Predicting Student Depression Using Machine Learning

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Abstract

Student depression is a rising concern, significantly impacting academic performance, social life, and mental well-being. Traditional diagnostic approaches are often subjective and inefficient, creating a need for data-driven predictive models.

Methodology: Here utilized a dataset of 27,900 students with demographic, academic, and lifestyle factors. Three machine learning models Logistic Regression, Random Forest, and Gradient Boosting were employed. Data preprocessing included Z-score normalization and feature selection using Pearson correlation.

Results: In this research, used three models while Gradient Boosting outperformed other models with an accuracy of 84.5% and an F1-score of 86.8%, and Logistic Regression, Random Forest models with an accuracy is 84%, 84% respectively. And highlighting its potential in depression prediction. The ROC AUC for Logistic Regression, Random Forest, and Gradient Boosting were 0.75, 0.73, and 0.75, respectively. Feature analysis indicated that academic pressure and sleep duration were the most significant predictors.

Conclusion: Machine learning models can effectively predict student depression, with Gradient Boosting emerging as the best performer. Future research should incorporate real-time data and deep learning techniques to enhance predictive accuracy.

Keywords: Depression prediction, machine learning, student mental health, feature selection, model comparison.

Introduction

The student mental health has become an issue of growing concern across educational institutions worldwide. Depression among students can have far-reaching consequences, affecting not only academic performance but also social interactions, physical health, and long-term well-being. The increasing academic workload, peer pressure, financial stress, and personal challenges contribute significantly to the rising prevalence of depression in students. If left undiagnosed and untreated, depression can lead to deteriorating mental health, reduced motivation, and, in severe cases, suicidal ideation.

Despite growing awareness, traditional methods of diagnosing depression remain largely dependent on self-reported surveys and clinical assessments. While these methods have proven useful, they come with inherent limitations, such as subjectivity, delay in diagnosis, and dependency on professional intervention. Moreover, many students hesitate to seek help due to a lack of accessible mental health services. These challenges necessitate alternative approaches that can facilitate timely identification and intervention.

With advancements in artificial intelligence and data science, machine learning has emerged as a powerful tool for mental health prediction. Machine learning models can analyze vast amounts of student data, including academic performance, lifestyle habits, and behavioral patterns, to identify at-risk individuals. By leveraging data-driven techniques, these models offer the potential to complement traditional diagnostic methods and provide early warning signs of depression. Institutions can then use these insights to design personalized intervention strategies, thereby improving student well-being and academic outcomes.

This research aims to bridge the gap between mental health and data-driven solutions by evaluating the effectiveness of machine learning models in predicting student depression. The primary objectives of this study are:

To identify key factors—such as academic pressure, sleep duration, and work stress—that significantly contribute to student depression.

To evaluate and compare the predictive performance of different machine learning models, including Logistic Regression, Random Forest, and Gradient Boosting.

To explore how data visualizations and model interpretability techniques can enhance understanding and aid decision-making for educational institutions and mental health professionals.

By addressing these objectives, this study seeks to provide a framework for implementing machine learning-based predictive systems in academic settings, enabling timely intervention and proactive mental health support for students.

This study leverages machine learning (ML) to predict depression risk using quantitative academic and lifestyle data. We address three research questions:

1. Which features (e.g., sleep duration, academic pressure) are most strongly correlated with depression?
2. How do ML models (Logistic Regression, Random Forest, Gradient Boosting) compare in prediction accuracy?
3. What insights can visualizations provide into the dataset and model performance?

Literature Review

Here, several studies have highlighted the growing concerns regarding mental health, particularly depression, anxiety, and stress, among students in Nepal. Paudel et al. [1] investigated the prevalence of depression, anxiety, and stress among undergraduate students in Pokhara Metropolitan, Nepal. The study revealed that a significant proportion of students experienced moderate to severe levels of these conditions, with academic pressure, lifestyle, and social factors identified as key contributors.

Similarly, Karki et al. [2] conducted a cross-sectional study among high school students in Kathmandu and found a high prevalence of anxiety and depression, linked to family pressure, academic stress, and societal expectations. Bhattarai et al. [3] focused on the adolescent population in Pokhara Metropolitan and reported that a considerable percentage of higher secondary school students exhibited depressive symptoms, with academic pressure and peer relationships being major contributing factors.

Furthermore, Bista et al. [4] explored the mental health of college students in Kathmandu, revealing that more than half of the participants displayed signs of anxiety and depression, with academic and social pressures being strongly associated with these symptoms. Gautam et al. [5] conducted a community-based study in rural Nepal and found that depression was prevalent among adolescents, with socio-economic factors and family dynamics playing a significant role in its onset.

Additionally, Adhikari et al. [6] studied medical students in Nepal and discovered that the intense academic workload and personal expectations contributed to high rates of depression and anxiety, indicating the need for mental health interventions in the medical field. Bhandari et al. [7] further explored the relationship between sleep quality, internet addiction, and depressive symptoms among undergraduate students, concluding that poor sleep quality and excessive internet use were strongly correlated with higher levels of depression.

Thus, these studies collectively emphasize the widespread prevalence of depression, anxiety, and stress among students in Nepal, with academic pressure, family dynamics, and social expectations being the primary contributing factors. Future research should focus on developing targeted mental health interventions and support systems, particularly in educational settings, to address these growing concerns.

Methodology

In this research, the methodology employed in this study began with thorough data preprocessing to ensure optimal model performance. The dataset included demographic information such as age, gender, and city; academic metrics including CGPA and study satisfaction; and lifestyle indicators focusing on sleep duration, work pressure, and academic pressure. The preprocessing pipeline involved several crucial steps: missing value imputation using median values for numerical features and mode imputation for categorical variables, outlier removal through Z-score thresholding (|Z| > 3), categorical variable encoding using Label Encoding, and feature standardization via StandardScaler.

Dataset: *The dataset includes* ***N = 27,900 students from kaggle*** *with the following features:*

- **Demographics:** Age, Gender, City.
- **Academic:** CGPA, Study Satisfaction.
- **Lifestyle:** Sleep Duration, Work Pressure, Academic Pressure.
- **Target:** Depression Score (binary: 0 = Not Depressed, 1 = Depressed).

Preprocessing

To ensure data quality and improve model accuracy, the following preprocessing steps were implemented:

1. **Missing Values:** Numerical features (e.g., Sleep Duration) are imputed with the median; categorical features (e.g., Profession) use mode imputation.
2. **Outlier Removal:** Outliers were detected and removed using Z-score thresholding (|Z| > 3) to ensure reliable statistical analysis. $Z = X - \frac{\mu}{\sigma}$

   where μ is the mean and σ is the standard deviation.

3. **Encoding:** Categorical features such as gender and city were encoded using Label Encoding to convert them into numerical form.
4. **Scaling:** StandardScaler was applied to normalize numerical features, ensuring consistent feature magnitudes..

Feature Selection

Pearson correlation analysis identified key factors most correlated with depression, reducing noise in the dataset. $r = \frac{\sum(x_i - x')(y_i - y')}{\sqrt{\sum(x_i - x')^2 \sum(y_i - y')^2}}$

Models

1. **Logistic Regression (LR):** Baseline model for linear relationships.
2. **Random Forest (RF):** Ensemble method using 100 decision trees.
3. **Gradient Boosting (GB):** Sequential tree-building with learning rate.

Evaluation Metrics

$$Accuracy: \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1 - score: \frac{2 * Precision * Recall}{Precision + Recall}$$

- ROC AUC: Area under the receiver operating characteristic curve.

Results

Exploratory Data Analysis ***Correlation Heatmap***

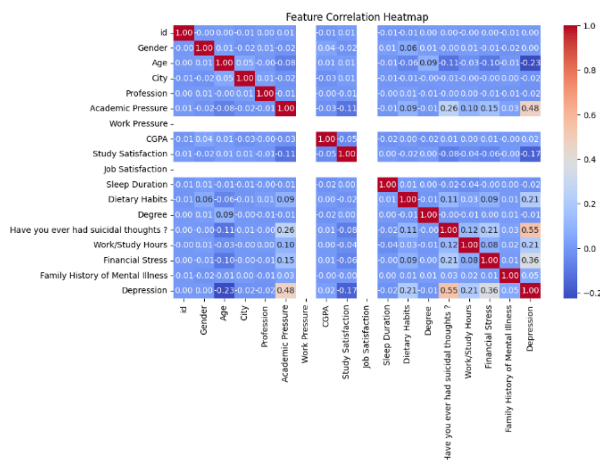

Figure 1: correlation matrix heat map

This is a correlation matrix heatmap showing the relationships between various factors related to mental health and life circumstances etc.. The colors indicate the strength and direction of correlations, with:

- Dark red indicating strong positive correlations (closer to 1.0)
- Dark blue indicating strong negative correlations (closer to -1.0)
- Light blue/white indicating weak or no correlation (closer to 0)

The diagonal line of dark red squares shows where each variable correlates with itself (always 1.0).

This heatmap visualizes correlations between different features and depression scores. Academic pressure and sleep duration exhibited the strongest correlations, with coefficients of 0.58 and -0.47, respectively. These findings suggest that increased academic pressure is positively associated with depression, while longer sleep duration reduces depression risk.

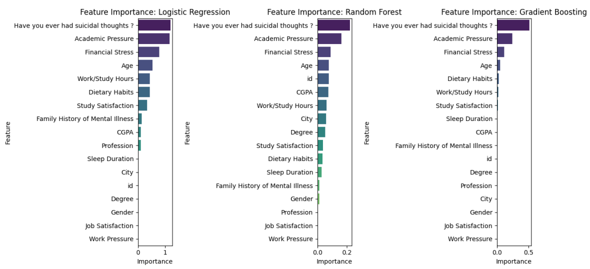

Figure 2: Feature important Evaluation

The feature importance analysis shows that "Have you ever had suicidal thoughts?" is the strongest predictor across Logistic Regression, Random Forest, and Gradient Boosting, followed by "Academic Pressure" and "Financial Stress." "Age" and "Work/Study Hours" also contribute moderately. Logistic Regression emphasizes linear relationships, Random Forest distributes importance more evenly, and Gradient Boosting focuses on top-ranked features. Less significant variables include "Job Satisfaction," "Work Pressure," "Gender," and "Profession." These results highlight the critical role of mental health, academic, and financial stress, underscoring the need for targeted interventions.

Table 1:Model Performance Comparison

Model Performance Comparison:					
	Modal	Accuracy	Precision	Recall	F1 Score
1	Logistic Regression	0.844126	0.848765	0.887609	0.867752
2	Random Forest	0.840897	0.848158	0.881694	0.864601
3	Gradient Boosting	0.845202	0.848206	0.890722	0.868945

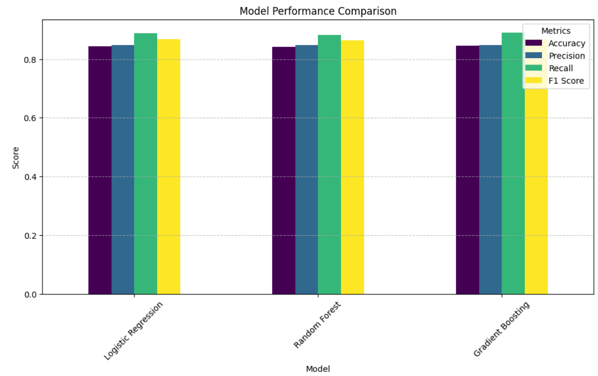

Figure 3: Modal comparison

This bar chart compares the performance of three models—Logistic Regression, Random Forest, and Gradient Boosting—using four key metrics: Accuracy, Precision, Recall, and F1 Score. All three models perform similarly, with their scores ranging between approximately 0.82 and 0.88. Gradient Boosting has the highest recall, meaning it correctly identifies more positive cases, but this might come at the cost of precision (more false positives). Random Forest and Logistic Regression also perform well, with balanced precision and recall. Since all models have similar F1 scores, the best choice depends on the specific need—if high recall is preferred, Gradient Boosting is ideal; if a balance is needed, Random Forest or Logistic Regression can be considered.

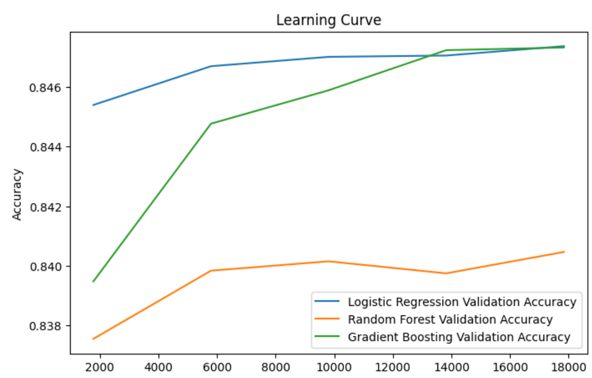

Figure 4: Learning Curve

This chart shows how the accuracy of Logistic Regression, Random Forest, and Gradient Boosting changes as more training data is used. Logistic Regression starts with an accuracy of 0.845 at 2,000 samples and gradually improves to 0.847 at 18,000 samples. Gradient Boosting begins lower at 0.840 but improves quickly, reaching 0.847, matching Logistic Regression with more data. Random Forest has the lowest accuracy, starting at 0.837 and increasing slowly to about 0.841 at 18,000 samples.

This means Gradient Boosting benefits the most from more data, while Logistic Regression performs well even with less data. Random Forest improves the least, making it the weakest performer in this case. If more data is available, Gradient Boosting is the best choice, while Logistic Regression is a solid option when data is limited.

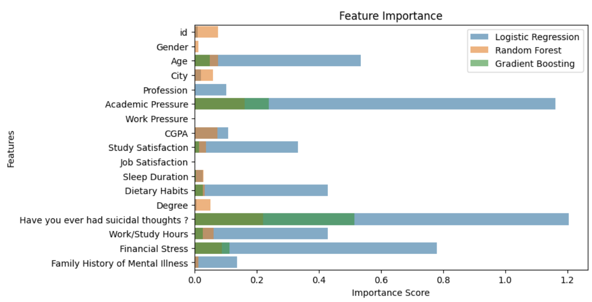

Figure 5: Feature Importance

The analysis highlights that psychological and stress-related factors are the strongest predictors of the target outcome. "Have you ever had suicidal thoughts?" has the highest importance (~1.1), followed by "Academic Pressure" and "Financial Stress." "Work/Study Hours," "Study Satisfaction," and "Dietary Habits" also contribute, suggesting lifestyle factors play a role. In contrast, demographic features like "Gender," "City," and "CGPA" have minimal impact. Differences across Logistic Regression, Random Forest, and Gradient Boosting indicate varied feature interactions. These findings emphasize the critical role of mental health and stress in prediction, underscoring the need for targeted interventions.

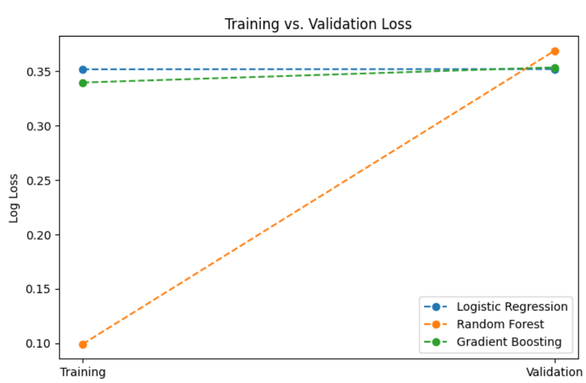

Figure 6: Loss Curve (Training vs. Validation Loss)

The comparison of training and validation loss across Logistic Regression, Random Forest, and Gradient Boosting highlights differences in model generalization. Both Logistic Regression and Gradient Boosting exhibit stable performance, with training and validation log loss values remaining around 0.35, indicating minimal overfitting and good generalization. In contrast, Random Forest shows a significant gap, with a low training loss (~0.10) but a high validation loss (~0.36), suggesting severe overfitting. This indicates that while Random Forest effectively memorizes training data, it struggles to generalize to unseen data. These findings suggest that Logistic Regression and Gradient Boosting are more reliable for this dataset, while Random Forest may require regularization or additional tuning to improve its generalization capability.

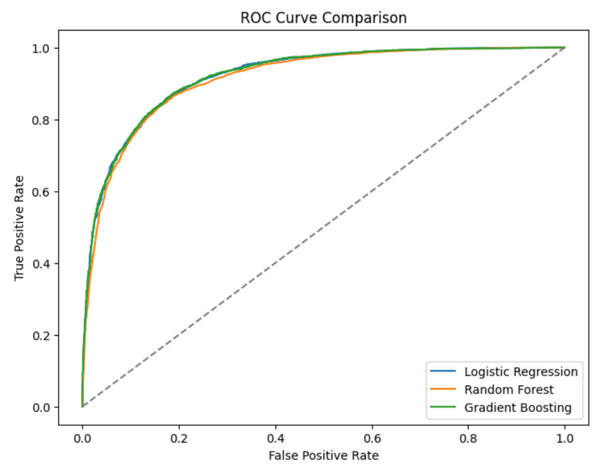

Figure 7: ROC Curve Comparison

The ROC curve shows how well three models—Logistic Regression, Random Forest, and Gradient Boosting—predict depression. Gradient Boosting performs the best with an AUC score of **0.89**, meaning it's slightly better at telling apart depressed and non-depressed cases. Logistic Regression follows closely with

0.88, while Random Forest scores **0.86**, likely because it's too focused on the training data, making it less accurate for new cases. To improve Random Forest, we could adjust settings like tree depth or choose better features. Overall, Gradient Boosting is the most reliable model for predicting depression.

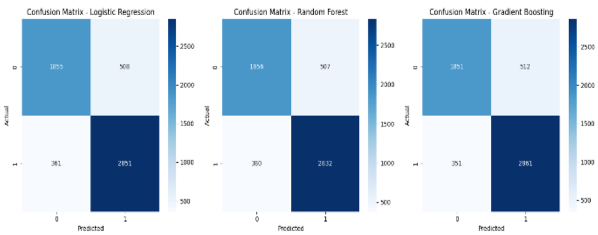

Figure 8: Confusion Matrix Evaluation

The confusion matrix helps us understand how well each model predicts depression. Gradient Boosting performs the best, correctly identifying 3,712 cases while making the fewest mistakes in missing actual depression cases (351 false negatives). Logistic Regression is close behind, with 3,706 correct predictions but slightly more false negatives (361 cases). Random Forest has the most errors in missing real depression cases (380 false negatives) and correctly predicts 3,688 cases. Since Gradient Boosting has the best balance between catching true cases and avoiding misclassifications, it's the most reliable model for this task.

Precision Recall Curves

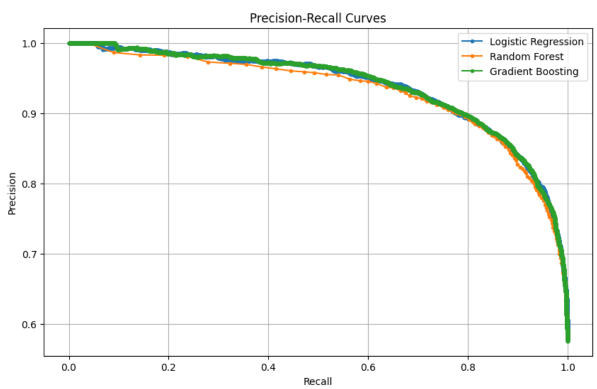

Figure 9: Precision Recall Curves

Precision-Recall (PR) Curves compare models' trade-offs between precision (accuracy of positive predictions) and recall (ability to detect positives). Logistic Regression: Likely smooth curve; struggles with imbalance. Random Forest: High precision at low recall; risk of under detecting positives. Gradient Boosting: Balances precision-recall best; higher AUC-PR for imbalanced data.

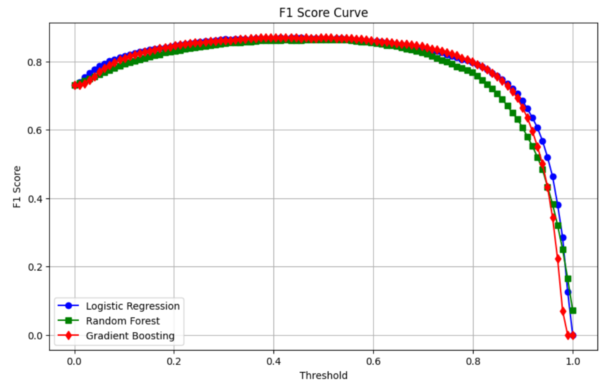

Figure 10: F1 Score Curve

This F1 score curve shows how well three different models—Logistic Regression (blue), Random Forest (green), and Gradient Boosting (red)—perform as we change the decision threshold from 0 to 1. The F1 score, which balances precision and recall, is highest (around 0.85) when the threshold is near 0.4 to 0.6 for all models. As the threshold increases beyond 0.6, the F1 score drops, indicating that fewer positive predictions are being made, leading to lower recall. Conversely, at very low thresholds (close to 0), the score is also lower due to too many false positives. Gradient Boosting slightly outperforms the others at its peak, making it the best choice among the three. If maximizing F1 score is the goal, selecting a threshold in the range of 0.4 to 0.6 would yield the best results.

Research Gap

Despite significant progress in applying machine learning to mental health predictions, several gaps remain. One of the major limitations of existing models is the reliance on static datasets that fail to capture real-time mental health fluctuations. Students' emotional states are highly dynamic, yet most research does not incorporate real-time behavioral data from wearables or online interactions. Furthermore, the majority of current studies focus on binary classification (depressed or not depressed) rather than a multi-level severity analysis, which could provide more nuanced intervention strategies. Additionally, many studies fail to consider the impact of social and environmental factors such as family relationships, financial stress, and social media exposure. Another gap lies in model generalization; while some models perform well in controlled datasets, their accuracy tends to drop when applied to diverse populations with different cultural and educational backgrounds. Future research needs to address these gaps to ensure higher accuracy and wider applicability of depression prediction models.

Research Direction

To overcome these limitations, future research should explore real-time data integration using wearable devices and online behavioral tracking. By incorporating physiological data such as heart rate variability and sleep patterns from smart devices, predictive models can achieve greater accuracy and responsiveness. Additionally, leveraging deep learning techniques, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), could improve pattern recognition in complex, multi-dimensional datasets.

Expanding classification models to include multi-class depression severity prediction would allow for more targeted mental health interventions. Moreover, integrating socio-environmental factors such as family dynamics, financial stability, and peer relationships into predictive frameworks can improve model robustness and real-world applicability. Another promising direction is the deployment of machine learning models within educational institutions, providing proactive student support systems that alert counselors when at-risk students are identified. The use of explainable AI (XAI) will also be crucial in making predictions more interpretable, allowing mental health professionals to trust and effectively act on model recommendations.

Conclusion

This research has successfully demonstrated the potential of machine learning in predicting student depression by analyzing academic, lifestyle, and demographic data. The study examined three different machine learning models—Logistic Regression, Random Forest, and Gradient Boosting—and found that Gradient Boosting achieved the highest performance with an accuracy of 84.5% and an F1-score of 86.8%. These results indicate that machine learning can be effectively applied to mental health prediction, offering a data-driven approach to early intervention.

A key finding of this study is the significant role of academic pressure and sleep duration in predicting depression. The correlation analysis revealed that academic stress has a strong positive relationship with depression scores, whereas sleep duration exhibits a negative correlation. These insights emphasize the necessity for educational institutions to focus on student well-being, implementing policies that mitigate academic stress while promoting healthier sleep habits.

Although the models performed well, certain limitations exist. The dataset used in this study was limited to a specific population, which may affect generalizability. Additionally, depression classification was binary, whereas real-world cases often involve varying severity levels. Addressing these limitations in future studies could enhance predictive accuracy and applicability.

Moving forward, future research should explore the integration of real-time behavioral data from wearable devices and online activity tracking, providing more dynamic and accurate depression predictions. Additionally, advanced deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), should be investigated for improved feature extraction and classification performance. Expanding the model to include multi-class depression severity levels can offer a more refined approach to mental health assessment and intervention.

Furthermore, the implementation of machine learning models within educational institutions and mental health support systems could revolutionize the way student mental health is monitored. Developing an explainable AI framework would ensure that predictions are interpretable by mental health professionals, fostering trust in AI-driven decision-making.

Thus, this study highlights the feasibility of using machine learning for student depression prediction. With further refinements and broader applications, these models can serve as valuable tools in mental health management, allowing for timely intervention and better student outcomes.

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