Mental Health Analysis: ML And Explainable AI Predict Depression Among Bangladeshi University Students

Sarzila Sahrin Jisha
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
sarzila.jisha1604@gmail.com

Shahriar Ayon
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
shahriarayon63@gmail.com

Sharia Arfin Tanim
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
shariaarfin096@gmail.com

Fahim Abdullah Md. Raeid
Artificial Intelligence Research and Innovation Lab
Dhaka, Bangladesh
fahim45147@gmail.com

Tahmid Enam Shrestha
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
tahmidenam12@gmail.com

Md Sadi Al Huda
Artificial Intelligence Research & Innovation Lab
Dhaka, Bangladesh
sadialhuda.aiub@gmail.com

Md. Asraf Ali
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
asrafali@aiub.edu

Abstract

This paper uses Machine-learning and Explainable AI techniques to investigate the prevalence of depression and its determinants among the Bangladeshi university students. Because of a variety of socioeconomic and cultural factors, young adults are disproportionately affected by depression, a common mental health issue. The study examines depression rates and contributing factors among Bangladeshi students across 39 features by utilizing a Kaggle dataset with 1,977 data points. With careful feature engineering and preprocessing, an improved dataset with eighteen columns was produced. Subsets of the dataset were used for training, testing, and validation of the models; among the evaluation metrics, the ensemble model that combines Support Vector Machine (SVR) and Linear Regression proved to be the most effective. Notably, when compared to individual ML models, the ensemble model performed better. The results emphasize how important it is to address depression in university settings with early detection and intervention techniques. All things considered, this study advances the field of mental health analysis and highlights the potential of machine learning and explainable artificial intelligence in detecting and treating mental health issues in young adults.

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CCS Concepts

• **Social and professional topics** → **Health care**; • **Computing methodologies** → *Machine learning*; Explainable artificial intelligence.

Keywords

Depression, Bangladeshi university students, Machine Learning, Mental health analysis, Socio-economic factors.

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1 Introduction

Depression, often referred to as the "common cold" of mental health, as shown in Figure 1 is the oldest recognized psychiatric disorder [18]. Its pervasive nature transcends cultural, geographical, and socioeconomic boundaries, making it a ubiquitous concern in global public health. It is a common mental illness, with statistics indicating that virtually everyone, at some point in their lives, experiences feelings of depression [5]. According to a recent report of WHO (World Health Organization) (WHO), depression affects approximately 280 million people worldwide. In Bangladesh alone, nearly 7.3 million adults grapple with the challenges posed by depression [10]. Of particular concern is the prevalence of depression among the youth demographic. Studies have consistently shown that depression disproportionately impacts young adults, influencing their lifestyle choices and cognitive processes [17]. Factors such as academic pressure, social media exposure, economic instability, and societal expectations contribute to the vulnerability of youths to mental health disorders like depression. The implications of untreated depression extend beyond individual well-being, affecting familial relationships, productivity, and societal cohesion. As the global burden of mental health disorders continues to rise, combating depression has emerged as a critical public health priority, particularly in young adults [12]. Efforts aimed at early detection, prevention, and treatment of depression are crucial in mitigating its adverse effects on individuals and communities. Furthermore, fostering mental health literacy, promoting access to mental health services, and reducing the stigma associated with seeking help are integral components of comprehensive mental health strategies.

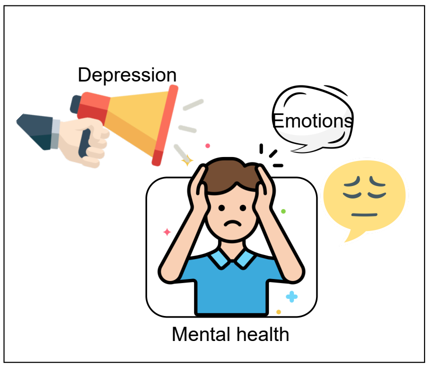

Figure 1: Complexity of Mental Health Problems in Human Beings.

In Bangladesh, the suicide rate among university students is rising alarmingly [5]. A news report indicates that 98 university student suicides were recorded in 2023 [1]. There is a lack of concern among general people in Bangladesh regarding common mental health problems [16]. 75% of the people do not receive any treatment for mental disorders. In more than 50% cases, depression was failed to recognize at primary stage. Social stigma is one of the barriers which highlights the necessity of an unobtrusive way to identify depression [2]. A significant number of students lack awareness about mental disorders, with an alarming 42.4% considering suicide due to anxiety and stress. No specific single cause is responsible of having depression. Young people are particularly vulnerable to this condition, often facing emotional or sexual violence, financial difficulties, and addiction to drugs [18] [5]. In 2020, the COVID-19 pandemic led to a further increase in depression cases. It has had a severe impact on students, exacerbating sleep disorders and contributing to poor dietary habits.

In the realm of mental health, machine learning is nevertheless a fairly recent innovation. With the advent of computational models, extensive research has been conducted on the development of machine learning models for depression identification. This papers objects to

- Comprehensive Exploration of Depression Among Bangladeshi University Students.
- The study utilizes machine-learning and explainable AI to illuminate the intricate factors underlying depression, aiming for enhanced comprehension of the condition.
- Identifying the critical elements and opportunities for mental health interventions.

2 Literature Review

University students are experiencing a mental health crisis. Siddiqua et al, 2023 [7] applied 10 ML and 2 DL models to predict the depression levels among university students in Bangladesh. Eight different depression measurement scales were used in this study. The results indicated that 36.7% of participants were classified as moderately depressed, while 25.4% were categorized as extremely depressed. The accuracies achieved for predicting depression levels were 98.08% with the Random Forest model, 94.23% with the Gradient Boosting model, and 92.31% with the CNN model. Previously, Choudhury et al, 2019 applied kNN, random forest and SVM to identify the depression of university students in its early stages, so that fast recovery can be ensured and suicide can be avoided.

Hussna et al, 2021 [11] highlighted the mental impact on students during Covid-19 from the perspective of 1182 university students. Faisal et al. (2022) [8] aimed to evaluate the prevalence of depressive symptoms and their impact on vulnerability by analyzing students' mental health during COVID-19. The study, which included 874 Bangladeshi university students, found that 72.1% exhibited symptoms of depression, and 53.9% had moderate to poor mental health. Path analysis indicated that 77.1% were concerned about the effects of COVID-19, and 88.1% were fearful about the future. The paper highlighted the high incidence of mental health issues and revealed that the predictors accounted for 14% of the variability in depression.

In addition, El Morr et al, 2024 [7] initialized LR, MLP, SVM, AdaBoost and 4 other ML predictive models to access Lebanese university students' depression, anxiety, and stress during Covid-19, comparing with 12 countries' student data. They found that 75.9% of students reported moderate to severe depression with a 10.18 mean (SD) depression score, whereas Random Forest achieved the best AUC at 78.27% for depression. This research also found 82.4% symptoms of depression levels in Bangladesh.

Koly et al, 2021 [13] employed a survey on 400 students of two renowned public universities, and found that depression prevalence was higher in females (57.7%). Poor academic performance (56.7%), habit of smoking (78%), exposure to addictive drugs (76.5%), excess use of social media (48.4%), irregular sleeping hours (43%), financial crisis (56.8%), previous history of depression (70%) were the factors associated with depressive symptoms among university students. In a similar way, Mamun et al, 2022 aimed to investigate the prevalence and associated risk predictors of depression, anxiety, and stress among Bangladeshi university students. This study concluded 590 students of Jahangirnagar University, where the prevalence of depression came out at 52.2%. Risk factors found out for depression included coming from a lower-class family, being a cigarette smoker, and engaging in less physical exercise. Ahmed et al, 2023 [2] aimed to develop a minimal system named "Mon-Majhi" to identify depression unobtrusively in real-time, with the help of machine learning models. Patient Health Questionnaire

Table 1: Literature Review on Mental Health Among Bangladeshi University Students

Article	Study Design & Objective	Key Findings
[15]	Cross-sectional survey aiming to investigate the prevalence and risk predictors of depression, anxiety, and stress among Bangladeshi university students at Jahangirnagar University.	- Prevalence rates: 52.2% depression, 58.1% anxiety, 24.9% stress. - No significant gender differences observed. - Risk factors: Lower socioeconomic status, smoking, less physical exercise, relationship status.
[14]	Systematic review assessing the prevalence and associated risk factors of mental health issues (depression, anxiety, stress) among Bangladeshi students during the COVID-19 pandemic.	- Prevalence rates: Depression (46.92%-82.4%), Anxiety (26.6%-96.82%), Stress (28.5%-70.1%). - Risk factors: Socio-demographic factors, health behaviors, COVID-19 related perceptions, pandemic impact, miscellaneous factors.
[3]	Online-based questionnaire study examining the mental health status of Bangladeshi university students during the COVID-19 lockdown.	- Mental health categorization: Mild (4.32%), Moderate (72.7%), Moderately severe (12.57%), Severe (10.41%). - Factors increasing mental health imbalances: Family members affected by COVID-19, insecurity, social media use, smoking. - Factors reducing mental health disturbances: Concern about studying, future career, family time, household chores. - Protective factors: Adequate sleep, participation in household chores.
[6]	Cross-sectional study among registered nurses in Bangladesh assessing the effects of the COVID-19 pandemic on mental health and the relationship between occupational factors and mental health symptoms.	- Prevalence rates: Mild to extremely severe depression (50.5%), anxiety (51.8%), and stress (41.7%). - Psychological impact of COVID-19: 61.9% of respondents reported mild to severe psychological impact. - Gender differences: Psychological symptoms more prevalent among female nurses. - Occupational factors: Complete personal protective equipment associated with lower levels of depression, anxiety, and stress. Emotional abuse at work associated with higher levels of mental health symptoms and greater psychological impact of the pandemic.

(PHQ) -9 was used, and 14 ML models were employed to evaluate 100 students' app data. This paper revealed that Light GBM model identified 82.4% depressed students with a precision of 75%. Also, 78% accuracy was gained by 5 classifiers based best Stacking model with 0.78 AUC score. Table 1 provides an overview of the study design, objectives, and key findings of each paper. By allowing for a comparison of their methodologies and results.

3 Methodology

This section describes the study's plan, which includes four main steps: data collection, preprocessing, model selection, and interpretation using the XAI framework. Figure 2 depicts a summarized methodology, providing a concise overview of the approach.

3.1 Data Collection and Processing

We used a Kaggle dataset [4] of 1,977 data points to capture depression levels among Bangladeshi university students and the contributing factors across 39 columns. Notably, the dataset has no null values. During the feature engineering phase, irrelevant features were removed, and categorical variables were transformed into numerical representations using label encoding. The preprocessing stage used a variety of techniques to refine the raw data, yielding a final dataset with 18 columns. These columns cover a wide range of topics, including causal factors, study pressure, and other important considerations. To optimize model performance, the dataset was divided into three subsets: training (80%), testing (20%), and validation (20% of the training data). So, it was partitioned into 1265 training, 316 validation, and 396 testing data points.

3.2 Machine Learning Model Selection

Following data pre-processing, we proceeded with the selection and evaluation of machine learning models based on their predictive accuracy. Below, we offer descriptions of each selected model.

During training, Random Forest Regression (RFR) creates a forest of decision trees and produces the average prediction of each tree for regression tasks. The K-Nearest Neighbors (KNN) algorithm predicts the output of a data point by determining the majority class among its k nearest neighbors in the feature space. With a margin of tolerance, Support Vector Regression (SVR) minimizes the error between the predicted and actual values by locating the ideal hyperplane in a high-dimensional space. LassoCV automatically selects the optimal regularization parameter using cross-validation. Linear regression models the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data. Our proposed ensemble model combines SVR and Linear Regression by averaging their predictions. Both models are trained on the same dataset, and during prediction, the average of their outputs is computed. To refine the ensemble's performance,

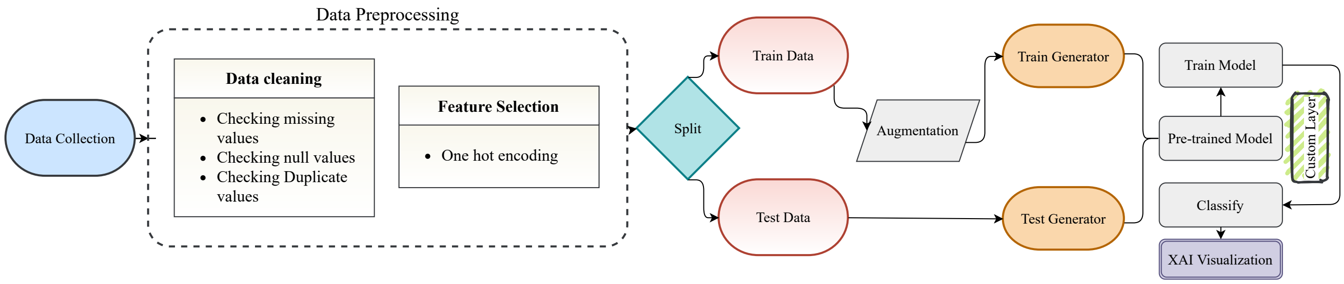

Figure 2: Proposed methodology for predicting depression level.

individual models can be assigned different weights based on their performance on validation data. The model equation is:

$$Y_{\text{ensemble}} = a \cdot \hat{Y}_{\text{SVR}} + (1 - a) \cdot \hat{Y}_{\text{linear}} \tag{1}$$

$\hat{Y}_{\text{SVR}}$ prediction from the Support Vector Regression (SVR) model, and $\hat{Y}_{\text{linear}}$ represents the prediction from the Linear Regression model.

3.3 Hyper-parameter Tuning

After pre-processing the data, the best models were selected. To enhance their performance, more hyper-parameter modifications were made, as shown in Table 2.

Table 2: Model Hyperparameters

Model	Hyperparameters
Random Forest	$n_{\text{estimators}} = 100$, $random\_state = 42$
KNN	$n_{\text{neighbors}} = 5$
SVR	Kernel = 'rbf', $C \sim U(0.1, 10)$, Gamma choices: 'scale', 'auto'
LassoCV	CV = 5, Fit_intercept = ✓/×
Linear Regression	Fit_intercept = ✓/×
Ensemble (SVR+Linear)	Kernel = 'auto', Linear Regression: Fit_intercept - ✓/×

Table 2 summarizes the hyperparameter configurations for each model. Random Forest Regression (RFR) uses 100 estimators for decision trees. Support Vector Regression (SVR) selects between 'linear' and 'rbf' kernels, with 'C' controlling the smoothness of the decision boundary and 'gamma' influencing individual sample impact. LassoCV employs 5-fold cross-validation. Linear Regression's fit_intercept parameter decides whether to calculate the intercept. Our ensemble model combines SVR and Linear Regression predictions, with SVR selecting 'auto' or 'linear' kernels and Linear Regression optionally fitting an intercept.

3.4 Evaluation Matrices

We evaluated the performance of the selected models using six key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R^2), Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE). Equation 2 presents a detailed breakdown of the equations for these evaluation metrics.

$$\begin{aligned}
MAE &= \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \\
MSE &= \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\
RMSE &= \sqrt{MSE} \\
R^2 &= 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \\
RMSLE &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(log\,(1+y_i) - log\,(1+\hat{y}_i)^2\right)} \\
MAPE &= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100
\end{aligned} \tag{2}$$

In the context of the equations, N denotes the number of samples, y_i refers to the actual values, $\hat{Y}_i$ represents the predicted values, and $\bar{Y}_i$ signifies the mean of the actual values.

3.5 Experimental Setup

We built and trained machine learning models using Google Colab, taking advantage of its accessible, free computing environment. Its cooperative features promoted effective teamwork and increased the output of research. All of the code was created with Scikit-Learn in Python 3.

3.6 Explainable Artificial Intelligence (XAI)

Give users a clear understanding of the factors influencing results and the reasoning behind the decisions made by machine learning models is the aim of explainable artificial intelligence (XAI). We used Local Interpretable Model-agnostic Explanations (LIME), a tool that uses feature impact quantification to explain AI predictions [9]. The following is a representation of the LIME explanation model equation:

$$\hat{g}\,(x) = argmin_{g \epsilon G} L\,(f, g, \pi_{x'}) + \Omega\,(g) \tag{3}$$

In LIME, the explanation model $\hat{g}(x)$ captures local nuances of the complex model's behavior by drawing from a set G of potential models, typically linear ones. It optimizes a loss function $L(f, g, \pi_{x'})$

to strike a balance between the explanation model's simplicity and interpretability, even amidst perturbations.

4 Experimental Results and Analysis

This section presents a comparative analysis of prediction results across different models using LIME explanations. Our ensemble model demonstrated superior performance compared to others, as elaborated below.

4.1 Performance of Different Models

Table 3 summarizes the ultimate prediction results for all models, obtained from the testing dataset.

Table 3 highlights the performance of each model across various evaluation metrics. In terms of MAE, the linear model achieved the best result at 1.94, narrowly surpassed by the ensemble model at 1.93. For MSE, the linear model exhibited the superior performance at 6.34 compared to the ensemble model's 6.36. In RMSE, both LassoCV, linear, and the ensemble model attained identical results at 2.52. Regarding R2, the ensemble model, along with linear and LassoCV, achieved the highest score of 0.85. In RMSLE, RFR demonstrated the best performance at 0.02, while the ensemble model achieved 0.22. Lastly, in MAPE, RFR and KNN yielded the poorest performances at 20.00%, while the ensemble model attained the highest score at 17.27%. As a whole, the results show that our proposed ensemble model outperforms all metrics.

Figure 3: Violin plot for depression vs age, gender.

In Figure 3, the violin plot shows that females aged 27-30 have higher levels of depression. Furthermore, it demonstrates that males over the age of 30 suffer from depression, while no females in that age range do. Figure 4, the bar plot shows that students in the liberal arts and social science departments are more depressed than students in other departments, who are generally less depressed.

4.2 Using LIME to Interpret Ensemble Model's Predictions

In our LIME explanation, we utilized both feature importance plots and tabular plots. In Figure 5, the feature importance plot highlights the top 7 features that contribute negatively to the model, indicated in red. Conversely, the top 7 features contributing positively are shown in green. Notably, the most influential negative feature is the frequency of a student feeling down or depressed, while the top positive feature is academic performance. In Figure 6, the tabular plot illustrates a similar trend. The highest negative influence value is 3.97, while the highest positive influence value is 0.33. Other features also contribute to the model, albeit to a lesser extent.

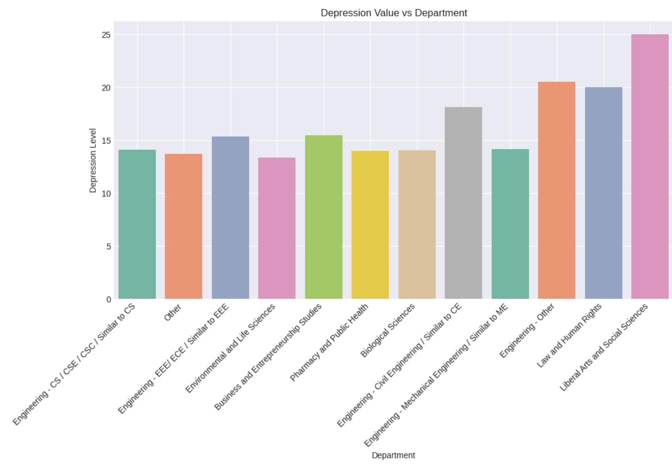

Figure 4: Bar plot for depression vs department.

4.3 Discussion

When it comes to depression level prediction, the ensemble model performs better than the other models. This is demonstrated by the fact that it consistently performs better than all other evaluated models, as shown in Figure 3,4 and summarized in Table 3. The LIME analysis provides insightful information about the variables affecting the model's predictions. With respect to the target variable, depression level, it consistently identifies certain features as top contributors that are correlated both positively and negatively. These results demonstrate how well these characteristics capture temporal dependencies and have a strong correlation with depression. When contrasted with these top contributors, other features have little effect on the predictions. We discovered significant insights while investigating the impact of student factors such as study habits and academic semester on depression. Notably, liberal arts and social science students were the most depressed, and depression rates varied by gender. We created a machine learning ensemble model using regression techniques to identify the factors closely associated with depression and predict their outcomes.

5 Conclusion & future work

In this paper, we show how machine learning and XAI can revolutionize mental health analysis, specifically in predicting depression among Bangladeshi university students. We demonstrated the effectiveness of various machine learning models and techniques, such as LIME, in understanding the underlying causes of depression and accurately predicting its occurrence. Our findings highlight the importance of using advanced analytics to address mental health issues, providing insights that can inform targeted interventions and

Table 3: Performance Metrics

Model	MAE	MSE	RMSE	R-squared	RMSLE	MAPE
Random Forest (100 Estimators)	2.03	7.02	2.65	0.83	0.02	20.00 %
KNN (5 Neighbors)	2.48	9.98	3.16	0.76	0.23	20.00 %
SVR	2.09	7.24	2.69	0.83	0.22	19.69 %
LassoCV Regression	1.96	6.36	2.52	0.85	0.21	17.76 %
Linear Regression	1.94	6.34	2.52	0.85	0.21	17.32 %
Ensemble (SVR + Linear)	**1.93**	**6.36**	**2.52**	**0.85**	**0.22**	**17.27 %**

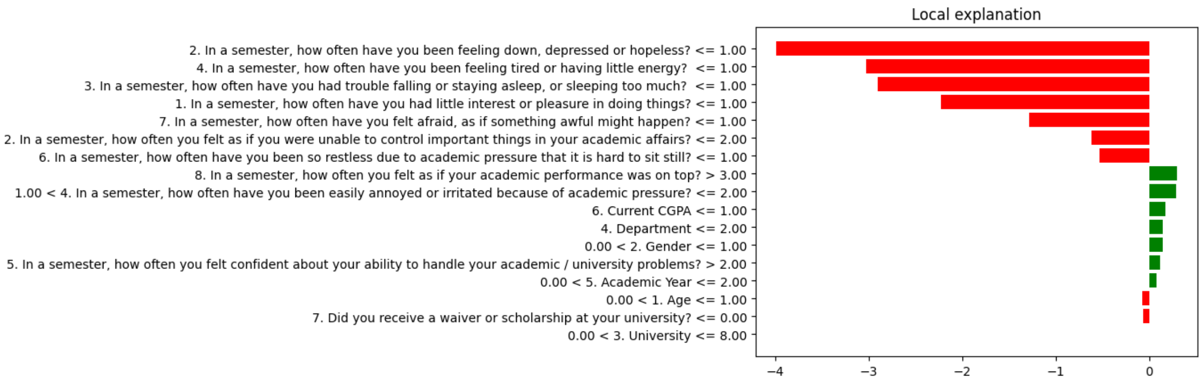

Figure 5: Lime feature importance plot.

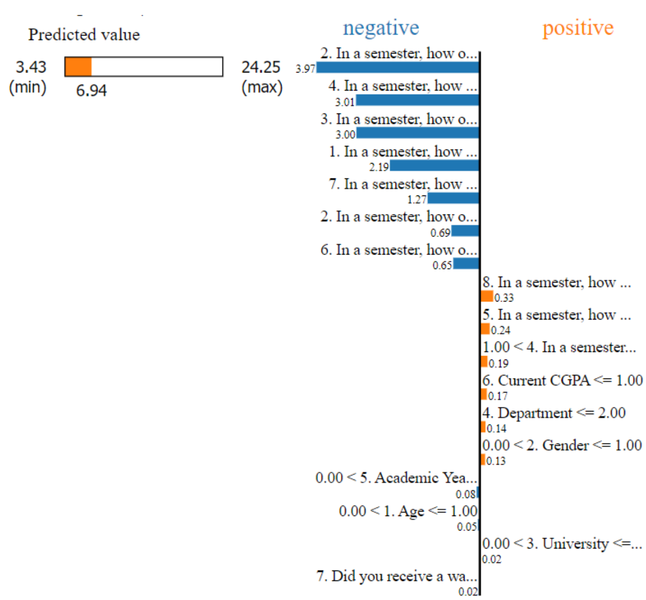

Figure 6: LIME tabular plot.

support systems for at-risk individuals. Further research can look into a variety of avenues to improve the predictive accuracy and practical utility of mental health analysis tools. This includes looking into larger and more diverse datasets to capture a broader range of factors influencing depression in university students. Furthermore, developing personalized prediction models based on individual characteristics and contextual factors can improve the accuracy of risk assessment and intervention strategies. Furthermore, incorporating real-time monitoring and feedback mechanisms into digital mental health platforms allows for proactive support and early intervention for students experiencing mental health issues. Overall, continued advances in ML and explainable AI have enormous potential to transform mental health care delivery and promote well-being among university populations.

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[4] Arfintanim. Year. Bangladeshi University Students Mental Health. Kaggle Dataset. https://www.kaggle.com/datasets/arfintanim/bangladeshi-university-students-mental-health Dataset Description: This dataset provides insights into various attributes related to Bangladeshi university students' academic experiences and demographics, sourced from Mendeley. It contains 39 columns with information on age, gender, university, department, academic year, current CGPA,

scholarship/waiver status, academic pressure metrics, and more. The dataset can be valuable for exploring factors influencing students' academic performance, well-being, and success. License: CC BY-SA 4.0.
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