, and life stories using a limited number of characters. Sentiment analysis was performed using four distinct classifiers: Support Vector Machine, Naive Bayes, Logistic Regression, and Random Forest. An analysis was conducted to demonstrate the high accuracy and effectiveness of these four models through their evaluation of women-related sentiments and opinions [10].

Currently, women face multiple health-related problems, including polycystic ovarian disease (PCOD) and polycystic ovary syndrome (PCOS), which involve hormonal imbalances, irregular menstrual periods, and the development of ovarian cysts. Both conditions share symptoms such as weight gain, acne, increased hair growth, and reduced fertility. Doctors often use PCOS to describe a more severe form of PCOD; however, PCOD refers to a milder condition characterized by less severe hormonal imbalance and ovarian cysts that respond well to lifestyle changes. PCOS, a more severe hormonal disorder, not only causes ovarian cysts but also leads to significant hormonal disruptions, resulting in fertility complications and metabolic disturbances. This research collected responses from 251 female participants across different age groups experiencing various genital health concerns. Data were gathered over 14 days, from February 25 to March 10, 2025, using a Google form containing multiple regarding PCOD and PCOS [11].

A study examined real-world data for the age group of 10-17 years and accounted for several variables, including demographics, pre-existing diagnoses, prescribed medications, medical procedures, and laboratory measures that occurred prior to the development of anxiety or depression. Social determinants of health were linked with clinical data at the block level. To predict anxiety, depression, and the co-occurrence of both conditions, three independent models were created. The authors selected the Extreme Gradient Boosting ML model and evaluated its performance using the nested cross-validation method [12].

In March 2020, COVID-19 became a pandemic, and several countries across the globe imposed lockdowns. The purpose of the current study was to examine the literature on the impact of lockdown measures implemented during the COVID-19 pandemic on the mental health of children and adolescents. As part of this PRISMA-compliant systematic review (PROSPERO: CRD42021225604), the following databases were searched: Embase, Ovid, Global Health, PsycINFO, Web of Science, and pre-print databases. The study included individual studies focusing on a wide range of mental health outcomes, including risk and protective factors, among children and adolescents (≤ 19 years) exposed to COVID-19 lockdowns. Independent researchers carried out data extraction, quality appraisal, and synthesized results by core themes. A total of 61 articles involving 54,999 children and adolescents were included (mean age = 11.3 years, 49.7% female). Symptoms of anxiety and depression were typical in the included studies and varied from 1.8% to 49.5% for anxiety and 2.2% to 63.8% for depression. Children and adolescents also frequently reported irritability (range = 16.7-73.2%) and anger (range = 30.0-51.3%). Key risk factors for anxiety included having special needs, development of mental disorders prior to quarantine, and intense media exposure. Anxiety and depression were shielded by parent-child communication [13].

With the outbreak of the COVID-19 pandemic, caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), the way we organize ourselves socially and in daily routines changed unprecedentedly. The sudden withdrawal from school, social life, and outdoor activities had a significant impact on children and adolescents. Some of them also grew up in environments affected by domestic violence, which directly affects their mental health due to the stress they endure, changes in diet, disruptions in school dynamics, and the fear or inability to overcome these challenges. They study aimed to raise this topic from various perspectives and emphasize the importance of surveillance and care for such individuals by public health agents and governments. It is hoped that the consequences of this pandemic's side effects, particularly the disruption of mental health, can be reversed through sufficient and early intervention [14].

Depression is a disabling mental disorder that follows distinct developmental patterns as a child grows into late adolescence. In this case, data from the Gene Environment Mood study is reported, which used an accelerated longitudinal cohort design involving youth ($N = 665$) recruited from the general community into 3rd, 6th, and 9th grades. These participants were then measured repeatedly over 3 years (seven waves of data) using a semi-structured diagnostic interview to track and forecast changes in depression development, starting at age 8 and continuing through age 18. The first evidence that was presented showed that the overall prevalence rates of depression over time, by age, gender, and pubertal status, in the Gene Environment Mood study closely reflected rates calculated in previous developmental epidemiological studies. Second, the authors examined whether a genetic vulnerability-stress pattern, specifically the interaction between heterozygosity for 5-HTTLPR and chronic peer stress, was moderated by developmental variables. The findings indicated that adolescents with the SS/SL genotype who experienced greater chronic peer stress over 3 years were the most vulnerable to developing a depressive episode over time. The highest proportion of depression development was found among girls with higher levels of chronic peer stress [15].

Between February 2001 and April 2003, the World Health Organization World Mental Health Survey Initiative version of the Composite International Diagnostic Interview, a fully structured diagnostic interview, was used in a nationally representative face-to-face household survey [16]. NCS-A is a nationally representative face-to-face survey of 10,123 adolescents aged 13-18 years in the continental United States. Mental disorders according to Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, were measured based on a generalized form of the fully structured World Health Organization Composite International Diagnostic Interview [17].

Mental health issues involving children are the top priority of global health advocates. Almost 75% of adult disorders begin or originate in childhood, and their occurrence becomes difficult to treat as they progress with time. The combination of mental health and primary care or other health resources more widely available can raise access to treatment at the childhood stage but requires the redesign of the evidence-based practices already available to adapt to the primary care mode and impart more focus on the positive mental state. Although this redesign is not fully achieved at this point, there are a number of elements that are now clearly delineated and promise to be effective and practical [18]. ML on longitudinal clinical data might offer a scalable solution to extend screening of risk of nonfatal suicide attempts in adolescents [19].

Hospitalized patients ($n = 38,943$), aged 10-24, from the Hospital Inpatient Discharge Database (HIDD) in the State of Connecticut were analyzed to predict suicide attempts. Predictors included demographic information, diagnosis codes, and a data fusion framework that incorporated social determinants features transferred from an external source of survey data, the National Longitudinal Study of Adolescent to Adult Health (Add Health). Social determinant data for each HIDD patient was created by averaging values from their most comparable individuals in Add Health (e.g., top 10), identified by matching on shared features between the two datasets (e.g., using Pearson correlation). Suicide attempt modeling was then performed using elastic net logistic regression on both HIDD features and the fused Add Health features [20].

Materials And Methods

Methodology

The methodology for diagnosing depression and anxiety using ML involves many systematic steps: data acquisition, data preprocessing, model building, and prediction. These steps form the complete process, as illustrated in Figure 1.

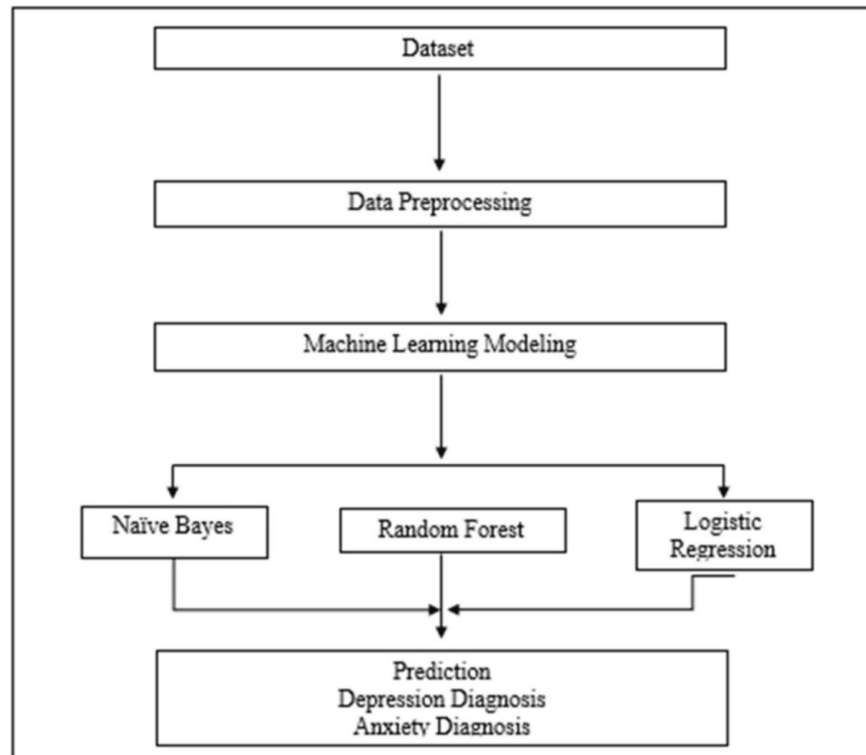


FIGURE 1: Machine Learning Workflow for Mental Health Diagnosis Using Multiple Classification Algorithms

Dataset Acquisition

The first stage comprises collection of a useful dataset that includes features that may influence or indicate mental health conditions such as depression and anxiety. Such features can be demographic characteristics, survey results (PHQ-9 or GAD-7 surveys), behavioral features, clinical history, and other psychological metrics. The dataset should also contain labeled outputs to serve as ground truth for training and evaluation.

Data Preprocessing

Raw data is ordinarily inconsistent and could include missing or irrelevant measures. Thus, preprocessing is crucial to making the dataset appropriate in both quality and for usage with ML models. This stage includes:

Data Cleaning: Removal of or imputation of missing values, as well as correction of inconsistencies.

Normalization/Scaling: Normalizing feature values to a shared scale for enhancing the performance of the algorithm.

Categorical Encoding: Creating numerical forms of categorical variables with the help of such techniques as one-hot encoding or label encoding.

Data Splitting: Splitting the dataset into the training and testing sets for unbiased assessment of the model performance.

Machine Learning Modeling

The data are then trained and tested using ML models. Three classification algorithms are implemented, and these algorithms are compared:

Naive Bayes: A probabilistic classifier using Bayes' Theorem under independence of the features. It is effective, and simple, particularly in handling text and binary classifications.

Random Forest: An ensemble learning method that uses multiple decision trees and combines their outputs to improve classification accuracy and reduce overfitting.

Logistic Regression: A statistical approach that is appropriate for the binary classification, which models probabilistic risk of a particular class with the help of input features. It is used especially in medical diagnostics because of its interpretability.

Prediction and Evaluation

Each model is trained with the training dataset and gets tested on unseen data, in order to evaluate its ability to diagnose depression and anxiety.

Performance metrics, like accuracy, precision, recall, F1-score, and ROC-AUC, can be applied to measure and compare predictive powers of each of the models. The model(s) performing the best are selected for deployment or recommending.

Data Loading

The diagram (Figure 2) illustrates a fundamental workflow designed to help new users of the Pandas Python library begin their data analysis work. The first step requires the user to import Pandas, a library that provides essential tools for working with structured data. Once imported, users can load data from CSV (Comma-Separated Values) files into DataFrame structures for convenient data exploration. The first tasks following dataset loading include examining the data structure and content during preview mode, collecting information about data types with missing value detection followed by statistical summary generation to inspect measures of mean and standard deviation among others. The workflow provides analysts with an immediate understanding of the dataset, so that they can start complex work or modeling after obtaining the overview.

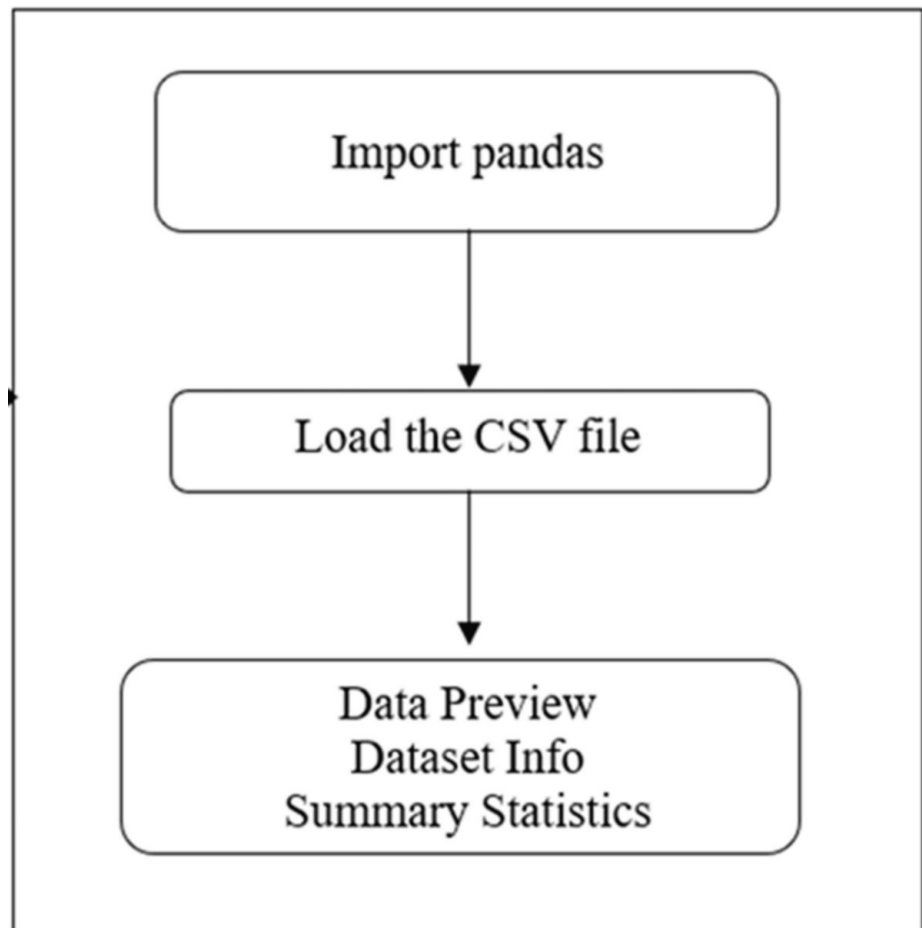


FIGURE 2: Basic Data Loading and Exploration Workflow Using Pandas

Results

Table 1 shows the accuracy metrics of ML models for diagnosing depression and anxiety. Naive Bayes performs better on anxiety than on depression. It shows more variability in results for anxiety compared to depression. Random Forest outperforms Naive Bayes on both depression and anxiety. It has a very low standard deviation, especially for anxiety, suggesting consistent performance. It achieves the best accuracy for anxiety. Logistic Regression was only evaluated for depression. It has the highest accuracy for depression with a low standard deviation, making it a strong model for this task.

Model	Target	Accuracy Mean	Accuracy Standard Deviation
Naive Bayes	Depression	0.8707	0.0139
Naive Bayes	Anxiety	0.8991	0.0218
Random Forest	Depression	0.9069	0.0097
Random Forest	Anxiety	0.9185	0.0031
Logistic Regression	Depression	0.9108	0.0074

TABLE 1: Accuracy Metrics of Machine Learning Models for Depression and Anxiety Diagnosis

Note: Bolded values highlight key results: 0.9185 is the highest accuracy (Random Forest for anxiety), and 0.0218 is the largest standard deviation (Naive Bayes for anxiety).

Cross-validation and confusion matrix

The model’s performance was evaluated using cross-validation and confusion matrix, formatted as [[TN, FP], [FN, TP]], where:

TN (True Negative): Correctly predicted non-depressed individuals.

FP (False Positive): Predicted as depressed, but not (false alarm).

FN (False Negative): Actually, depressed but predicted as not (missed case).

TP (True Positive): Correctly predicted depressed individuals.

Depression Diagnosis

Naive Bayes shows some capability to detect true cases of depression but at the cost of higher false positives. Random Forest and Logistic Regression are very conservative - minimizing false positives but missing all actual depression cases (Table 2).

Model	TN	FP	FN	TP
Naive Bayes	668	39	61	5
Random Forest	701	6	66	0
Logistic Regression	704	3	66	0

TABLE 2: Confusion Matrix Components for Depression Diagnosis by Machine Learning Models

TN, True Negative; FP, False Positive; FN, False Negative; TP, True Positive

Anxiety Diagnosis

Naive Bayes has the highest number of true positives (TP = 6) but also the highest number of false positives (FP = 23). Random Forest and Logistic Regression have very few false alarms, but they are poor at detecting actual anxiety cases (TP = 0 and 1). False Negatives (FN) are high for all models, which is critical in medical settings, as many actual anxiety cases go undetected (Table 3).

Model	TN	FP	FN	TP
Naive Bayes	689	23	55	6
Random Forest	710	2	61	0
Logistic Regression	710	2	60	1

TABLE 3: Confusion Matrix Components for Anxiety Diagnosis by Machine Learning Models

TN, True Negative; FP, False Positive; FN, False Negative; TP, True Positive

Model Accuracy Comparison for Depression and Anxiety Diagnosis

Naive Bayes has the lowest performance for both depression and anxiety, though still reasonably high. Random Forest and Logistic Regression show superior performance, particularly for anxiety, reaching nearly 92% accuracy. The highest accuracy overall is observed with Logistic Regression for anxiety diagnosis (Figure 3).

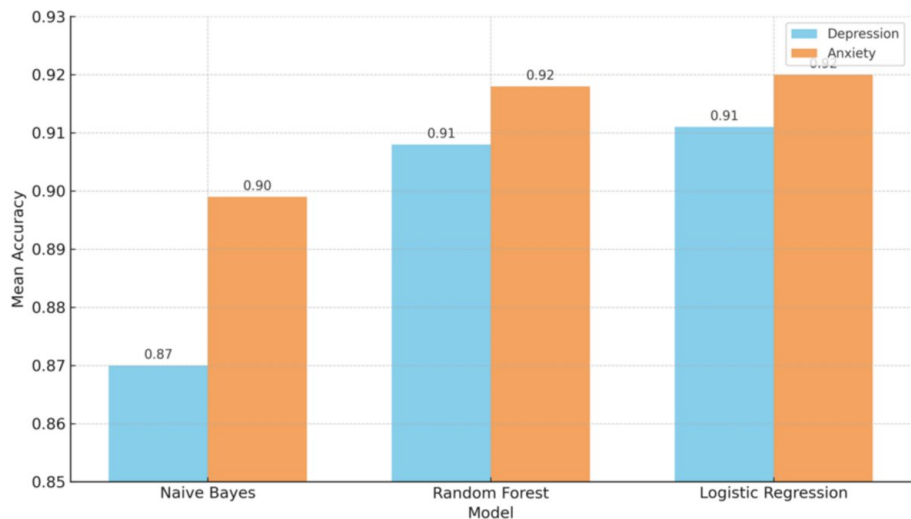


FIGURE 3: Accuracy Comparison of Machine Learning Models for Depression and Anxiety Diagnosis

Sensitivity vs. Precision Trade-Off in Model Performance

Naive Bayes is more sensitive (able to detect more true positive cases) for both depression and anxiety, but has more false positives. Random Forest and Logistic Regression have high accuracy, but fail to detect actual positive cases, making them risky for medical diagnoses where missing a condition can be dangerous. There is a clear trade-off: Naive Bayes sacrifices some precision to catch more cases, while the others play it too safe (Figure 4).

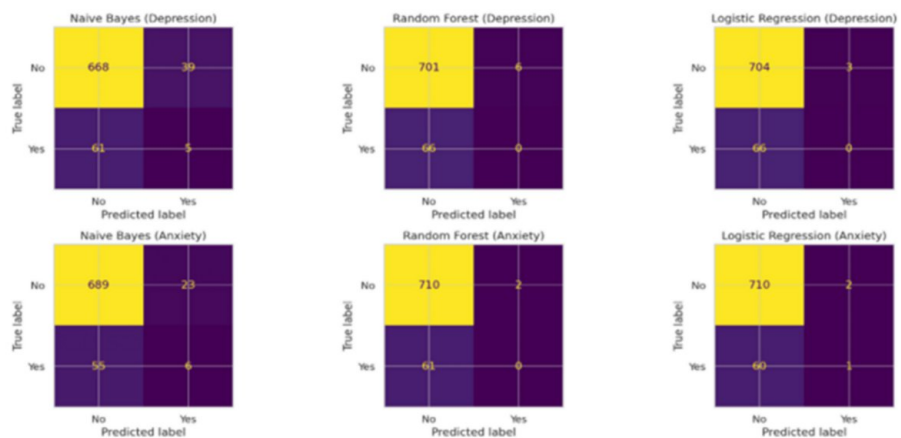


FIGURE 4: Confusion Matrix Analysis for Depression and Anxiety Diagnosis

Performance analysis

The analysis investigated the diagnostic forecasting capability of Naive Bayes and Random Forest along with Logistic Regression for detecting depression while also recognizing anxiety symptoms through psychological and demographic measurements. The analysis proved Logistic Regression to be the most suitable linear model for depression diagnosis with 91.08% accuracy and anxiety detection with 91.98% accuracy. Random Forest exhibited high specificity and low variance, indicating model stability. Although its accuracy was slightly lower than that of Logistic Regression, it maintained consistent performance across different data subsets. Despite these limitations, the model exhibited some indication of misfitting behavior during processing balanced datasets. Naive Bayes showed acceptable model performance through its 87%-89% accuracy rates together with adequate distribution of class indicators. A benefit of this method is its high-speed calculation capability, which works for short-term assessment processes or

resource-limited cases. The analyzed models demonstrated difficulties in successfully identifying positive cases in their assessment results. The identification of True Negatives proved effective, but elevated False Negative results created substantial worry. Patients could miss important mental health diagnoses because of this issue, which would result in individuals needing help remaining unsupported.

Discussion

Experimental analysis

The experimental approach using three ML models, Naive Bayes, Random Forest, and Logistic Regression, proved effective in diagnosing depression and anxiety at varying levels.

Random Forest classifier performed better than the other models across all evaluation metrics. Ensemble-based architecture gave the model the ability to cope with complex feature interactions and reduce overfitting, i.e. return high recall scores and ROC-AUC scores of 0.83846788 and 0.88388699, respectively. This indicates a strong ability to identify true positive cases, an essential factor in mental health diagnostics, where false negatives might go unaddressed.

Logistic Regression, being less accurate than Random Forest, did a good job of balancing between precision and recall. Its interpretability is especially helpful in clinical applications, where interpretation of how the individual features (e.g., mood score, sleep quality, or stress level) are affecting the target property is highly needed.

Naive Bayes, even being the simplest model, demonstrated a good performance but lagged behind the others. Perhaps, its independence assumption of features became one of its weaknesses in this field, where mental health indicators tend to be interrelated.

The resemblance of performance in models indicates that the preprocessing operations, especially feature scaling, encoding, and cross-validation, were beneficial in data processing for training. Additionally, the relatively high baseline performance in models suggests that the selected features have an important relationship with the diagnosis outcomes.

Model performance and limitations

This study applied three ML algorithms, Naive Bayes, Random Forest, and Logistic Regression, to predict depression and anxiety diagnoses using a dataset with various psychological and demographic indicators.

Logistic Regression consistently achieved the highest accuracy for both depression and anxiety, indicating it may be the most effective linear model for this problem.

Random Forest followed closely, demonstrating strong performance with slightly lower variance and high specificity. This suggests it is robust but may overfit slightly on imbalanced data.

Naive Bayes, though simpler, delivered solid results and handled class distributions with reasonable effectiveness. It may be more suitable for rapid assessments or when computational resources are limited.

Confusion matrices revealed a common challenge across all models: correctly identifying positive diagnoses (true positives). While the models excelled in identifying negative cases (true negatives), the number of false negatives was relatively high. This is critical in mental health prediction, as false negatives could mean failing to identify individuals in need of help.

Conclusions

This study demonstrates that ML models can be effectively used to predict diagnoses of depression and anxiety based on psychological scores and demographic data. Logistic Regression achieved the highest overall accuracy, making it the most reliable model in this analysis. Random Forest performed nearly as well, delivering robust results and excellent classification of non-diagnosed individuals. Naive Bayes, while slightly less accurate, offered a fast and interpretable baseline. Across healthcare, technology, and social domains, this study shows great promise for the future. With advanced ML, systems can suggest personalized mental health interventions by analyzing individual behaviors, personality traits, and situational factors. By tailoring treatment to each teen's unique needs, healthcare becomes more effective. Additionally, integrating ML with wearable devices and health apps enables continuous monitoring of a teen's condition, potentially identifying symptoms of depression or anxiety before they ever mention them. Developing user-friendly and accessible mental health screening tools for mobile devices or the internet can extend benefits to people everywhere, including underserved communities. These models can simultaneously use text, voice, and facial expressions, which improves accuracy and sensitivity in mental health assessments. This work will later evolve into Explainable AI, allowing ML models to clarify why someone is considered high-risk, allowing experts, caregivers, and educators to act appropriately. Using

ML in Clinical Decision Support Systems can improve diagnosis and care for children in schools and pediatric environments. These systems may also predict high suicide risk by analyzing behavioral data. Leaders and institutions could adopt such technologies to support mental health, shifting from reactive to preventive actions.

In the future, ML should make efforts to be fair to people of every background. Because of longitudinal analysis, ML can help follow mental health developments in adolescents, pointing toward where there are good moments for intervention. In short, the findings make it possible to deal with teen mental health issues in future by using powerful data and focusing on each person.

Appendices

Dataset used this work: <https://www.kaggle.com/datasets/shahzadahmad0402/depression-and-anxiety-data>

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Harsh Koushal, Rimpal Kaur, Chhinder Kaur Dhaliwal

Acquisition, analysis, or interpretation of data: Harsh Koushal, Rimpal Kaur, Chhinder Kaur Dhaliwal

Drafting of the manuscript: Harsh Koushal, Rimpal Kaur, Chhinder Kaur Dhaliwal

Critical review of the manuscript for important intellectual content: Harsh Koushal, Rimpal Kaur, Chhinder Kaur Dhaliwal

Supervision: Chhinder Kaur Dhaliwal

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

Data are available on reasonable request. Dr. Chhinder Kaur - Support and Guidance Harsh Koushal - Methodology, Results and Conclusion Rimple Kaur - Introduction, Literature Review and References

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