Addressing the Mental Health Crisis: Understanding Suicidal Risk Factors in University Students Through Interpretable Machine Learning

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Abstract. Mental health issues among college students have become a major worldwide issue, especially impacting young adults going through crucial transitional periods. This crisis particularly affects Bangladesh, a developing South Asian country. Students there experience high rates of anxiety, depression, and suicidal thoughts, but the country has very limited mental health support services. Despite this gravity, research on Bangladeshi students' mental health is still scattered and limited by small sample sizes and a narrow demographic focus, making it challenging to develop effective intervention strategies. This study presents StudentSafe, an extensive dataset comprising 4,004 meticulously collected records from 99 Bangladeshi universities using structured questionnaires that have been verified by psychiatrists. The dataset contains demographic data, family background variables, academic performance indicators, and psychological health measures. We employed multiple machine learning algorithms to predict suicidal risk tendencies, with XGBoost achieving optimal performance at 75.36% F1-score, surpassing previous comparable studies. To ensure transparency and actionable insights, we integrated LIME and SHAP explainability frameworks, revealing that device usage patterns, institution type, academic achievement, and family environment constitute the primary determinants of suicide risk prediction among Bangladeshi students. We found that these factors are much stronger predictors than basic demographic information. This suggests we can develop specific, targeted interventions based on these key factors. This research provides Bangladeshi universities, policymakers, and mental health professionals with an evidence-based foundation for developing early warning systems and culturally appropriate support mechanisms in resource-constrained educational environments.

Keywords: Mental health, Suicidal Risks, Bangladeshi university students, Machine learning, Explainable AI, StudentSafe dataset

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1 Introduction

One of the most pressing public health issues of the twenty-first century is mental health, and university students are a particularly vulnerable group that faces particular transitional pressures as they move from adolescence to adulthood [1]. One in seven teenagers and young adults worldwide suffer from mental health conditions like anxiety, depression, or illnesses linked to stress, according to recent global data [2]. Surveys from developed countries show that more than 40% of university students report having significant stress or depressive symptoms during their academic tenure [3]. This is just one example of the alarming rates of psychological distress that are regularly highlighted by international research. Untreated mental health issues often lead to poor academic performance, study disengagement, and in severe situations, suicidal thoughts and actions.

University students are the foundation of any country's future workforce and are essential forces behind social and economic advancement, so the importance of addressing student mental health goes far beyond personal wellbeing. Suicide is the third leading cause of death for people aged 15 to 29 worldwide, accounting for about 746,000 deaths per year [4]. Young adults in educational settings are especially affected by this ongoing crisis, as social isolation, financial constraints, academic pressures, and uncertain career prospects all combine to create environments of ongoing psychological distress.

Bangladesh, a developing South Asian nation with more than 150 universities and millions of students enrolled, is particularly affected by the mental health crisis. Bangladeshi university students deal with a number of difficulties, including a lot of homework and persistent worries about competitive job markets where unemployment is still a big problem. In addition to having one of the lowest psychiatrist-to-patient ratios in the world, university counseling services are either nonexistent or inadequate [5]. Because mental health issues are stigmatized, they are often invisible and underreported, actively discouraging students from seeking professional help [6]. Recent studies have revealed alarmingly high prevalence rates: 4.4% have attempted suicide [7], 13.4% have had suicidal thoughts within the last year, 83.3% have moderate to severe anxiety, and 84.7% report depression [8]. According to meta-analytical research, the pooled lifetime prevalence of suicidal ideation among young people in Bangladesh is 24.2

Despite growing recognition of this crisis, research within Bangladesh remains fragmented and underdeveloped. As a result, we decided to use it as our case study. Existing research has generally been limited in scope, relying on small samples that do not capture the institutional and demographic diversity, or focusing narrowly on particular subgroups [9]. The lack of extensive, representative datasets has made it especially difficult to develop preventative initiatives or put early warning systems in place. Lawmakers, educators, and healthcare professionals lack the evidence base they need to respond appropriately in the absence of thorough empirical data. These important gaps are filled by this study's contributions, which include:

- **Dataset Development**: We developed the StudentSafe dataset comprising 4,004 Bangladeshi university students (3,888 after preprocessing) from diverse institutions, incorporating demographic, academic, family background and mental health indicators collected through physical surveys and structured questionnaires designed with an expert psychiatrist.
- **Classifier Model Development**: We evaluated several machine learning models, including stacked ensemble demonstrating robust predictive capability based on academic, psychological, and social stress indicators.
- **Interpretability**: We integrated LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) to ensure interpretability, revealing the factors affecting their attempts toward life ending decisions.

The abstract level implementation of this study, from dataset development to interpretable model analysis, is depicted in Figure 7.

2 Related Work

The prevalence of anxiety, depression, insomnia, and suicidal thoughts has increased recently, making mental health among Bangladeshi university students a significant research topic. According to certain research, Bangladeshi university students have experienced significantly higher levels of psychological distress than those in other groups. For instance, a prospective study recently referenced 83.3% of students reporting moderate to severe anxiety and 84.7% depression, with social media addiction, academic performance, and income at home listed as primary drivers [8]. A cross-sectional high prevalence study reported 13.4% suicidal ideation in the last year, 6% suicide plans over life, and 4.4% suicide attempts, with females having higher levels of risk [7].

Studies considered several domains to analyze suicidal cases worldwide. The tendencies are alarmingly prevalent among university students, with meta-analysis revealing a 27.1% lifetime suicidal ideation rate and 3.1% lifetime suicide attempt rate [10]. Predicting suicidal motive of students using machine learning models has been an emergence where several scholars attempted to conduct research on this matter. Various factors affecting suicide in students such as psychological [11], socioeconomic, family environmen and mental health conditions [12]. The random forest algorithm exhibited high accuracy (89.0%) in predicting students who maintained well-being or absence of suicidal ideation [13].

Mahmud et al. [14] created machine learning models to predict acts of suicide and discovered that, with 79% accuracy, Support Vector Machine was the most reliable model. Relationship status, family environment, mental health indicators (such as anxiety and depression), and stressors associated to the pandemic were important predictive variables. In [15], researchers employed machine learning in a similar manner, and the best accurate model for forecasting suicidal ideation was CatBoost. Suicidal thoughts were found to be 20.5% common, with differences across behaviors and demographics. Suicidality rates were greater among female participants, those living in rural areas, and those from joint families.

Studies related to model interpretation are not prevalent in research on suicidal ideation. Common tools for explaining model classifications include LIME and SHAP [16]. Hao et al. [17] used SHAP for explainability in conjunction with machine learning models, such as Random Forest. Although integrating interpretability to identify suicidal factors among Bangladeshi students is a significant research challenge, it remains largely unexplored. In order to provide trustworthy and culturally appropriate insights into the mental health of South Asian students, this study combines model transparency with expert-informed data to discover important predictors of suicide ideation and emotional distress using XAI technologies like SHAP and LIME.

3 StudentSafe Development

Data Collection

We developed the StudentSafe dataset of 4004 instances through a systematic three-month data collection campaign (May-August 2025) targeting bachelor's and master's students across 99 institutions in Bangladesh. Data were collected primarily through in-person campus surveys, with online questionnaires via Google Forms distributed to students we could not reach directly. The survey instrument was designed in consultation with an expert psychiatrist to ensure clinical validity and ethical appropriateness. Previous studies (i.e., [7], [18], [14]) were considered to develop the questionnaire encompassing four primary dimensions: demographic characteristics, family background, academic history, and mental health indicators. All participants provided informed consent with assurance of complete anonymity.

Data Preprocessing

The data preprocessing pipeline reduced the initial 4,004 responses to a final dataset of 3,888 samples through systematic removal of null values, CGPA bounding (2.0-4.0 range), age filtering (18-35 years), and label encoding of categorical variables. The raw dataset underwent rigorous preprocessing to ensure quality and analytical validity through the systematic steps outlined in Table 1.

Dataset Statistics

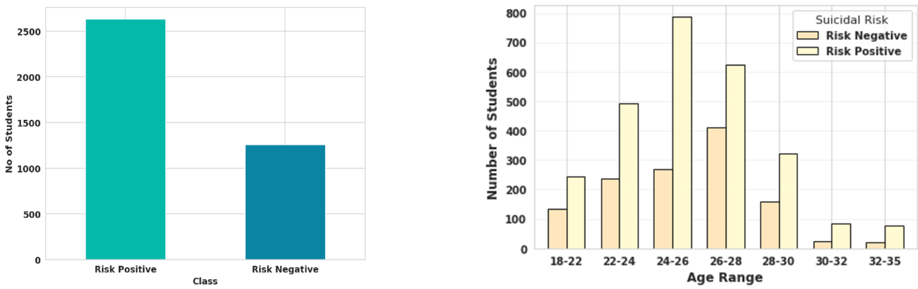
Table 1: Data Preprocessing Pipeline

Step	Operation	Rationale	n
1	Initial Collection	Survey distribution	4,003
2	Null Removal	Eliminate blank responses	4,003
3	CGPA Bounding	Delimit range in 2.0 to 4.0	3,995
4	Age Filtering	Focus on 18-35 year demographic	3,888
5	Final Collection	Cleaned and Refined	3,888
6	Label Encoding	Convert categorical to numerical	3,888

The StudentSafe dataset comprises 3,888 cleaned student responses encompassing four primary dimensions as summarized in Table 2. As the dataset contains multiple suicidal thought indicators, we consolidated them into two classes: Risk Positive (with 2nd, 3rd, and 4th determiners) and Risk Negative (with 1st determiner). The dataset exhibits significant class imbalance (see Figure 1(a)) with 67.7% classified as Risk Positive (n=2,632) and 32.3% as Risk Negative (n=1,256), subsequently addressed through SMOTE during model training.

Table 2: StudentSafe dataset feature description and characteristics.

Feature Dimension (n)	Description
Demographic & Socio-Economic (7)	Age, gender, religious identity, frequency of religious activities, residence type (urban/rural), marital status, and availability of income source.
Academic & Institutional (10)	Education level, institution name and type (public/national/private), field of study, year of study, CGPA, class participation, university satisfaction rating (1-5 scale), academic gap experience, session jam occurrence, and ragging victimization.
Family Background & Parental (6)	Family structure (joint/nuclear), family environment for studying (friendly/unfriendly), father's education level (primary/secondary/higher), father's occupation, mother's education level, and mother's occupation.
Health Behaviors & Psychological Well-Being (6)	Frequency of career depression, anxiety episodes, insomnia experiences, electronic device usage, psychoactive substance use, and cigarette smoking.
Suicidal Tendency Determiner	Four-level ordinal response representing the severity of suicidal intent: (1) *Never*; (2) *Thought but no plan*; (3) *Planned but not attempted*; (4) *Attempted once or more.*



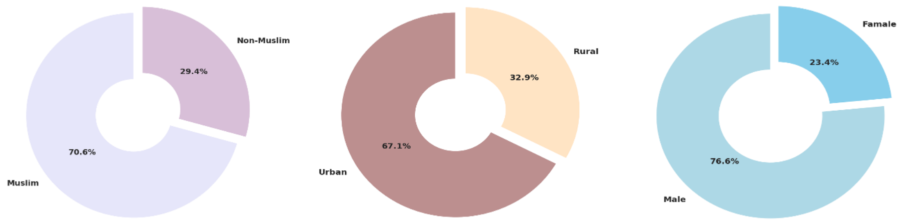
(a) (b)

Fig. 1: StudentSafe data distribution; (a) class labels, (b) age range.

Dataset Characteristics

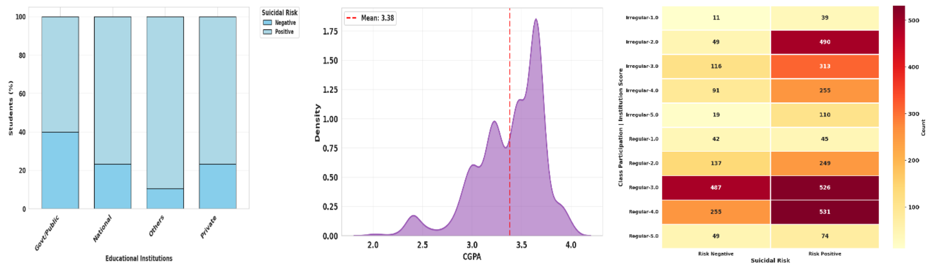
According to the age distribution shown in Figure 1(b), students between the ages of 24 and 26 make up the largest group (about 1,050 students), followed by those between the ages of 26 to 28 and 22 to 24. All age groups have risk-positive cases, however the 24-28 age group has the highest concentrations, whereas the 30-35 age group has significantly fewer cases overall.

Compared to non-Muslim students (29.4%), the majority of the dataset's students (70.6%) are Muslim (Figure 2). 32.9% of students are from rural areas, whilst 67.1% of students live in urban areas. Male students make up 76.6% of the dataset, however female students make up 23.4%, indicating a notable male majority in the gender distribution.



(a) religion (b) residence (c) gender

Fig. 2: Demographic and personal factors of the students.

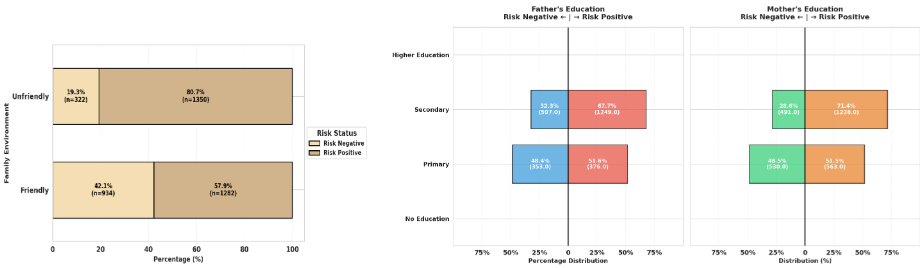


(a) institutions type (b) cgpa distribution (c) participation-satisfaction

Fig. 3: StudentSafe academic data in different directions.

The Figure 3 illustrates that, students who are from government institutions; roughly 60% of them have no intent to finish their lives and 40% have that desire. While "Others" category institutions exhibit the lowest risk-positive percentage at almost 90% risk-negative, national and private institutions exhibit larger risk-positive proportions (roughly 75-77%). With a mean of 3.38, the CGPA distribution shows a right-skewed pattern, suggesting that most students continue to perform academically above average, with the largest density falling between 3.5 and 4.0. The complex relationship between students' suicidal risk and their involvement in class and their institutional satisfaction scores is illustrated by the heatmap. Remarkably, students who attend regularly (especially Regular-3.0 and Regular-4.0) and have higher institutional ratings also have higher risk-positive counts, whereas students who attend irregularly and have the lowest institutional ratings (Irregular-1.0) have lower absolute numbers but still significant risk proportions.

Unfriendly family environments in Figure 4 demonstrate a pronounced association with suicidal risk, exhibiting 80.7% risk-positive cases compared to 19.3% risk-negative. Parental education distribution reveals that students with secondary-educated fathers show 67.7% risk-positive prevalence, while those with secondary-educated mothers exhibit 71.4% suicidal tendency. Students from families with primary or no formal parental education represent smaller dataset proportions, though maintaining elevated risk-positive percentages exceeding 60%. Factors such as frequent anxiety (53.9%), rare career depression (57.3%), and regular insomnia (51.7%) are indicating substantial mental health challenges across the student population.



(a) (b)

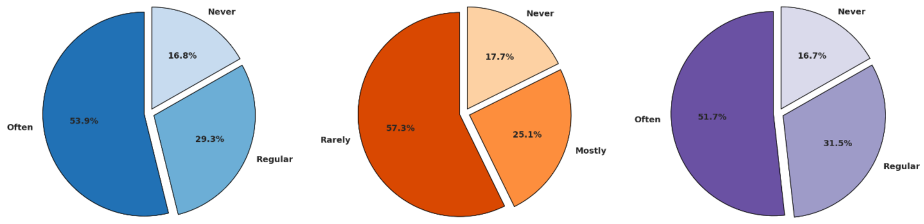
Fig. 4: Suicidal risk impact on; (a) family friendliness, (b) parents education.

Figure 6 shows that while substance use has the highest risk association, with 79.8% of frequent users classified as risk-positive, smoking is 76.4% risk-positive among frequent smokers. In contrast, device usage shows the opposite pattern, with frequent users exhibiting a higher risk prevalence (89.0% risk-positive) than regular users (47.2% risk-positive), suggesting that complex dynamics of digital engagement influence mental health outcomes.

4 Methodology

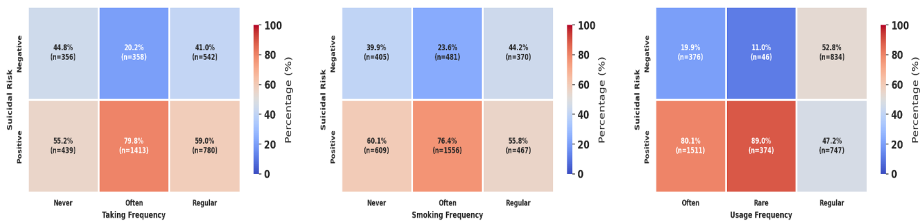
According to Figure 7, this study uses a methodical technique to forecast suicide inclinations in students. The methodology comprises data collection, preprocessing, data visualization, data oversampling, machine learning prediction, and model interpretation phases.

Data were collected through structured surveys from 4,004 university students, forming the StudentSafe dataset with 29 predictive features across four dimensions as described in Section 3. To address class imbalance, oversampling



(a) anxiety (b) career Depression (c) insomnia

Fig. 5: Frequency distribution of mental health conditions.



(a) substance taking (b) smoking (c) device usage

Fig. 6: Factors affecting students health in StudentSafe.

techniques were applied before partitioning the dataset into training, validation, and test sets using a 70:10:20 ratio. Multiple machine learning classifiers were implemented to predict the suicidal risks: (a) Risk Positive, (b) Risk Negative. Detailed results are presented in subsequent sections.

Data Oversampling

Figure 1(a) shows how imbalanced our dataset is. Thus, we used the training set to use SMOTE (Synthetic Minority Oversampling Technique). Thus, there are an equal number of examples of each classes in the training set.

Classifier Models

A wide range of machine learning classifiers were used in this study to assess performance on the assigned task. From basic statistical models to sophisticated ensemble techniques, the chosen algorithms cover a broad range of approaches.

– **Logistic Regression (LR):** With regularization strength C=1 and L2 regularization, the model used the saga solver. Convergence was guaranteed across all classes by setting the maximum iteration count at 5000.
– **Support Vector Classifier:** To create a decision boundary based on hyperplanes, a linear kernel was chosen. For the purpose of supporting ROC

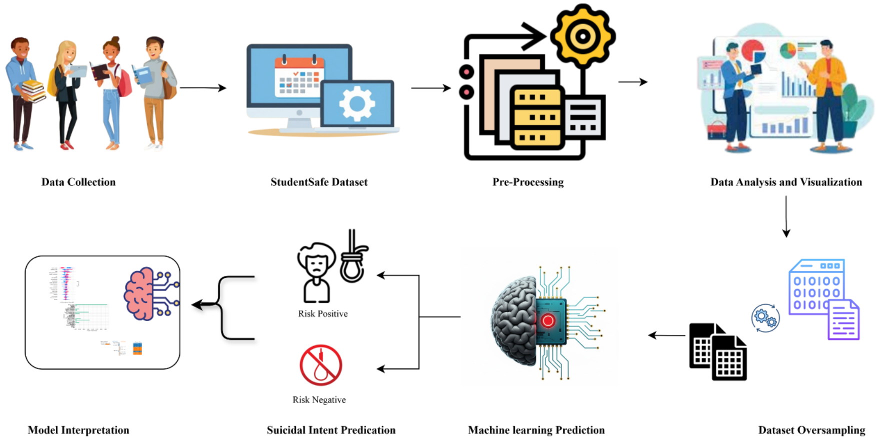


Fig. 7: Overview diagram of the suicidal tend analysis.

curve analysis and multi-class performance evaluation, probability estimates were enabled.

- **K-Nearest Neighbors (KNN):** The classifier utilized 3 nearest neighbors (k=3) with Manhattan distance as the proximity measure. Distance-weighted voting was applied, assigning greater influence to neighbors closer to the query point.
- **Multinomial Naive Bayes (MNB):** Zero-probability instances were handled by incorporating Laplace smoothing with alpha=0.01. The training data distribution was used to estimate the class prior probability.
- **Decision Tree (DT):** The classifier employed entropy as the impurity criterion with depth limited to 5 levels. A maximum of 30 leaf nodes were allowed, and nodes needed at least 150 samples for splitting and 50 samples for leaf development in order to control model complexity.
- **Random Forest (RF):** An ensemble of 200 decision trees was constructed without bootstrap sampling. Trees were allowed unrestricted depth growth with minimal constraints on node splitting (min_samples_split=2,min_samples_leaf=1).
- **AdaBoost (ADA):** 150 weak learners using the ‘SAMME.R‘ algorithm and a learning rate of 0.05 made up the boosting ensemble. As base estimators, decision trees with a maximum depth of five were used.
- **XGBoost (XGB):** The gradient boosting classifier was implemented with default hyperparameters, allowing automatic optimization of tree structure and regularization parameters.
- **LightGBM (LGBM):** The default configuration options for this gradient boosting framework were used when it was deployed. The verbosity parameter was suppressed during training in order to preserve clean execution logs.

Stacking Ensemble Models

Stacking combines predictions from multiple base learners using a meta-classifier trained on their outputs. After training base models on the original data, a second-level classifier uses out-of-fold estimates from cross-validation to learn how to appropriately weight its predictions. This approach leverages the complementary strengths of diverse algorithms while reducing overfitting. Using combinations of RF, XGB, DT, LR, ADA, KNN, and LGBM as base learners, five stacking configurations were assessed using 5-fold cross-validation.

5 Result Analysis

This section outlines the different performance analyses, such as evaluation matrices, error analysis, comparing related work, and ultimately the logic behind the models' comprehension through the use of interpretable AI techniques.

Evaluation Metrics

Model performance was systematically evaluated using weighted average precision, recall, F1-score, and accuracy to ensure robust assessment across imbalanced classes. Detailed results for all the models are presented in Table 3.

Table 3: Illustration of the performance of various machine learning models.

Classifier	**Precision**	**Recall**	**Accuracy**	**F1-score**
ML Models				
Logistic Regression (LR)	69.72	67.74	67.74	68.42
Support Vector Classifier (SVC)	71.13	69.15	69.15	69.82
K-Nearest Neighbors (KNN)	73.06	69.15	69.15	70.08
Multinomial Naive Bayes (MNB)	69.14	65.81	65.81	66.77
Decision Tree (DT)	73.79	71.98	71.98	72.57
Random Forest (RF)	73.88	74.16	74.16	74.01
AdaBoost (ADA)	72.96	73.39	73.39	73.14
LightGBM (LGBM)	74.73	75.06	75.06	74.87
XGBoost (XGB)	75.21	75.58	75.58	**75.36**
Stacking Ensemble (SE) Models				
SE 1 (RF+XGB+DT+LR+LGBM)	74.10	74.94	74.94	74.29
SE 2 (KNN+XGB+ADA+LR+LGBM)	74.92	75.19	75.19	75.04
SE 3 (RF+XGB+DT+ADA+LR)	74.56	75.19	75.19	74.76
SE 4 (RF+XGB+DT+LR+ADA+LGBM)	74.57	75.58	75.58	74.45
SE 5 (RF+ADA+XGB+LGBM+LGBC)	74.56	75.19	75.19	74.76

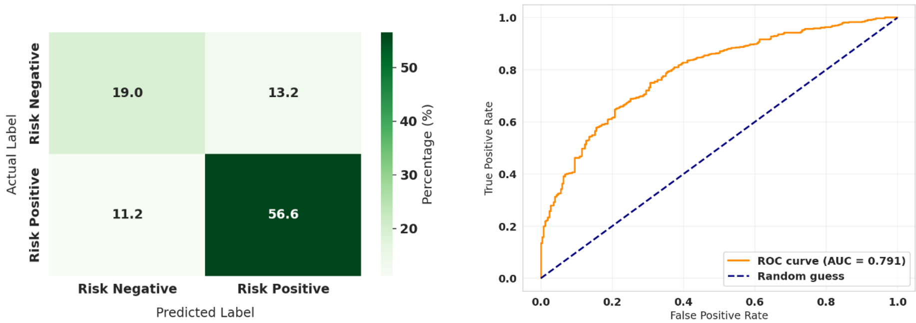
Performance Analysis.

XGBoost (XGB) which is our proposed model, achieved the highest F1-score of 75.36% among all machine learning classifiers, with accuracy of 75.58%. With a balanced precision-recall performance and an F1-score of 74.87%, LightGBM (LGBM) showed competitive performances. In every case, ensemble approaches performed better than conventional classifiers. AdaBoost (ADA) came in at 73.14%, Random Forest (RF) at 74.01%, and Decision Tree (DT) at 72.57%, indicating that single classifiers performed moderately. The dataset's F1-score for Multinomial Naive Bayes (MNB) was the lowest, indicating poor efficacy.

Results from the stacking ensemble (SE) configurations were not entirely consistent; SE 2 had the greatest F1-score of 75.04%, followed by SE 3 and SE 5. With the lowest F1-score (74.45%), SE 4 notably equaled the greatest accuracy of 75.58%, indicating possible overfitting.

Error Analysis

As represented in Figure 8(a), the confusion matrix analysis reveals that the model achieved 56.6% accuracy in identifying risk-positive cases, whereas 69.8% misclassification occurred for risk-negative instances. Conversely, 30.2% of risk-negative cases were correctly classified, with substantial misidentification in the minority class.



(a) (b)

Fig. 8: Performance evaluation of the proposed model; (a) confusion matrix, (b) ROC curve.

The ROC curve (Figure 8(b)) shows strong discriminatory power with an AUC of 0.791, showing that the model is better than random classification at differentiating across risk categories.

Performance Comparison with related studies

Table 4 presents a performance comparison where our proposed model achieves 75.58% accuracy, outperforming SVC at 69.15% [14] and Random Forest at 74.16% [13]. This 1.42 percentage point improvement demonstrates enhanced capability in suicidal risk prediction for student populations.

Explainability Analysis

To understand the decision-making process of our best-performing XgGBoost model, we employed LIME and SHAP techniques. Figure 9 illustrates LIME explanation for a sample instance classified as risk-positive with 96% perfection.

Table 4: Comparison of model accuracy with related studies.

Related Studies	Classifiers	Accuracy (%)
Mahmud et al. [14]	SVC	69.15
Nicola et al.[13]	Random Forest	74.16
Proposed	XGBoost	**75.58**

Risk-positive indicators include lower university satisfaction (2.00), moderate CGPA (2.80), and regular device usage (0.00), mother's non-conventional occupation (2.00), and ambiguous career depression status (2.00). Risk-negative factors comprise friendly family environment (0.00), aged (28.00), first-year academic standing (1.00), joint family structure (0.00), though these protective elements exerted limited countervailing influence.

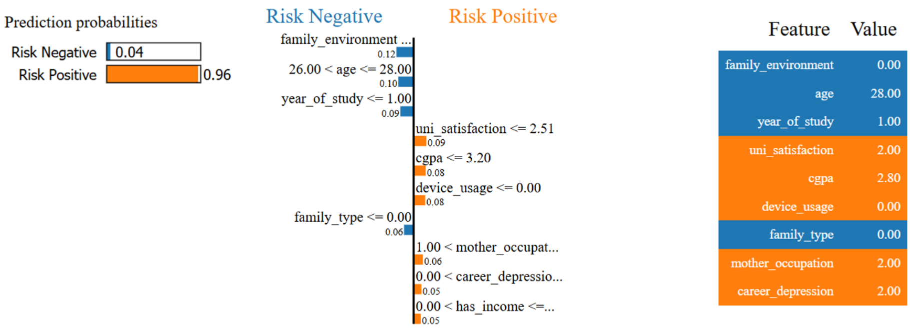


Fig. 9: LIME representation on a random sample of StudentSafe dataset.

Figure 10 reveals that device usage, institution type, CGPA, and family environment constitute the primary determinants of suicidal risk prediction. Behavioral and contextual variables demonstrate considerably stronger predictive power compared to demographic characteristics, whereas psychological factors such as career depression and insomnia maintain moderate but stable influence on classification outcomes.

6 Acknowledgements

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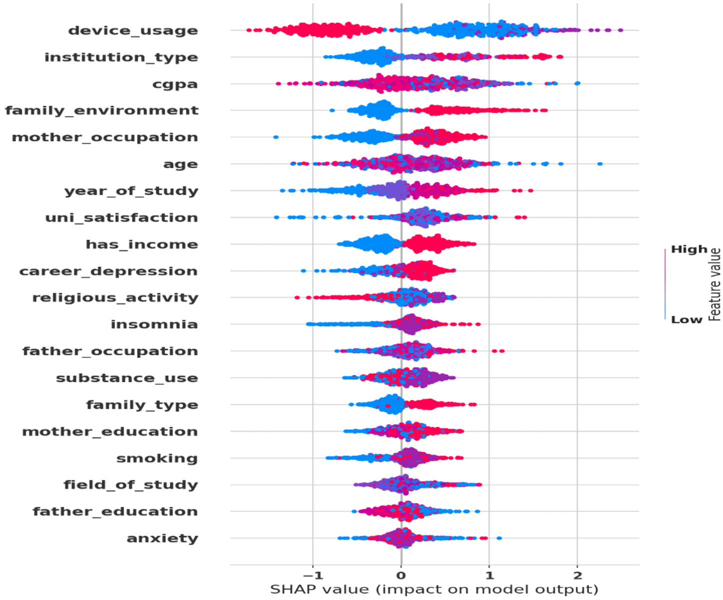

Fig. 10: Summary plot of SHAP showing the global impact of features on suicidal risk prediction.

7 Conclusion and Future Work

Conclusion

University students' mental health crises presents a serious public health concern, particularly in developing nations with inadequate support networks and mental health facilities. To address the alarmingly high rate of suicidal ideation among Bangladeshi college students, we developed StudentSafe, a large dataset of 4,004 student records gathered from 99 different higher education institutions. Every record was carefully gathered using questionnaires validated by psychiatric experts and classified into two categories: students at risk and those not at risk. Using this dataset, we tested multiple machine learning algorithms that analyzed various student characteristics including demographics, academic performance, family circumstances, and mental health indicators. XGBoost outperformed all other evaluated models, achieving an F1-score of 75.36%. By using the LIME and SHAP explainability methodologies, we improved our research and found that the main factors influencing suicide risk projections were device usage patterns, type of institution, academic grades, and family condition.

Future Work

In order to expand this study framework across the nation, our long-term goal is to form cooperative alliances with both domestic and foreign organizations while working with the government and the psychological authorities of the nation. For this project to provide comprehensive intervention strategies targeted at lowering student suicide rates, large-scale data gathering efforts across larger student populations are needed. The development of real-time monitoring technologies that are integrated with university infrastructures would ultimately allow for prompt, morally sound intervention tactics that put the mental health and wellbeing of students first.

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