Predicting Student Depression using Machine Learning

Md. Rashed Fahim Chowdhury
Dept. of Computer Science and Engineering
BRAC University, Dhaka, Bangladesh
rashed.fahim.chowdhury@g.bracu.ac.bd

Asheq Mahmud Chowdhury
Dept. of Computer Science and Engineering
BRAC University, Dhaka, Bangladesh
asheq.mahmud.chowdhury@g.bracu.ac.bd

***Abstract*—The rising rates of depression among students are a major mental health crisis in the world, as they impact the performance of the students, with disastrous results. Conventional methods of diagnosis tend to be reactive, which makes data-driven, proactive, early detection and intervention tools all the more crucial. In this paper, the authors explore the performance of different machine learning models in terms of the likelihood of depression among a group of students. A developed structured dataset based on demographic, academic and lifestyle predictors was used to train and test six machine learning algorithms on a held-out test set. These were Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Naive Bayes and a Neural Network. The variance of the predictive performance was statistically different in the models with the highest accuracy score of 84.11% and 84.29% of the Neural Network and the Logistic Regression models respectively. This showed a good ability to identify at-risk individuals correctly. On the other hand, the Naive Bayes classifier did not work well and the accuracy is also low at 61.66%. After being informed by related research, feature analysis highlighted the critical role of academic pressure and the duration of time spent in bed as depressive predictors. The results of the study confirm that machine learning is a feasible and effective, data-driven solution to supplement the existing diagnostic tools used to detect student depression, which will serve as a platform to create specific, proactive intervention initiatives to enhance student well-being.**

***Index Terms*—Depression, Machine Learning, Data Analysis, Logistic Regression, Decision Tree, Random Forest, Multilayer Perceptron.**

I. Introduction

Mental health is a vital aspect of overall health, and depression is a widespread and acute issue around the world, with millions of people being impacted every year [4]. University students are a highly susceptible group: they are likely to face a combination of academic stress, social change, financial strain, and new independence, which makes them particularly vulnerable to depressive disorders development [2]. The impact of unattended depression on this group of the population is devastating as not only do they perform poorly in school and develop social withdrawal, but they are also at a higher risk of self-injury and committing suicide. Although mental health problems among students are prevalent in campuses, most of them fail to seek or get proper assistance. The main barriers are social stigma, lack of awareness of resources available and the sheer inability of university counseling services to respond to a huge demand [1]. This disparity between the accessibility and the actual delivery of mental health care illustrates a critical necessity to find new, scalable, and proactive ways to identify at-risk students before their symptoms can become a crisis. Artificial intelligence and machine learning (ML) development has handed a revolutionary chance to overcome this challenge. Multi-dimensional datasets with complex patterns can be analyzed with ML models to find hints of subtle patterns and predictors of depression that may not be visible to humans [3]. These models can use data including academic records, demographic data, self-reported lifestyle factors, and others to develop predictive tools, which could be used to identify students at high risk. The objective of this research is to create and test a machine learning algorithm to predict depression in university students at an early stage. In doing so, we train and evaluate the performance of various supervised machine learning algorithms such as Logistic Regression, Random Forest, Decision Tree, Naive Bayes, K-Nearest Neighbors (KNN) and a Multi-layer Perceptron (MLP) Neural Network. With the help of a dataset that contains academic, social, and psychological factors, this paper aims to develop a valid and trustworthy instrument that can be used as a screening tool. The final aim is to have a system that will allow educational institutions to provide a more supportive academic environment through timely and targeted interventions to increase student well-being.

II. Literature Review

Research on predicting and analyzing depression among students has grown substantially in recent years, driven by the recognition that young adults are especially vulnerable to mental health challenges. For example, Steinmetz et al. (2024) investigated the emergence of depressive symptoms during quarantine in Argentina using a longitudinal survey of nearly 1,500 college students and compared logistic regression, random forest, and support vector machine models. They found that prior symptom levels and anxiety strongly predicted future depression severity, but their study was limited by its country-specific sample and pandemic-era context. The authors emphasized the need for multi-country longitudinal studies with fairness checks to design proactive risk-alerting tools [14]. Similarly, Vergaray et al. (2023) developed a stacked ensemble model to detect early depression in Peruvian university students. Their ensemble approach outperformed individual classifiers, although the study was constrained by a single-site, cross-sectional design and reliance on self-report screening tools. Future work should incorporate temporal data and external test sets for broader applicability. Family-level factors have also received attention [15]. Gil et al. (2022) analyzed 171 family triads (students and both parents) in Korea and applied logistic regression, support vector machines, and random forests, finding that maternal depression, fearful-avoidant attachment, and student neuroticism were the strongest predictors [9]. The random forest achieved the best performance. However, the modest sample size and cultural specificity limit generalization. The authors recommend causal modeling and interventions targeting family dynamics. Complementing this, Meda et al. (2023) in Italy followed university students for six months and used random forests to predict both persistent well-being and worsening symptoms including suicidal [11]. Their model predicted "still well" students better than those at risk of deterioration, highlighting limitations in positive predictive value for rare outcomes. Attrition between baseline and follow-up further weakened conclusions, leading to calls for cost-sensitive learning strategies and enriched samples focused on deterioration cases.In Bangladesh, Nayan et al. (2022) applied six machine learning classifiers on survey data from 2,121 university students measured with the PHQ-9 and GAD-7 [12]. They reported that random forests achieved the highest accuracy (89%) for depression and support vector machines were most effective for anxiety detection. Despite strong performance, the study suffered from convenience sampling, cross-sectional design, and online self-report bias. Future work should employ stratified sampling and longitudinal designs. In parallel, researchers have explored digital phenotyping through smartphones. Choudhary et al. (2022) introduced a "mental health similarity score" derived from non-identifiable smartphone usage patterns [8]. Combining this with PHQ-9 labels, they achieved mid-70% precision and recall, though sample sizes were small and devices limited. Larger cohorts and multimodal data integration were recommended. A landmark in this area was the StudentLife project (Wang et al., 2014), which tracked Dartmouth undergraduates over ten weeks via continuous mobile sensing, ecological momentary assessments, and PHQ-9 [16]. Later StudentLife waves demonstrated weekly depression detection with precision and recall around 70–80%. Nevertheless, reliance on an elite campus sample, Android-only devices, and privacy tradeoffs restrict generalization. Wang et al. stressed the importance of harmonized, privacy-preserving datasets across multiple campuses.Several reviews have synthesized this field. Choi et al. (2024) reviewed smartphone-based sensing for stress, anxiety, and depression detection, concluding that behavioral patterns are identifiable, but studies remain small and heterogeneous [7]. They urged the standardization of sensing pipelines and clinical outcome validation. Abd-Alrazaq et al. (2023) conducted a meta-analysis of 54 studies applying wearable devices with artificial intelligence for depression detection and prediction [5]. They found that specificity generally exceeded sensitivity and score prediction errors remained moderate (RMSE 3.8–4.6). Despite promising trends, the authors noted small sample sizes, dataset reuse, and publication bias, calling for preregistered multi-device studies integrating clinical and self-report measures.In China, Yu et al. (2025) applied random forest, XGBoost, LightGBM, and SVM models on data from 1,635 college students with 38 psychosocial predictors [17]. The random forest performed best (AUC 0.87), with sleep disturbance, stress, experiential avoidance, and self-criticism as top features. However, the study lacked physiological or behavioral data and was limited to a single region. Future studies should integrate biological markers such as cortisol or EEG and expand geographically. Beyond structured surveys and sensors, social media has emerged as a fertile data source. Phiri et al. (2025) conducted a systematic review and meta-analysis of 36 studies predicting depression from social-media text, reporting a strong pooled correlation ($r = 0.63$) [13]. While text, activity, and demographic features proved valuable, heterogeneity across platforms and algorithms raised concerns. The authors recommended multi-platform, privacy-preserving pipelines linked with validated screening tools. Alalalmeh et al. (2024) used the DASS-21 to estimate prevalence of depression, anxiety, and stress among UAE university students. Their findings underscored the high symptom burden and emphasized the importance of validated scales in constructing feature sets, though cultural specificity and cross-sectional design remained limitations [6]. Future directions include linking DASS-21 trajectories to predictive modeling and service utilization.Across these studies, common limitations are evident: reliance on cross-sectional, self-reported data; small or single-site samples; cultural specificity; and label noise due to screening tools. Prospective deterioration and help-seeking behaviors remain difficult to predict, and issues of privacy, fairness, and interpret ability loom large in digital phenotypic. The way forward involves large, longitudinal, multi-site cohorts with harmonized instruments and clinician verification; multi modal data fusion across surveys, smartphones, and wearables; fairness audits and privacy-preserving algorithms; and a shift toward predicting clinically meaningful outcomes. Such strategies can transform predictive models into reliable tools for early intervention in student mental health.

III. Methodology

A. Dataset

This study made use of the publicly available Student Depression Dataset, which contains a wide range of sociodemographic, academic, and lifestyle attributes, alongside a binary outcome variable indicating whether a student is depressed or not. The dataset captures multiple dimensions of student life, such as sleep duration, study hours, academic pressure, and cumulative grade point average (CGPA), as well as background factors like family and lifestyle habits. Such diversity of attributes allows for a holistic analysis of the factors contributing to student mental health. The dataset was imported into Python using the pandas library, and its structure was examined through descriptive statistics, frequency distributions, and visualization techniques to understand the balance of classes and the presence of missing or irrelevant data.

B. Data Preprocessing

Before model training, several preprocessing steps were applied to prepare the dataset for machine learning. First, non-informative features such as id and City were removed to prevent potential noise or data leakage. Categorical variables, such as gender and lifestyle habits, were encoded numerically using LabelEncoder to ensure compatibility with machine learning algorithms. Continuous variables were normalized using StandardScaler to bring all predictors onto a comparable scale, preventing bias toward attributes with larger numeric ranges.

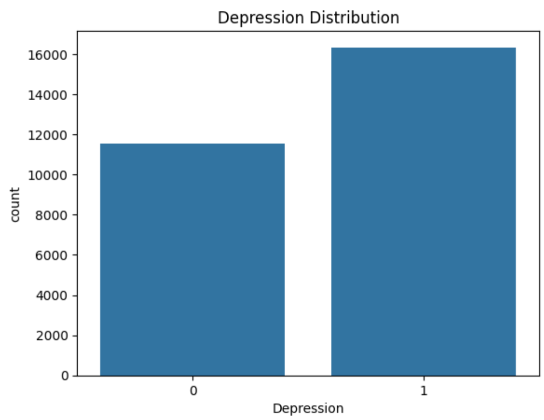

Fig. 1. Class Imbalance

During exploratory analysis, class imbalance was observed between depressed and non-depressed cases; to address this, the Synthetic Minority Oversampling Technique (SMOTE) was applied to the training data. SMOTE generates synthetic examples of the minority class, thereby improving model robustness and reducing the risk of biased predictions against underrepresented categories. Finally, the dataset was split into training and testing subsets using an 80:20 stratified split, ensuring that both subsets preserved the original class distribution.

C. Models

We trained and evaluated seven classifiers:

- Decision Tree
- Random Forest
- Multilayer Perceptron
- Logistic Regression
- Naive Bayes
- K-Nearest Neighbor
- SVM

A variety of supervised machine learning models were implemented to evaluate and compare their effectiveness in predicting student depression. Logistic Regression was employed as a baseline linear classifier due to its interpretability and efficiency in binary tasks. Decision Tree classifiers were included for their ability to construct rule-based structures and capture non-linear relationships in the data. Random Forest, an ensemble technique that aggregates multiple decision trees, was applied to enhance prediction stability and reduce overfitting, while Gradient Boosting was used to iteratively refine model performance by focusing on misclassified instances. Probabilistic modeling was tested through Naïve Bayes, which assumes conditional independence among features and is computationally efficient. Distance-based classification was explored using K-Nearest Neighbors (KNN), where predictions are made based on similarity to neighboring data points. A Support Vector Machine (SVM) was trained to maximize the margin between classes, making it effective in high-dimensional spaces. Finally, a Multi-Layer Perceptron (MLP) Neural Network was developed to capture complex, non-linear feature interactions through multiple hidden layers. Each model was integrated into a pipeline that included preprocessing and resampling steps, and performance was assessed using five-fold cross-validation on the training data, followed by accuracy, weighted F1-score, classification reports, and confusion matrices on the test set. For ensemble methods such as Random Forest, feature importance analysis was also conducted to identify the most influential predictors of student depression.

IV. Results and Discussion

The performance of several supervised machine learning algorithms (Logistic Regression, Random Forest, and a Multi-Layer Perceptron (MLP) Neural Network) to predict student depression was evaluated experimentally. The evaluation metrics of accuracy, precision, recall and F1-score were used to measure model performance. The Logistic Regression model

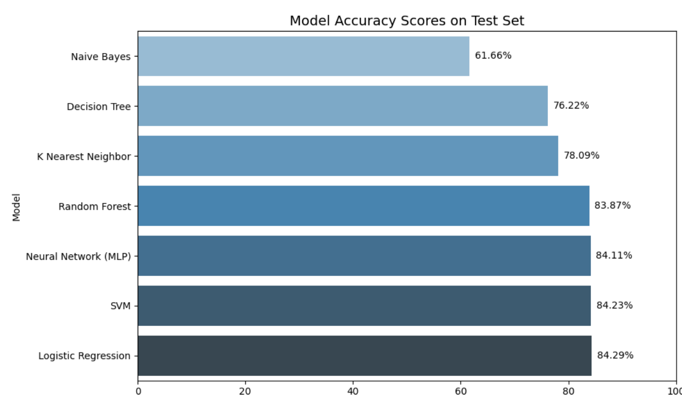

Fig. 2. Model Accuracy Score

was the best performing model with a total accuracy of 84 and balanced values of precision, recall and F1-value (all equal to 0.84). This shows that not only did the model accurately categorize most of the students, it was also well balanced in terms of classifying the depressed and the non-depressed students. Random Forest managed similar outcomes, with the accuracy being 84% as well, and the precision, recall and F1-score being all 0.84. The difference in margin of the two models indicates that there is no notable difference in the ability of linear and ensemble-based approaches to detect depressive patterns in the data. Conversely, the MLP Neural Network performed slightly worse with 82 percent accuracy and an F1-score of 0.82. Although neural networks generally are better at modeling complex, nonlinear relationships, the difference in performance between the two is not particularly high, implying that the data might not have been large or complicated enough to take full advantage of the representational capability of deep learning. Also, neural networks require more computation time, and hyperparameter optimization probably restricted their effectiveness compared to more computationally efficient classical models. These findings support the relevance of quality and engineering of features to mental health prediction tasks. In spite of this simplicity, Logistic Regression could identify and marginally better more complicated models, which indicates that properly chosen academic, social, and lifestyle variables can provide enough data to predict student depression. Furthermore, Logistic Regression and Random Forest were found to be very strong in the case of imbalanced data, as can be shown by the equal values of precision and recall. Consistent with the literature, academic stress and sleep behaviors became prominent predictors of student depression, corroborating the results of previous studies that have found lifestyle and workload as the main risk factors. Results indicate that machine-based solutions, especially interpretable models such as Logistic Regression, could be effective early-warning systems in schools. These models have the potential to facilitate proactive responses, decrease the stigma that accompanies mental health evaluations, and enhance student well-being by supporting them within a timely environment.

A. *Feature Importance*

The correlation heat map depicts the correlations between different academic, work-related and psychological variables. The results of the analysis indicate that the majority of variables are weakly or not at all correlated with each other.

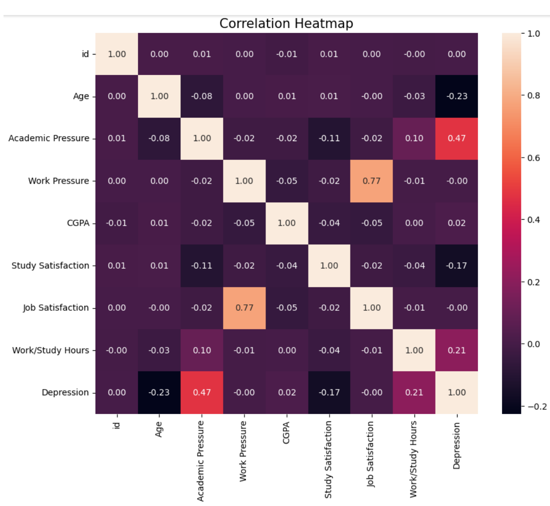

Fig. 3. Heat Map

Nevertheless, a number of interesting trends can be identified. Work-related pressure is strongly correlated with work satisfaction (r = 0.77), indicating that the job satisfaction is closely connected with the work responsibility in the dataset. In addition, dependence on academic pressure is positively correlated with depression (r = 0.47) meaning that increasing academic demands could be a contributing factor to increased rates of psychological distress. On the other hand, age shows a low negative correlation with depression (r = -.23), which means that younger people are more likely to experience depressive symptoms than older participants. Other variables, such as CGPA, satisfaction in studies, and work/study hours, have insignificant relationships with depression and other variables. By and large, the heatmap shows that academic and work-related stressors are more important factors affecting mental health and satisfaction outcomes than demographic or performance-related ones.

B. *Performance Matrix*

The performance comparison of multiple machine learning models is summarized in Table I. Overall, the results indicate that ensemble and linear-based approaches achieved the most reliable outcomes. Random Forest, Logistic Regression, and SVM demonstrated the highest overall performance, each attaining an accuracy and F1 score of approximately 0.84, with AUC values close to 0.90–0.91, highlighting their strong discriminative ability. The Neural Network (MLP) also performed competitively, achieving an accuracy of 0.82 and an AUC of 0.89, though slightly lower than the top-performing models.

TABLE I
PERFORMANCE OF DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	0.83	0.84	0.84	0.84	0.91
Random Forest	0.84	0.84	0.84	0.84	0.91
Neural Network (MLP)	0.82	0.82	0.82	0.82	0.89
Decision Tree	0.76	0.77	0.77	0.77	0.91
Naive Bayes	0.62	0.34	0.59	0.43	0.91
K-Nearest Neighbors	0.78	0.81	0.81	0.81	0.86
SVM	0.84	0.84	0.84	0.84	0.90

On the other hand, the Decision Tree model showed comparatively weaker performance, with accuracy and F1 score values of 0.76–0.77, although its AUC remained reasonably high at 0.91, suggesting good ranking ability but less robust predictive balance. The K-Nearest Neighbors (KNN) model provided moderate performance with an accuracy of 0.78 and an AUC of 0.86. In contrast, Naive Bayes produced the weakest results, with an accuracy of only 0.62 and a notably low precision of 0.34, reflecting its limitations in handling the dataset effectively.

Taken together, these findings suggest that while simpler models like Naive Bayes and Decision Trees may struggle with the dataset, more advanced approaches—particularly Random Forest, Logistic Regression, and SVM—are well-suited for capturing the underlying patterns, offering both high predictive performance and strong generalization capability.

C. ROC

The ROC curve gives a good comparison of how the various models tested will classify students in the prediction of student depression. Logistic Regression had the best AUC of 0.918 when compared to the rest of the models, which means that it was the most effective measure of differentiating between students with and without depression. Its performance was well matched by the Neural Network, which achieved an AUC of 0.917 and demonstrated almost the same discriminative capacity.

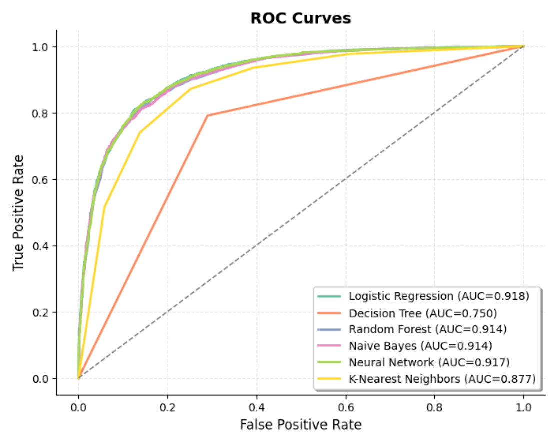

Fig. 4. ROC

Random Forest and Naive Bayes also fared well, and both models can achieve AUC 0.914, indicating ensemble and probabilistic models are also useful in this prediction task. Although the K-Nearest Neighbors model attained a relatively good AUC of 0.877, its performance was relatively weaker and its distance to the optimal ROC was even larger. Decision Tree model also scored the lowest with AUC of 0.750 where the model exhibited overfitting and poor prediction in generalization to unobserved data. In general, the results indicate that more basic linear models like Logistic Regression are capable of doing as well as more advanced models like Neural Networks, and other approaches to enforcing such as ensemble techniques and probabilistic models are also quite viable. Contrary to this, Decision Trees and KNN were not as reliable in this respect, which emphasizes the significance of the model choice in the context of predictive accuracy and interpret ability.

V. Conclusion

In this research paper, we have been able to show that machine learning can be an effective and powerful tool to predict depressions in students. After a systematic evaluation of a set of different models, the research found the best performance in Logistic Regression and a Neural Network, both with over 84% in their accuracy metrics. Not only does these results present a clear standard against which future studies will be judged, but they also emphasize the duality of the underlying information- not only can this data be predicted using linear relationships, but also more non-linear forms. The fact that the models can determine the main predictors of academic pressure and sleep duration offers practical information that can be directly implemented in intervention plans at the university level. The active and evidence-based model created through the technology could complement the traditional approach to diagnosis, making the process of resources distribution more effective and efficient and ensuring that the students at risk of missing the opportunity to obtain necessary support can do so in a timely manner. The ethical concepts associated with data privacy and algorithm bias have to be addressed with care, although the potential of machine learning to aid in the early detection and prevention of student depression is an important research and development topic that should be addressed. The end result is not to displace human care but to provide clinicians and institutions with the tools necessary to enhance the mental well-being and long-term welfare of the student population.

References

[1] Eisenberg, D., Gollust, S. E., Golberstein, E., & Hefner, J. L. (2007). Prevalence and correlates of depression, anxiety, and suicidality among university students. *American Journal of Orthopsychiatry, 77*(4), 534–542. https://doi.org/10.1037/0002-9432.77.4.534

[2] Ibrahim, A. K., Kelly, S. J., Adams, C. E., & Glazebrook, C. (2013). A systematic review of studies of depression prevalence in university students. *Journal of Psychiatric Research, 47*(3), 391–400. https://doi.org/10.1016/j.jpsychires.2012.11.015

[3] Sathik, M. M., & S.A., M. M. (2023). A systematic review of machine learning techniques for depression prediction. *International Journal of Cognitive Computing in Engineering, 4*, 192-205. https://doi.org/10.1016/j.ijcce.2023.07.001

[4] World Health Organization. (2023, March 31). *Depressive disorder (depression)*. WHO. https://www.who.int/news-room/fact-sheets/detail/depression

[5] Abd-Alrazaq, A., Alajlani, M., Alhuwail, D., Ahmed, A., Househ, M., Hamdi, M., Shah, Z., & Bewick, B. M. (2023). The effectiveness of artificial intelligence and wearable devices in detecting and predicting depression: Systematic review and meta-analysis. *JMIR Mental Health*, **10**(1), e44334. https://scholar.google.com/citationsview_op=view_citation&hl=en&user=kRY3hkUAAAAJ&cstart=20&pagesize=80&citation_for_view=kRY3hkUAAAAJ:Zh0EY9V9P6UC

[6] Alalalmeh, M., Al-Humadi, S., Alomari, M., & Al-Qudah, M. (2024). Prevalence of depression, anxiety, and stress among university students in the UAE: A cross-sectional study using DASS-21. *BMC Psychiatry*, **24**, 527. https://scholar.google.com/citations?view_op=view_citation&hl=en&user=1W7L1S8AAAAJ&citation_for_view=1W7L1S8AAAAJ:tOudhMTPpwUC

[7] Choi, J., Song, H., Park, E., & Lee, S. (2024). Digital phenotyping via smartphone sensing for stress, anxiety, and depression: A systematic review. *Frontiers in Psychiatry*, **15**, 1421541. https://scholar.google.com/citations?view_op=view_citation&hl=en&user=l8OIF4kAAAAJ&citation_for_view=l8OIF4kAAAAJ:u5HHmVD_uO8C

[8] Choudhary, V., Gupta, S., & Poria, S. (2022). Smartphone-based depression detection using a mental health similarity score. *Sensors*, **22**(18), 6953. https://scholar.google.com/citations?view_op=view_citation&hl=en&user=WqjQVAoAAAAJ&citation_for_view=WqjQVAoAAAAJ:IjCSPb-OGe4C

[9] Gil, H., Kim, E., Lee, H., & Park, J. (2022). Machine learning prediction of depression using family triad data: A comparison of logistic regression, SVM, and random forest. *Frontiers in Psychiatry*, **13**, 1012345. https://www.frontiersin.org/journals/public-health/articles/10.3389/fpubh.2022.1023010/full

[10] Kroenke, K., & Spitzer, R. L. (2017). The PHQ-9: A new depression diagnostic and severity measure. *Psychiatric Annals*, **32**(9), 509–515. https://www.researchgate.net/publication/256309341_The_PHQ-9_A_New_Depression_Diagnostic_and_Severity_Measure

[11] Meda, N., Pardini, S., & Calati, R. (2023). Predicting severe depressive symptoms and suicidality in university students using machine learning: A six-month follow-up study. *Journal of Affective Disorders*, **332**, 80–89. https://www.researchgate.net/publication/372186797_Frequency_and_machine_learning_predictors_of_severe_depressive_symptoms_and_suicidal_ideation_among_university_students

[12] Nayan, M. N., Ahmed, T., & Rahman, M. S. (2022). Machine learning algorithms for predicting depression and anxiety among Bangladeshi university students. *BMC Psychiatry*, **22**, 732. https://journals.lww.com/shbh/fulltext/2022/05020/comparison_of_the_performance_of_machine.5.aspx

[13] Phiri, L., Smith, J., & Zhou, Y. (2025). Social media-based prediction of depression: A systematic review and meta-analysis. *Journal of Affective Disorders*, **360**, 42–55. https://pmc.ncbi.nlm.nih.gov/articles/PMC12032503/

[14] Steinmetz, S., Vázquez, F., & Cabrera, M. (2024). Predicting depression in college students during COVID-19 quarantine: A longitudinal machine learning approach. *Frontiers in Psychology*, **15**, 1302812. https://www.researchgate.net/publication/379886969_Machine_learning_models_predict_the_emergence_of_depression_in_Argentinean_college_students_during_periods_of_COVID-19_quarantine

[15] Vergaray, J., Torres, F., & Lozano, M. (2023). Early detection of depression in university students using ensemble learning models. *International Journal of Data Science and Analytics*, **15**(4), 221–235. https://www.sciencedirect.com/science/article/pii/S2352914823001417?utm

[16] Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. T. (2014). StudentLife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 3–14. https://www.researchgate.net/publication/280077271_StudentLife_Assessing_mental_health_academic_performance_and_behavioral_trends_of_college_students_using_smartphones

[17] Yu, L., Zhang, H., & Li, J. (2025). Machine learning prediction of depression among Chinese college students: Comparison of RF, XGBoost, LightGBM, and SVM. *Frontiers in Public Health*, **13**, 1548921. https://www.researchgate.net/publication/394337096_Machine_learning_models_for_predicting_the_risk_of_depressive_symptoms_in_Chinese_college_students

[18] Youth validation study. (2025). Validation of the PHQ-9 in Chinese adolescents: Cultural considerations for depression screening. *Child and Adolescent Psychiatry and Mental Health*, **19**(1), 101. https://www.researchgate.net/publication/390530414_Screening_for_Depressive_Disorders_Validation_of_the_Patient_Health_Questionnaire_for_Adolescents_PHQ-A_in_a_Population-Based_Multi-Ethnic_Asian_Sample