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EARLY DETECTION OF DEPRESSION AMONG STUDENTS USING AI-DRIVEN PREDICTIVE MODELS

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Abstract
Depression among university students is a growing concern, significantly affecting academic performance, emotional well-being, and social interactions. Traditional methods for detecting depression, such as self-report questionnaires and clinical interviews, face challenges related to stigma and accessibility. In this study, we leverage machine learning techniques to develop an efficient predictive model for detecting depression in students based on behavioral, psychophysiological, and demographic factors. We applied multiple classification algorithms using a publicly available dataset, including Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, K-nearest neighbors (K-NN), and Naïve Bayes. Performance evaluation was conducted using accuracy, precision, recall, and F1-score. Results indicate that Logistic Regression outperforms other models, achieving an accuracy of 92%, making it a reliable predictor of depression among students. Our findings highlight the potential of machine learning in mental health applications and suggest the need for AI-driven tools to support early intervention strategies in academic institutions. Future work should explore the integration of real-time data sources and deep learning techniques to further enhance prediction accuracy.

INTRODUCTION

In the fast-changing and competitive academic environment of today, the mental well-being and health of students have never been more important. Of many mental health issues, depression has become a highly prevalent and troubling one. Not only does it impair students' concentration on academic work but also their emotional stability, social functioning, and general quality of life. The high expectation to perform well academically, combined with individual and societal expectations, tends to create the stressed environment that may lead to feelings of isolation, anxiety, and hopelessness.

If not addressed, depression can also severely impede a student's academic performance, personal development, and future prospects. As interest in student mental health keeps escalating, researchers and institutions are resorting more and more to emerging solutions, such as machine learning and artificial intelligence, to identify and treat the early symptoms of depression. With the use of technology, we can learn more about students' emotional health and strive to establish more caring and supportive learning environments.

The college or university transition, combined with academic pressure, financial needs, and social pressures, typically places students at an increased risk of developing depressive tendencies. If undetected and untreated, depression has the potential to cause serious repercussions, such as long-term mental health disorders, poor grades, and, in extreme situations, self-injury or suicide [1,2]. Despite increased sensitivity, numerous students are reluctant to access professional intervention because of stigma, ignorance, or inaccessibility of campus mental health facilities [3]. Conventional diagnoses of depression like self-reporting questionnaires, clinical interviews, and psychological testing are limited in their use. Numerous students fail to acknowledge the symptoms or do not report openly about their difficulty because they are afraid of judgments [4]. Second, mental health workers tend to be under-resourced, so that timely interventions can rarely be implemented for all such students. That is where technology, especially artificial intelligence (AI) and machine learning (ML), can act as a game-changer to fill the gap [5].

Machine learning provides a data-driven means of forecasting depression through the study of multiple indicators such as school performance, behavior patterns, sleep patterns, social media usage, and even biological data [6]. In contrast to traditional techniques, ML models can detect finer patterns in students' behavior that can signal nascent symptoms of depression, facilitating early interventions before the condition gets out of hand [7]. By using algorithms like decision trees, support vector machines (SVM), random forests, K-Nearest Neighbor (KNN), Naïve Bayes and decision tree, researchers can create predictive models with high reliability and accuracy [8].

This research is set to develop an efficient machine learning model to detect depression in students using several parameters, allowing institutes and mental health professionals to recognize at-risk individuals in advance. Through the use of AI-driven information and human-based mental health measures, we believe it is possible to design a system that not only identifies depression but also encourages an encouraging environment for students [9].

The remainder of this paper is organized as follows: Section 2 discusses previous work in predicting depression and the application of machine learning in mental health. Section 3 describes the methodology, from data gathering to model selection. Section 4 reports the experimental results and measures model performance using appropriate metrics. Section 5 discusses the implications of our results, possible limitations, and suggestions for future research. Lastly, Section 6 offers a conclusion and indicates directions for future research in this area.

2. Related work

There have been many studies investigating the use of machine learning for anticipating depression among students. A predictive model for diagnosing elderly patients' anxiety and depression utilizing machine learning classifiers, and the Random Forest resulted in the maximum accuracy of 91% [10]. A framework for categorizing online communities of mental health-related content with 85% classification accuracy on identifying depression-related content [11]. Twitter data to predict the onset of mental illness, using linguistic feature analysis and machine learning algorithms to reach a predictive accuracy of 70%. Also, a deep learning method using audio and text sequence modeling was presented to identify depression in interview data [12, 13]. To provide a comprehensive overview of prior research, the following table summarizes existing studies on depression prediction using machine learning.

Table 1: Research Studies on predicting depression

No.	Title	Author	Contribution	Method Used	Results
[14]	Prediction of depression status in college students using a Naive Bayes classifier based machine learning model	Fred Torres Cruz, Evelyn Eliana Coaquira Flores.	Developed a Naive Bayes classifier-based model to predict depression levels in university students.	Naive Bayes Classifier	Accuracy: 78.03%
[15]	Machine Learning Models to Classify and Predict Depression in College Students	Orlando Iparraguirre-Villanueva, Cleoge Paulino-Moreno.	Utilized machine learning models to classify and predict depression in college students	Logistic Regression, K-Nearest Neighbor, Decision Tree	Best: LR (Accuracy: 77%)
[16]	Machine Learning Models Predict the Emergence of Depression in Argentinean College Students During Periods of COVID-19 Quarantine	Lorena Cecilia López Steinmetz, Margarita Sison.	Developed and compared machine learning models to predict depression in Argentinean students during the COVID-19 quarantine.	Support Vector Machine, Logistic Regression, Random Forest	Best: SVM, LogReg (AUPRC: 0.76, 95% CI: 0.69, 0.81
[17]	Assessment and Prediction of Depression and Anxiety Risk Factors in Schoolchildren: Machine Learning Techniques Performance Analysis	Radwan Qasrawi, Stephanny Paola Vicuna Polo.	Assessed and predicted depression and anxiety risk factors in schoolchildren using machine learning techniques.	Support Vector Machine, Random Forest, Neural Network, Decision Tree, Naive Bayes	Best: SVM (Accuracy: 92.5%).
[18]	Predicting anxiety and depression in elderly patients using machine learning technology	Sau, A., Bhakta, I. (2017)	Developed a predictive model to diagnose anxiety and depression among elderly patients	Bayesian Network, Naïve Bayes, Logistic Regression, Multiple Layer Perceptron, K-Star, Random Sub-Space (RS), J48, Decision Tree, Random Forest, Random Tree	Best: RF (Accuracy: 89%).
[19]	Machine Learning Models for Predicting Risk of Depression in Korean College Students	Min Gi, Seung-Sup Kim, Eun-Jeong Ma	Investigated ML models to predict depression risk among Korean college students, identifying significant family and individual factors.	Sparse Logistic Regression, Support Vector Machine, Random Forest	Best: SVM (Accuracy: 86.27%)
[20]	Supervised Machine Learning Models for Depression Sentiment Analysis	Ibidun Christiana Obagbuwa, Samantha Danster, Onil Colin Chibaya	Utilized ML models and sentiment analysis techniques to predict depression levels in social media users' posts.	Support Vector Machine, Logistic Regression, Random Forest, Extreme Gradient Boosting	Best: LogReg (Accuracy: 96.3%)
[21]	Machine Learning	Y Zhai, Y Zhang, Z	Developed predictive	Xtreme Gradient	Best: XGBoost

	Predictive Models to Guide Prevention and Intervention of Anxiety and Depressive Disorders Among U.S. College Students	Chu	models to identify U.S. college students at heightened risk of anxiety and depressive disorders.	Boosting, Random Forest, Decision Tree, Logistic Regression	(Accuracy: 77%).
[22]	Depression Detection in Social Media Posts Using Transformer-Based Models	Kerasiotis, M., Ilias, L. and Askounis.	Applied transformer-based models to detect depression in social media posts.	Transformer-Based Models	Precision, Recall, and F1-scores of 84.26%, 84.18%, and 84.15%.

3. Methodology

This research utilizes a quantitative approach to examine the influence of Depression on mental well-being among students through classification methods like Random Forests, Decision Tree, SVM, Logistic Regression, K-NN and Naïve Bayes for analyzing. The data was obtained from the Kaggle website to provide a representative sample. Data preprocessing included dataset cleaning, feature engineering, and handling missing values. The dataset was split into training and testing sets. Feature importance and model interpretation techniques were applied to understand the influence of contained behavioral, psychophysiological, and demographic factors, while ethical considerations ensured data confidentiality and compliance with regulations. Despite limitations, this methodology aims to provide valuable insights whether the student is at risk of depression or not.

3.1 Overview of dataset

This dataset for the current research project was retrieved from the website kaggle.com and shared publicly with anyone. The dataset contained behavioral, psychophysiological, and demographic data that were collected from participants aged 18-35 years for the prediction of depression. The dataset contained 502 rows and 11 columns.

3.2 Variable studied

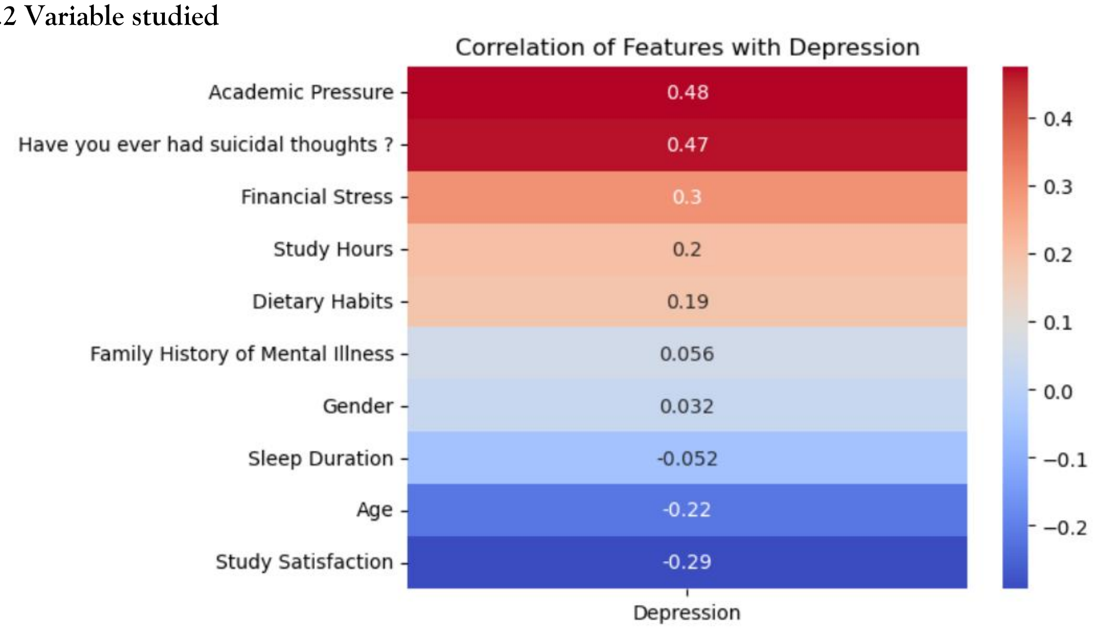

Figure 1: Variable studied

3.3 Tools and framework

Jupyter, an interactive computing environment, was used for machine learning research. It allowed for data analysis, preprocessing, and the application of various classification algorithms. The research focused on building predictive models and evaluating their performance using real-world datasets.

3.4 Data Preprocessing

The preprocessing commenced with an exploration of dataset, where missing values were examined to ensure consistency and completeness in data. Depending on the attribute's nature and distribution, missing values were either dropped or imputed to preserve the integrity of the dataset while minimizing bias. Irrelevant columns like "Age", "Gender" was removed. Categorical variables were then transformed into numerical representations through label encoding or one-hot encoding techniques. After data cleaning, the dataset contained 501 rows and 9 columns. It was then divided into training and testing set, 75% data allocated for training and 25% for testing.

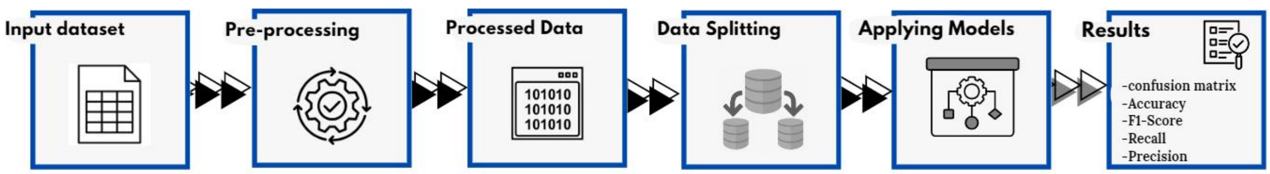

Figure 2: Flow of proposed study

3.5 Performance evaluation metrices

In Jupyter, various machine learning algorithms were implemented to analyze the dataset. The algorithms include Logistic regression, Support Vector Machine (SVM), Random Forest, Decision Tree, Naïve Bayes and K-Nearest Neighbors (k-NN). The proposed machine learning methods have been evaluated by analyzing their performance by confusion matrix.

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positive (TPs)	False Positive (FPs)
False Negative (0)	Fasle Positive (FNs)	True Negative (TNs)

Figure 3: Confusion matrix

The confusion matrix shown in figure is divided into four categories:

1. True Positives (TP): Instances where the model correctly predicts the presence of depression.
2. True Negatives (TN): Instances where the model correctly predicts the absence of depression.
3. False Positives (FP): Instances where the model incorrectly predicts absence of depression (a Type I error).
4. False Negatives (FN): Instances where the model incorrectly predicts the presence of depression when it is present (a Type II error).

The confusion matrix allows us to calculate several evaluation metrices:

$$Accurcay\ Rate = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

4. Results

The results of the comparative analysis of classification algorithms with different performance measures for data splits (75%) are shown in this section. The evaluation process and ranking criteria is based on four key factors: Accuracy, Recall, Precision and F1-Score.

4.1 Model Performance Analysis

Table 2: Comparison of machine learning model.

Model	Performance metrics			
	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.92	0.91	0.94	0.93
Decision Tree	0.82	0.86	0.81	0.83
Random Forest	0.88	0.88	0.91	0.90
Support Vector Machine	0.90	0.9	0.93	0.91
K-Nearest Neighbors (k-NN)	0.79	0.81	0.81	0.81
Naive Bayes	0.89	0.89	0.93	0.91

4.1.1 Logistic Regression

A statistical approach applied to binary prediction; Logistic Regression evaluates the likelihood of an outcome given input attributes. It is widely applied in medical and psychological research owing to its simplicity and efficiency in predicting categorical results. Logistic Regression achieved 92% accuracy, in addition to 91% precision, 94% recall, and 93% F1-score, demonstrating strong overall performance in accurate student-at-risk prediction.

4.1.2 Decision Tree

A supervised learning algorithm which makes predictions by recursively partitioning data based on feature values. It is a hierarchical algorithm, and therefore it would be most suitable to understand decision-making mechanisms for mental health predictions. While the model was 82% accurate, it fell a bit short of 81% recall, which meant that the model had missed some depression cases. However, its precision of 86% shows that when the model predicted a student to be at risk, it was extremely trustworthy. Its F1-score of 83% shows moderate balance but also points to where the model could be optimized.

4.1.3 Random Forest

An ensemble learning method that combines multiple decision trees to enhance prediction accuracy and reduce overfitting. By aggregating results from different trees, it provides robust and reliable classifications, making it suitable for complex datasets. This ensemble model performed well, with an **accuracy of 88%**. It maintained a strong balance between **precision (88%) and recall (91%)**, meaning it effectively identified at-risk students while minimizing false positives. The **F1-score of 90%** further confirms its reliability as a robust classifier.

4.1.4 Support Vector Machine (SVM)

A highly efficient classification model that identifies an optimal hyperplane to distinguish various classes in high-dimensional space. With 90% accuracy, SVM ranked among the best performers. It achieved a 90% precision and 93% recall, indicating it was classifying students with depression accurately and making hardly any misclassifications. Its 91% F1-score indicates a well-balanced forecasting capability.

4.1.5 K-Nearest Neighbors (k-NN)

A non-parametric algorithm that classifies data points based on the majority class of their closest neighbors. It is simple yet effective for pattern recognition, particularly in small datasets with clearly defined clusters. This model achieved a lower **accuracy of 79%**, meaning it struggled more compared to other models. Its **precision and recall (both at 81%)** indicate that it was fairly consistent but not as precise in differentiating students at risk from those not at risk. The **F1-score of 81%** suggests that while it performed adequately, it may not be the most reliable choice for this problem.

4.1.6 Naïve Bayes

A probabilistic classifier based on Bayes' Theorem, assuming independence among input features. Despite its simplicity, Naïve Bayes performs well with text-based data, making it suitable for analyzing survey responses or social media content related to mental health. This model achieved **89% accuracy**, performing slightly better than Random Forest. Its **precision of 89%** and **recall of 93%** highlight its strength in correctly identifying at-risk students while minimizing false positives. The **F1-score of 91%** confirms its strong overall performance.

4.2 Comparative Analysis

To assess the effectiveness of our models, we compared our results with those reported in Qasrawi et al. (2023) [17], which examined depression and anxiety risk factors in schoolchildren using machine learning techniques. Their study evaluated several models, including Support Vector Machine (SVM), Random Forest, Decision Tree, Artificial Neural Networks (ANN), and Naïve Bayes, with SVM achieving the highest accuracy (92.5%) for depression prediction.

Table 3: Depression Prediction Accuracy Comparison

Model	Proposed Study	Related Study
Logistic Regression	0.92	Not reported
Decision Tree	0.82	0.88
Random Forest	0.88	0.76
SVM	0.9	0.92
K-Nearest Neighbors (k-NN)	0.79	Not reported
Naïve Bayes	0.89	0.87

Our results indicate that Logistic Regression (92%) and SVM (90%) performed competitively with the findings. While their SVM model (92.5%) achieved the highest accuracy in their study, our Logistic Regression model (92%) closely matches this performance, suggesting its effectiveness in depression prediction.

Additionally, our Random Forest model (88%) significantly outperformed their Random Forest model (76.4%), highlighting the impact of dataset differences, feature selection, and hyperparameter tuning on model performance. Similarly, our Naïve Bayes model (89%) slightly outperforms theirs (87.1%), further demonstrating the reliability of our approach.

The slight variations in accuracy between the two studies may be due to differences in data sources, feature engineering methods, and the target population (schoolchildren vs. college students). Future research could focus on combining multiple datasets and exploring ensemble techniques to enhance predictive accuracy across different demographics.

5. Conclusion

Depression among university students is a serious concern that can impact not only academic performance but also emotional well-being and daily life. Traditional methods for detecting depression, like self-reported surveys and clinical assessments, often come with barriers such as stigma and limited accessibility. This is where machine learning offers a promising solution. In this study, we explored various machine learning models to predict depression based on behavioral, psychophysiological, and demographic factors. Among the models tested, Logistic Regression performed the best, achieving an impressive accuracy of 92%. This suggests that AI-driven approaches can be effective in identifying students at risk, potentially enabling earlier interventions and better support systems. Our research highlights the value of integrating technology into mental health screening. By using predictive models, universities and mental health professionals can proactively reach out to students who may need help, rather than waiting for them to seek support. Looking ahead, future work could explore real-time data sources—like social media activity and wearable devices—to further enhance prediction accuracy. Additionally, deep learning and ensemble models could refine these predictions even more. Ultimately, combining AI-driven insights with compassionate, human-centered mental health interventions can help create a more supportive academic environment. With the right tools and strategies, we can take meaningful steps toward improving student well-being and ensuring that no one struggling with depression goes unnoticed.

REFERENCES

1. Hussain, M., Sultan, S., & Malik, R. (2020). Depression and anxiety among university students: A review of literature.
2. Ibrahim, A. K., Kelly, S. J., Adams, C. E., & Glazebrook, C. (2019). A systematic review of studies on depression prevalence among university students.
3. Latif, S., 2024. Robust Decision Support System for Stress Prediction Using Ensemble Techniques. Journal of Innovative Computing and Emerging Technologies, 4(2).
4. Horgan, A., Sweeney, J., Behan, L., & McCarthy, G. (2021). Depression and anxiety in college students: A study of prevalence and help-seeking behavior.
5. Tadesse, M. M., Lin, H., Xu, B., & Yang, L. (2019). Detection of depression-related posts in social media using a machine learning approach.
6. Shatte, A. B., Hutchinson, D. M., & Teague, S. J. (2019). Machine learning in mental health: A scoping review of methods and applications.
7. Acharya, U. R., Sudarshan, V. K., Adeli, H., & et al. (2018). Automated detection of depression using nonlinear signal processing methods.
8. Dhamija, S., Choudhury, T., & Kumar, A. (2021). Predicting depression in students using machine learning algorithms: A comparative analysis.
9. Latif, S. and Mussarrat, N., 2024. Impact of Digital Technologies on Consumer E-Purchasing Decisions Using Ensemble Techniques. International Journal of Information Systems and Computer Technologies, 4(1), pp.10-19.
10. Sau, A. and Bhakta, I., 2017. Predicting anxiety and depression in elderly patients using machine learning technology. Healthcare Technology Letters, 4(6), pp.238-243.
11. Saha, B., Nguyen, T., Phung, D. and Venkatesh, S., 2016. A framework for classifying online mental health-related communities with an interest in depression. IEEE journal of biomedical and health informatics, 20(4), pp.1008-1015.
12. Reece, A.G., Reagan, A.J., Lix, K.L., Dodds, P.S., Danforth, C.M. and Langer, E.J., 2017. Forecasting the onset and course of mental illness with Twitter data. Scientific reports, 7(1), p.13006.
13. Al Hanai, T., Ghassemi, M.M. and Glass, J.R., 2018, September. Detecting Depression with Audio/Text Sequence Modeling of Interviews. In Interspeech (pp. 1716-1720).
14. Cruz, F.T., Flores, E.E.C. and Quispe, S.J.C., 2023. Prediction of depression status in college students using a Naive Bayes classifier based machine learning model. arXiv preprint arXiv:2307.14371.
15. Iparraguirre-Villanueva, O. (2024) "Machine Learning Models to Classify and Predict Depression in College Students", International Journal of Interactive Mobile Technologies (iJIM), 18(14), pp. pp. 148–163. doi: 10.3991/ijim.v18i14.48669.
16. López Steinmetz, L.C., Sison, M., Zhumagambetov, R., Godoy, J.C. and Haufe, S., 2024. Machine learning models predict the emergence of depression in Argentinean college students during periods of COVID-19 quarantine. Frontiers in Psychiatry, 15, p.1376784.
17. Qasrawi, R., Polo, S.P.V., Al-Halawa, D.A., Hallaq, S. and Abdeen, Z., 2022. Assessment and prediction of depression and anxiety risk factors in schoolchildren: machine learning techniques performance analysis. JMIR formative research, 6(8), p.e32736.
18. Sau, A. and Bhakta, I., 2017. Predicting anxiety and depression in elderly patients using

machine learning technology. Healthcare Technology Letters, 4(6), pp.238-243.

19. Gil, M., Kim, S.S. and Min, E.J., 2022. Machine learning models for predicting risk of depression in Korean college students: identifying family and individual factors. Frontiers in Public Health, 10, p.1023010.
20. Obagbuwa, I.C., Danster, S. and Chibaya, O.C., 2023. Supervised machine learning models for depression sentiment analysis. Frontiers in Artificial Intelligence, 6, p.1230649.
21. Zhai, Y., Zhang, Y., Chu, Z., Geng, B., Almaawali, M., Fulmer, R., Lin, Y.W.D., Xu, Z., Daniels, A.D., Liu, Y. and Chen, Q., 2025. Machine learning predictive models to guide prevention and intervention allocation for anxiety and depressive disorders among college students. Journal of Counseling & Development, 103(1), pp.110-125.
22. Kerasiotis, M., Ilias, L. and Askounis, D., 2024. Depression detection in social media posts using transformer-based models and auxiliary features. Social Network Analysis and Mining, 14(1), p.196.