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An Explainable Machine Learning Study of Behavioral and Psychological Determinants of Depression in the Academic Environment

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Abstract

Depression is a significant and growing concern within academic environments, affecting both students and staff due to factors such as academic pressure, financial stress, and lifestyle challenges. This study explores the use of machine learning, specifically a Random Forest classifier, to predict depression risk among students using behavioral, psychological, and demographic data. A dataset of 27,788 student records was analyzed after thorough preprocessing and exploratory data analysis. The model achieved strong performance, with an accuracy of 83.52% and an AUC of 0.91, indicating reliable classification of depression status. Local Interpretable Model-agnostic Explanations (LIME) were employed to enhance interpretability, revealing key predictive features such as suicidal ideation, academic pressure, sleep duration, and dietary habits. These interpretable insights align with existing psychological research and provide actionable information for mental health professionals. The findings highlight the value of explainable AI in educational settings, offering a scalable and transparent approach to early depression detection and intervention. Future work should focus on longitudinal data integration, multimodal inputs, and real-world implementation to strengthen the model's utility and impact.

1. Introduction

Depression has become a growing concern in academic settings, particularly among students who face constant pressure to perform [1]. Academic environments often demand long hours, tight deadlines, and high achievement, all of which can negatively impact mental health [2]. Unlike the general population, students may experience depression that is closely tied to academic stressors, such as performance anxiety, fear of failure, and competition. These stressors can contribute to patterns of rumination, self-criticism, and reduced self-efficacy, which are distinct from depression triggers in other demographics [3].

Studies indicate that depression is prevalent among students, with one study finding a 39.1% prevalence of depressive symptoms among undergraduate health

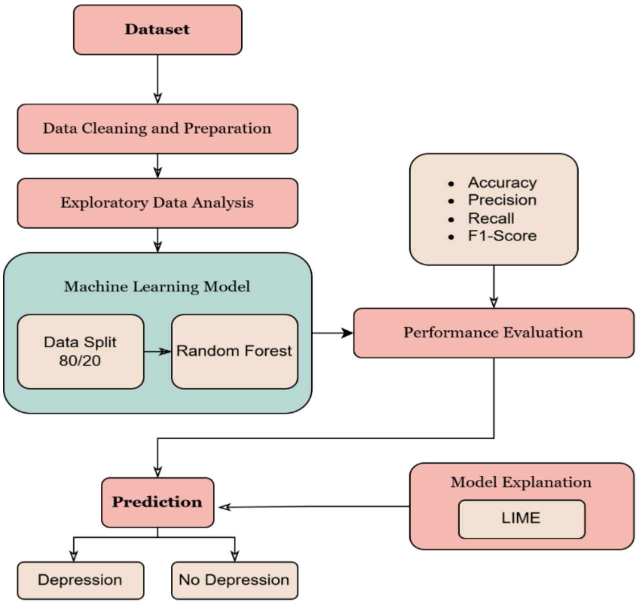

Figure 1. Overview of the machine learning pipeline used in the study.

science students, with moderate to severe symptoms affecting 17.1% of them [4]. Moreover, increased educational attainment has been causally linked to a reduced risk of depression, with each year of education reducing the odds of depression by approximately 1% [5]. Depression not only affects emotional well-being but also impairs academic performance, relationships, and long-term career outcomes. Students experiencing depressive symptoms are more likely to suffer from fatigue and excessive daytime sleepiness, with significant associations observed between depression and these factors [6].

Despite rising awareness, many individuals struggling with depression in academic environments remain undiagnosed or unsupported. One major challenge is understanding the complex interplay of psychological, behavioral, and environmental factors that contribute to depression [7]. Traditional screening methods, which often rely on self-report surveys, tend to be limited in scope and may not capture the full range of influences. For instance, a national study found that 39.1% of undergraduate health science students reported depressive symptoms, underlining the need for better detection tools that account for various factors [4]. Furthermore, a study of medical students revealed that only 32% received adequate treatment, suggesting significant gaps in support systems [8]. There is an urgent need for more comprehensive tools that can detect early signs of depression by considering a broader range of individual and environmental factors.

Recent research in mental health and artificial intelligence (AI) offers promising alternatives. Unlike traditional methods that rely solely on static self-reports, machine learning models can incorporate and dynamically analyze diverse, real-time data sources, such as social media activity, passive behavioral data (e.g., sleep or communication patterns), and digital interaction metrics. For instance, Jiang et al. demonstrated improved diagnostic accuracy for major depressive disorder by combining neuroimaging data with plasma biomarkers, highlighting the potential of multimodal approaches in psychiatric AI [9]. Similarly, Thekkekara et al. achieved high accuracy (up to 96.7%) in detecting depression from behavioral data such as social media posts, while enhancing model interpretability using attention mechanisms [10]. These findings suggest that machine learning is not simply repackaging self-reported information but offering a fundamentally richer, more nuanced framework that may be especially valuable in fast-paced, high-pressure academic environments where early and accurate detection is critical.

However, many models still act as “black boxes,” offering little insight into why a prediction is made [11]. This limitation reduces their applicability in clinical and academic settings, where interpretability is vital. A systematic review confirmed that although AI tools are increasingly effective in diagnosing and managing depression, real-world implementation hinges on transparency and stakeholder trust [12]. Our work addresses this challenge using the explainable AI technique LIME (Local Interpretable Model-agnostic Explanations) to uncover which psychological or behavioral features influence predictions. These methods help bridge the gap between model performance and human understanding, supporting more trustworthy, ethical, and actionable insights in mental health care [13, 14].

This study aims to use machine learning to identify and explain the behavioral and psychological factors that contribute to depression in academic environments. We want to create models that perform well and offer clear insights into the factors driving their predictions. This can help inform mental health support strategies and guide future research in educational and clinical settings.

2. Materials and Methods

The methodology of this study, as illustrated in Figure 1, follows a structured machine learning pipeline designed to identify and interpret psychological and behavioral factors contributing to depression in academic settings. The process begins with acquiring a dataset, followed by thorough data cleaning and preparation to ensure consistency and reliability. Exploratory data analysis (EDA) is conducted to uncover initial insights and guide

Table 1. Overview of variables in the dataset.

Variable Name	Type	Values / Categories	Description
Gender	Categorical	Male, Female	Respondent's self-reported gender identity.
Age	Numerical	18 to 35 (filtered)	Age of the respondent in years.
Academic Pressure	Ordinal	0–5	Perceived academic stress, with higher values indicating greater pressure.
CGPA	Numerical	0.00 to 10.00	Cumulative Grade Point Average (academic performance metric).
Study Satisfaction	Ordinal	0–5	Satisfaction with the current study experience increases with satisfaction.
Sleep Duration	Categorical	'Less than 5 hours', '5-6 hours', '7-8 hours', 'More than 8 hours'	Reported average sleep duration per night.
Dietary Habits	Categorical	Healthy, Moderate, Unhealthy	Quality of daily dietary patterns.
Have you ever had suicidal thoughts?	Binary	Yes, No	Indicates past suicidal ideation.
Study Hours	Numerical	0 to 12 hours/day	Average number of hours spent studying daily.
Financial Stress	Ordinal	1 (low) to 5 (high)	Degree of financial strain as self-reported by the respondent.
Family History of Mental Illness	Binary	Yes, No	Indicates whether a family history of mental illness is present.
Depression	Binary	1 = No, 0 = Yes	The main outcome variable indicates the presence of depressive symptoms.

feature selection. The data is then split into training and testing subsets before being used to train a Random Forest classifier. Model performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score. To ensure interpretability, LIME is applied to explain the model's predictions. The model ultimately classifies individuals into "Depression" or "No Depression" categories, facilitating actionable mental health interventions.

2.1. Data Source and Study Population

The dataset used in this study was retrieved from Kaggle, an open-access data science platform that hosts a wide range of user-contributed datasets for educational and research purposes. Adil Shamim originally published the dataset to explore behavioral, psychological, and lifestyle variables associated with mental health outcomes, including depression, across various demographic groups [15].

2.2. Data Cleaning and Preparation

Several preprocessing steps were carried out to ensure the dataset was suitable for analysis. First, the data was filtered to include only respondents who identified as "Students." Records of individuals over 35 were excluded to focus on traditional-age students and reduce variability linked to life-stage differences. Entries with missing, ambiguous, or invalid responses were removed. The target variable, Depression, was recoded from binary numerical values (0 = Yes, 1 = No) to categorical labels ("Yes" and "No") for improved clarity. All categorical and ordinal variables were appropriately encoded for statistical analysis and visualization. Following these procedures, the final cleaned dataset included 27,788 complete student records, ready for analysis. The study variables were selected for their relevance to academic stress, lifestyle patterns, and psychosocial health. Table 1 provides a detailed overview of the variables used in the final analysis, including data types, value ranges, and operational definitions.

2.3. Exploratory Data Analysis

We conducted an exploratory data analysis (EDA) on both categorical and numerical variables to better understand the dataset and identify potential depression-related patterns. This step helps to reveal underlying distributions, correlations, and outliers that may influence model performance and interpretability.

Categorical variables such as Gender, Sleep Duration, Dietary Habits, Suicidal Thoughts, and Family History of Mental Illness were visualized using bar plots to compare their distributions across depression labels ("Yes" vs "No"). This allowed us to observe imbalances or associations between categorical features and depression outcomes.

Numerical variables such as Age, CGPA, and Study Hours, along with ordinal features like Academic Pressure, Study Satisfaction, and Financial Stress, were analyzed using histograms. This helped highlight differences in central tendencies and variances between students with and without depression.

2.4. Machine Learning Model

To develop a predictive model for depression, the dataset underwent several preprocessing steps to ensure compatibility with machine learning algorithms. First, numerical and ordinal variables were standardized using z-score normalization [16, 17]. This step ensures that all features contribute equally during training, regardless of their original scales. Next, categorical variables were transformed using one-hot encoding. This encoding method creates binary columns for each category level, allowing the model to process categorical data without introducing ordinal bias [18]. Following preprocessing, the dataset was randomly split into a training set (80%) and a testing set (20%) [19]. This stratified split helps the model generalize by learning from most data while reserving a portion for unbiased performance evaluation.

Given its suitability for handling mixed data types and strong baseline performance in classification tasks, we employed a Random Forest classifier for this study. Random Forest is an ensemble method that constructs multiple decision trees and aggregates their predictions through majority voting, offering robustness against overfitting and strong generalization performance [20, 21]. It is particularly effective when working with datasets that include numerical and categorical features, as in this study. While alternative algorithms such as gradient boosting or support vector machines may offer marginal performance gains, Random Forest was selected for its balance of accuracy, interpretability, and computational efficiency. The model was implemented using the default hyperparameters from scikit-learn [22], as the primary aim was not optimization but rather to demonstrate the feasibility of explainable machine learning.

2.5. Performance Evaluation

The performance of the Random Forest classifier was assessed using accuracy, precision, recall, and F1-score on the test dataset [23]. These metrics offer a comprehensive view of the model's ability to identify students with and without depression correctly. Accuracy reflects the overall correctness of the predictions, while precision measures how many students predicted to be depressed were [24]. Recall indicates the proportion of true depression cases the model detected, and the F1-score provides a balanced measure of precision and recall [25]. The model demonstrated satisfactory performance across all metrics, suggesting it can effectively classify depression cases in academic settings. These results establish a reliable baseline for further analysis and support using explainable AI techniques to interpret the model's decisions.

2.6. Model Explanation

To interpret the predictions made by the Random Forest classifier, we applied LIME, a popular explainable AI technique [26]. LIME works by generating local surrogate models that approximate the behavior of complex models for individual predictions. This method allowed us to pinpoint the features that influenced the model's predictions for individual cases. When we used LIME on the test data, we could visualize and rank the most relevant behavioral and psychological factors associated with depression classification. Frequently influential features included suicidal ideation, academic pressure, financial stress, sleep duration, and dietary habits. These case-level explanations aligned with patterns observed during exploratory analysis and offered transparent insights that can support more targeted mental health interventions.

3. Results and Discussion

3.1. Results of Exploratory Data Analysis

Figure 2 presents the results of the EDA, highlighting key categorical variables and their distribution according to depression status. Several noteworthy patterns emerge. Gender-wise, both male and female students reported depression, though males showed slightly higher overall numbers. Sleep duration appears to be associated with depression, with shorter sleep durations (especially category 0) linked to higher counts of depression cases. Dietary habits also show a relationship; students with unhealthy diets (category 0) had a greater incidence of depression compared to those reporting healthier habits.

The variable "Have you ever had suicidal thoughts?" revealed a strong association with depression: a significantly larger number of those who answered "Yes" were also categorized as depressed. Similarly, students with a family history of mental illness showed higher depression rates than those without. Overall, the distribution of depression status across these variables suggests that psychosocial and lifestyle factors, such as sleep, diet, financial or emotional stress, and family mental health background, play a meaningful role in depression outcomes in academic populations.

Continuing the exploratory analysis, Figure 3 presents the distribution of key numerical and ordinal variables considered in the model. The age distribution is uniform across the included range (18 to 35 years), ensuring a representative sample of traditional college-aged

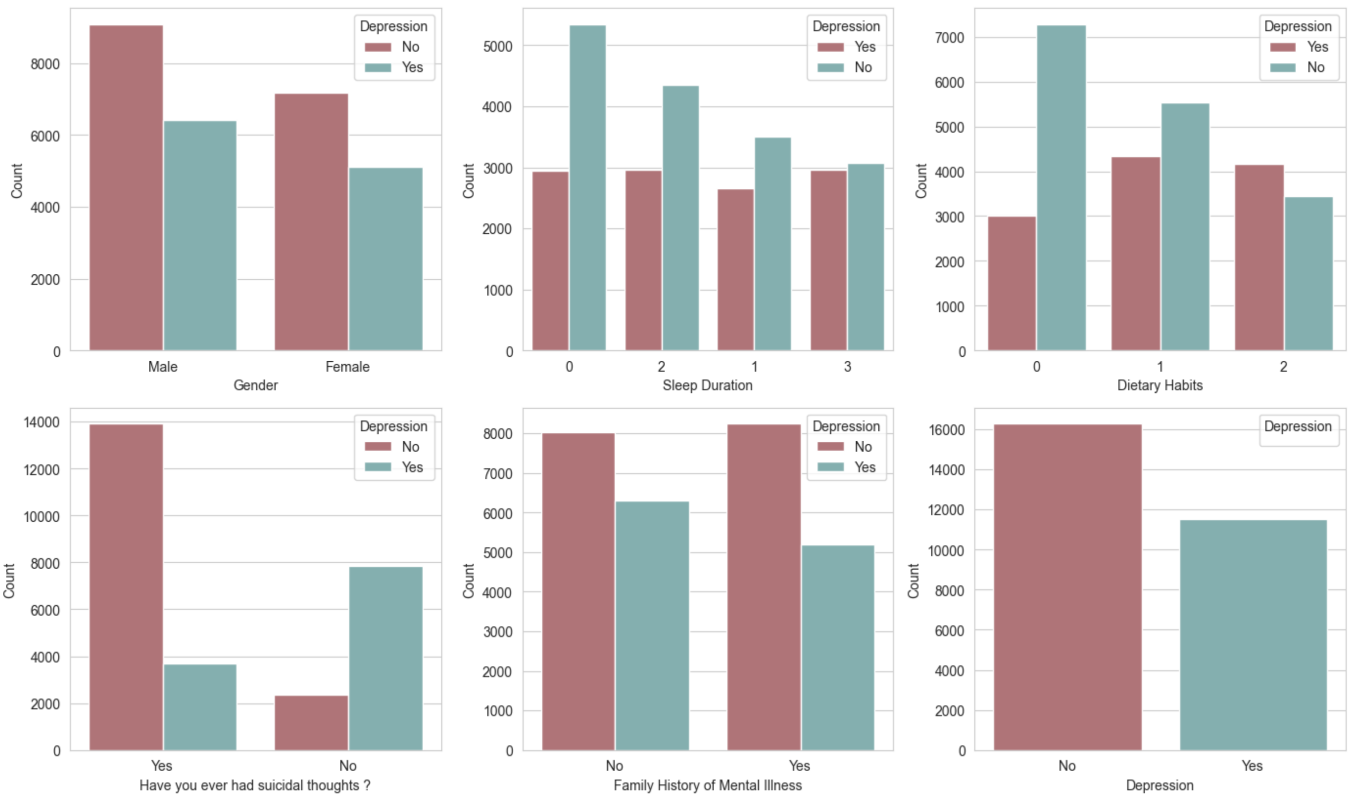

Figure 2. Bar plots showing the distribution of depression status across key categorical variables.

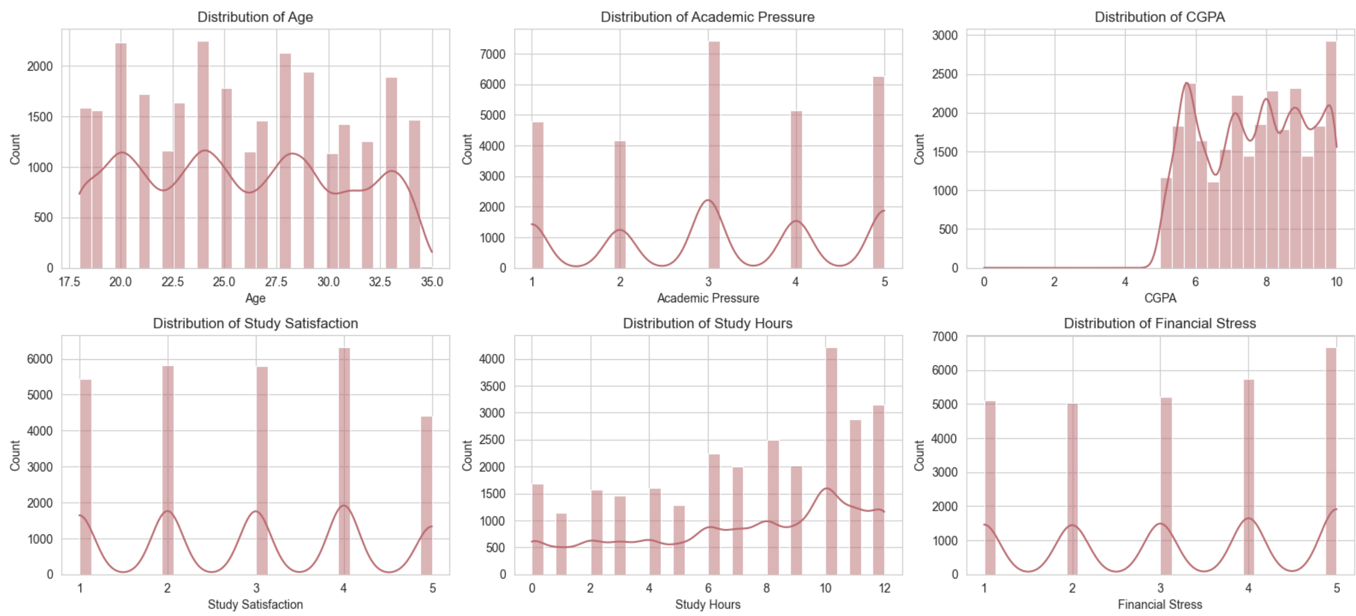

Figure 3. Histograms with KDE plots showing the distributions of numerical and ordinal variables.

students. Academic and financial stress both exhibit distributions skewed toward higher stress levels, indicating that many students experience considerable academic and financial burdens. These variables are notable given their known associations with mental health challenges.

The CGPA distribution is right-skewed, with most students scoring between 7 and 10, suggesting relatively high academic performance among the sample. Interestingly, this implies that depression may not be solely linked to poor academic outcomes. The distributions of study satisfaction and financial stress reveal peaks at lower satisfaction and higher stress ratings, further emphasizing the environmental and psychological stressors prevalent in academic life. Study hours show a more variable distribution, with some

Table 2. Performance metrics of the Random Forest classifier in detecting depression among students.

Metrics	Value (%)
Accuracy	83.52
Precision	81.01
Recall	78.98
F1-Score	79.98

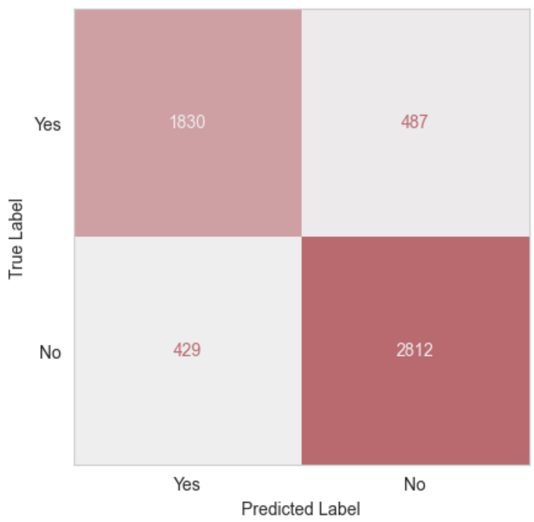

Figure 4. Confusion matrix showing the Random Forest model classification outcomes on the test dataset.

students studying up to 12 hours daily, which is another potential contributor to mental fatigue and depressive symptoms.

In summary, the exploratory data analysis revealed several important trends linking behavioral, psychological, and demographic variables to depression among students. Categorical variables such as suicidal thoughts, family history of mental illness, dietary habits, and sleep duration demonstrated clear associations with depression prevalence. Similarly, ordinal and numerical variables, including academic pressure, financial stress, and study satisfaction, displayed patterns suggesting that elevated stress and lower satisfaction may contribute to mental health challenges. These findings highlight the multifactorial nature of depression in academic environments and justify the use of machine learning to uncover further and interpret these complex relationships.

3.2. Results of Machine Learning Model

The performance of the Random Forest classifier in predicting depression status is summarized in Table 2. The model achieved an accuracy of 83.52%, correctly classifying over four-fifths of the test samples. While this indicates strong overall performance, accuracy alone does not fully reflect the impact of misclassifications in real-world educational or clinical settings. The model's precision of 81.01% means that when it predicted a student to be depressed, it was correct in most cases, which helps reduce the number of false positives. However, false positives may still lead to unnecessary psychological referrals, increased anxiety for students, and additional strain on limited campus mental health resources.

More importantly, the recall of 78.98% shows that the model was able to identify most students with depression, but it also means that approximately 21% of actual cases were missed. These false negatives are particularly concerning because undetected depression can lead to serious consequences such as academic decline, social isolation, or worsening mental health. The F1-score of 79.98% offers a balanced view of the model's precision and recall, indicating consistent overall performance. These results indicate that the Random Forest model offers a reliable baseline for classification while preserving interpretability, an essential feature for applying AI in educational or clinical settings. They also validate the significance of the selected behavioral and psychological features, reinforcing their relevance in predicting mental health outcomes.

Further insight into the model's performance is provided by the confusion matrix shown in Figure 4. The matrix illustrates the number of true positives, false positives, true negatives, and false negatives made by the Random Forest classifier on the test dataset. Out of all students who were truly depressed, 1,830 were correctly identified (true positives), while 487 were incorrectly classified as not depressed (false negatives). On the other hand, among those not experiencing depression, 2,812 were correctly predicted (true negatives), and 429 were mistakenly identified as depressed (false positives).

This confusion matrix reinforces the previously reported performance metrics by highlighting a reasonably strong balance between sensitivity and specificity. The number of false negatives is moderate, indicating that the model captures most depression cases while keeping misclassification relatively low. This balance is particularly important in mental health prediction tasks, where the cost of missing a true case (false negative) can be more severe than incorrectly flagging a non-depressed individual.

The ROC (Receiver Operating Characteristic) curve displayed in Figure 5 further validates the model's discriminative ability. The curve plots the true positive rate against the false positive rate at various classification thresholds, offering a comprehensive view of the model's performance across different decision boundaries. The Area Under the Curve (AUC) is 0.91, indicating excellent

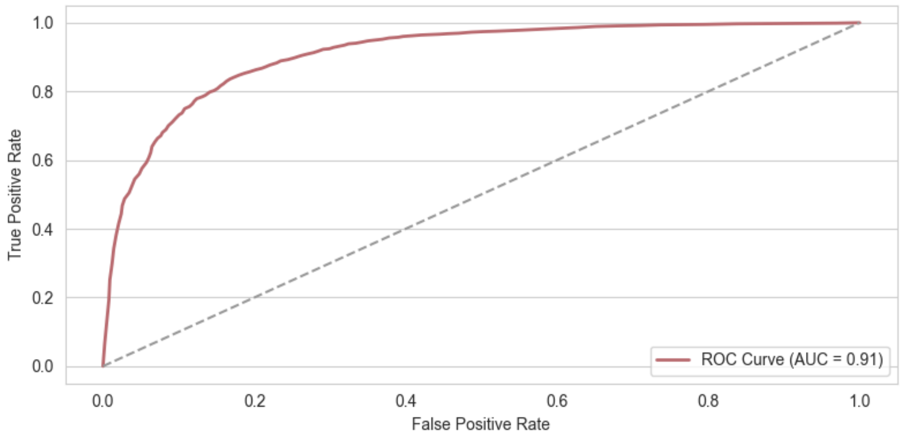

Figure 5. Receiver Operating Characteristic (ROC) curve for the Random Forest model.

performance. An AUC value close to 1.0 suggests that the model is highly effective in distinguishing between students with and without depression.

This high AUC score confirms that the Random Forest classifier performs well at a single threshold and maintains strong predictive power across a range of threshold settings. Such robustness is particularly valuable in mental health applications, where different use cases (e.g., conservative screening vs. broader outreach) may require flexible threshold tuning.

3.3. Model Interpretability with LIME

To make the model's predictions more transparent and actionable, we applied LIME to interpret individual predictions. Figure 6 shows a LIME explanation for a student classified as "Not Depressed," revealing the top contributing features and their directional impact on the model's decision.

In this example, low academic pressure (Academic Pressure > 0.62) emerged as the strongest indicator supporting the "No Depression" prediction. Conversely, factors such as low financial stress, fewer study hours, and moderately healthy dietary habits also contributed negatively toward a depression classification, reinforcing the model's confidence in a healthy mental state. Other contributing variables, like moderate age, adequate sleep, and absence of family mental illness history, offered additional support to the prediction.

This explanation highlights how the model incorporates a mix of behavioral, psychological, and demographic features to form a nuanced understanding of mental health risk. LIME allows stakeholders to inspect and validate individual predictions, making the model accurate, interpretable, and trustworthy in real-world applications.

To complement the previous example, Figure 7 displays a LIME explanation for a prediction classified as "Depression." In this case, the strongest contributors to the depression classification include high academic pressure, significant financial stress, and older age, all of which align with known risk factors for student mental health challenges. Additional features that supported the "Depression" outcome were low study satisfaction, suboptimal dietary habits, and a positive family history of mental illness.

Interestingly, the presence of suicidal thoughts was the single most decisive factor, strongly reinforcing the depression prediction. Variables like limited sleep duration and fewer study hours contributed modestly to the model's classification. The combined effect of these features demonstrates how multifaceted and interrelated the risk factors for depression can be.

This instance underscores the utility of explainable AI in flagging at-risk individuals and illuminating the specific factors driving that risk. Such interpretability enables more targeted and empathetic interventions, making the tool practical for academic counselors and mental health professionals.

3.4. Discussion

This study shows that machine learning, especially explainable models like the one used here, can help identify signs of depression among students in academic settings. The Random Forest classifier performed well, with an accuracy of 83.52% and an AUC of 0.91. More importantly, using LIME allowed us to understand which specific factors contributed to the predictions for each student. Academic pressure, financial stress, sleep duration, study satisfaction, and suicidal thoughts were among the most influential factors. These findings align with what we already know from psychological and

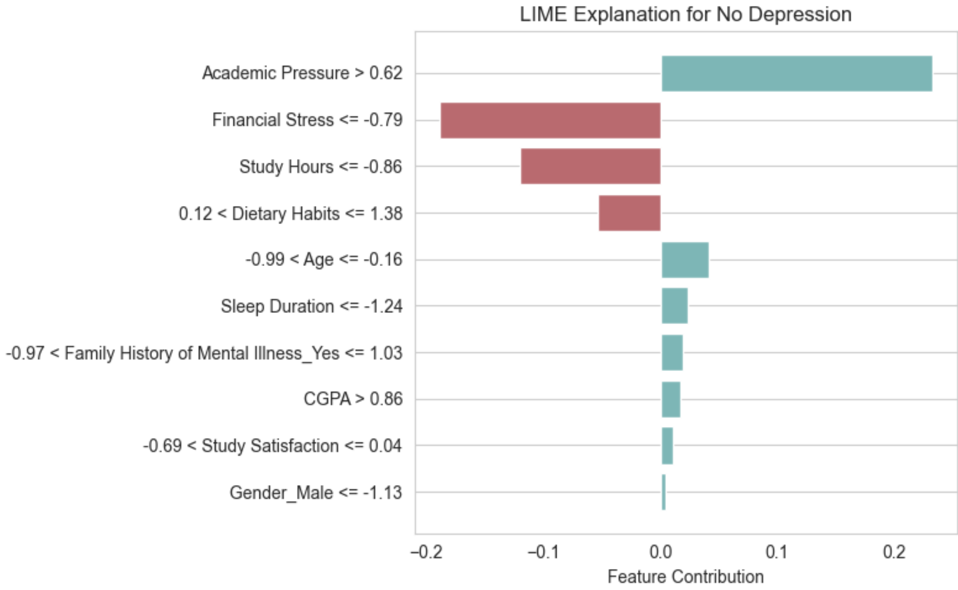

Figure 6. LIME explanation for a "No Depression" prediction.

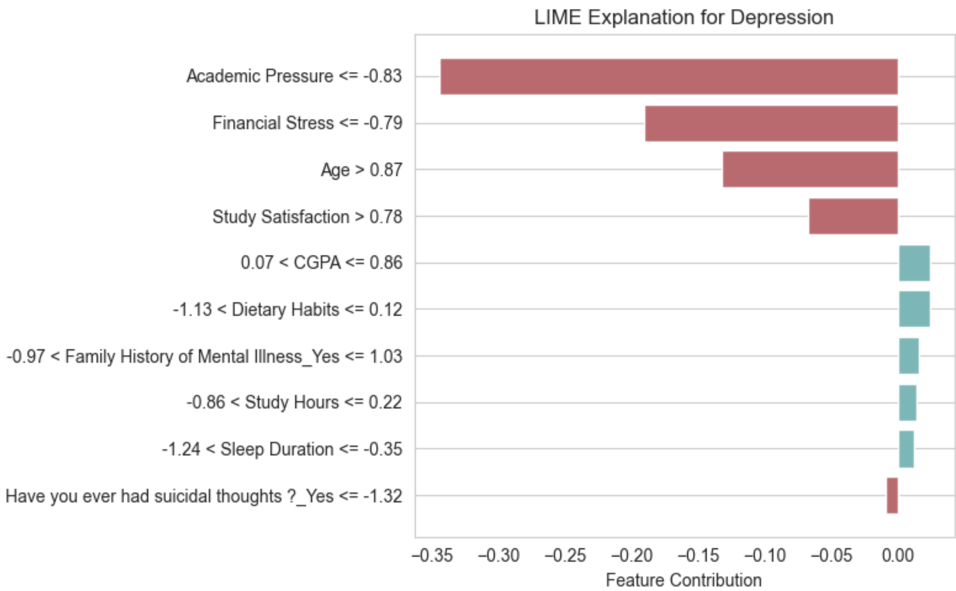

Figure 7. LIME explanation for a "Depression" prediction.

educational research [27, 28], but offer a new way to spot patterns in large groups of students.

The results have practical implications for schools, colleges, and universities. Instead of relying only on clinical assessments, institutions can use behavioral and lifestyle information, often easier to collect in educational settings, to flag students who may be struggling. Because the model can explain its predictions, staff members such as academic advisors, counselors, or support officers can better understand what might affect a student's mental health. This could help them design targeted programs around managing academic stress, improving study habits, supporting sleep and nutrition, or offering financial advice. Another benefit is transparency. One of the challenges of using AI in education is the lack of trust from students and staff. Models like the one in this study can show why a student was classified a certain way, helping to build confidence in the system and avoid the feeling that decisions are being made without explanation.

However, the study has several limitations that may affect the reliability and generalizability of its findings. The dataset was sourced from a public platform and is based entirely on self-reported data, vulnerable to biases such as social desirability, inaccurate recall, or underreporting of symptoms. These biases can distort the true prevalence and severity of depression, potentially leading the model to learn patterns that do not generalize well to broader or more diverse student populations. Additionally, the dataset lacks important contextual variables, such as academic workload, financial stress, or access to support services, which are known to influence student mental health. The absence of these potential confounders limits the model's ability to account for key factors that might mediate or moderate depressive symptoms.

Furthermore, the data were collected simultaneously, providing only a snapshot rather than a dynamic view of mental health over a semester or academic year. This temporal limitation restricts the model's ability to detect fluctuations in mental health that may be critical for timely intervention. While LIME was used to provide interpretability at the individual level, it does not offer comprehensive insights into global model behavior or reveal potential biases across subgroups. Future research should prioritize longitudinal data collection, inclusion of contextual variables, and diverse sampling to improve the robustness and applicability of predictive models in real-world educational settings.

Future research should examine how students' mental health changes over time and consider a wider range of data sources, like academic records, attendance, or digital behavior (with proper consent and safeguards). Testing these models in real-world settings, especially in schools or universities with different resources and student needs, will also be important. Using other explanation tools like SHAP could help provide individual and group-level insights.

4. Conclusions

This study highlights the potential of explainable machine learning to identify behavioral and psychological factors associated with depression in academic contexts. Using a Random Forest classifier combined with LIME explanations, the model achieved 83.52% accuracy and an AUC of 0.91, offering predictive strength and interpretability. Key features such as academic pressure, financial stress, sleep patterns, dietary habits, and suicidal ideation were consistently associated with depression risk. While these findings suggest that interpretable machine learning can uncover meaningful patterns in student mental health data, several methodological limitations must be considered. Using a publicly available, self-reported dataset introduces concerns about data quality, including possible response biases and missing contextual variables. In addition, the reliance on a single train-test split without external validation or established clinical benchmarks limits the generalizability and robustness of the results. Future work should incorporate validated, longitudinal datasets, adopt more rigorous evaluation methods, and compare performance against existing screening tools to better assess the practical utility of these approaches in educational settings.

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