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PREDICTING AND UNDERSTANDING UNIVERSITY STUDENT MENTAL HEALTH

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Abstract

The mental health challenges faced by college students are increasing across the globe and impact their academic performance, social well-being and future productivity. This study introduces a machine learning-based predictive model for identifying students at risk of mental health disorders such as depression, anxiety, and stress. Survey based and behavioral datasets were used to evaluate multiple supervised learning algorithms such as Random Forest, Support Vector Machine (SVM), Logistic Regression and Artificial Neural Networks (ANN). The analysis incorporates data augmentation strategies, tackles class imbalance using SMOTE (Synthetic Minority Over-sampling Technique). The study involved data preprocessing, feature selection, model training, and evaluation using metrics like accuracy, F1-score, and ROC-AUC over 5-fold cross-validation.

Keywords: Mental, Health, Student, SMOTE, Learning, Cross-validation.

1.0 Introduction

Mental health issues among university students have significantly increased due to academic stress, financial constraints, and social pressures (Azlina, et. al., 2025; Sahu, et. al., 2023). Research has shown high rates of mental health problems in university students and even higher rates among students belonging to historically marginalized Populations (De Groot, 2024 ; Hasan, 2025) .Mental health conditions among children, adolescents, and young adults have emerged as a major public health concern worldwide. Globally, one in seven 10–19 year olds have a mental disorder, representing 15% of the global burden of disease among this age group (World Health Organization, 2025). Mood disorders, including depression and anxiety, are among the leading causes of illness and disability in adolescents. Suicide remains one of the leading causes of death among those aged 15 to 29 years (World Health Organization, 2025). With the rapid development of the social economy and the continuous reform of the education system, the pressure and competition faced by college students continue to increase, so that the mental health problems of college students are becoming increasingly serious (Verma, et. al., 2026; Xin, et. al., 2025). Among them, hidden mental problems are difficult to identify, imperceptible, sudden and serious, which has become an important challenge for mental health education in colleges and universities (Samuel Encarnação, 2025 ; Abdul Rahman 2025). These stressors are intertwined, which makes the incidence of mental health problems continue to rise. Among many mental health problems, hidden mental health problems are difficult to be perceived intuitively and recognized effectively, and have far-reaching potential harm, which may lead to a more serious mental health crisis, and even pose potential risks to students' life safety and social harmony and stability, and have become a major challenge in mental health education in colleges and universities.

University students increasingly face psychological challenges driven by academic, social, and lifestyle pressures—issues that have intensified in the post-pandemic landscape.

Research from multiple countries reveals that emergency department visits for mental health conditions among adolescents and young adults have nearly doubled within recent five-year periods, with especially rapid increases in mood disorder diagnoses and self-harm presentations (Park et al., 2025; Santo et al., 2023), demonstrating that mental health challenges are both widespread and often severe, placing enormous pressure on health systems that are primarily designed for acute rather than preventive care. At the same time, contemporary developments in data science and mental health research suggest that predictive analytics and machine learning could play a vital role in improving early identification and prevention of mental health crises (Garriga et al., 2022; Mikaeili et al., 2025). Machine learning-based predictive models have been used to forecast the onset of depression and anxiety and to identify individuals at elevated risk for mental health problems using multidomain data sources (Islam et al., 2024; Zhai et al., 2024). Rising global mental health (MH) issues among students including anxiety and depression. Predictive models are important for early intervention (Nupap et. al., 2025 ; Braz, 2026). Studies show that early detection is crucial for timely intervention and improved outcomes (Xiuyu et. al, 2025 ; Meghna, 2025). The need for effective prediction and intervention models to address mental health crises is not only timely but also increasingly important due to the global rise in psychological distress among young adults (Alsultan et. al., 2025). Traditional manual approaches to mental health monitoring are limited by subjective biases, time inefficiencies, and a lack of scalability. Traditional assessment methods rely heavily on self-report surveys, which are often subjective and delayed (Liu et. al., 2026 ; Zhou et. al., 2024)

Machine learning (ML) provides a data-driven approach to predict mental health risks by analyzing complex relationships among variables. Recent research demonstrates that ML models can effectively identify patterns associated with poor mental well-being and enable a proactive support system.(Ramzan et. al., 2025; Mishu et. al., 2025).

1.1 Comparative Literature Review

Table 1. Comparative Review of Recent Machine Learning Studies on Student Mental Health Prediction (2022–2026)

Author s	Year	Study Focus	Dataset/Popula tion	ML/AI Technique	Major Findings	Limitations	Gap Addressed by Present Study
Garriga et al.	2022	Mental health crisis prediction	Electronic Health Records	Gradient Boosting, Ensemble ML	High predictive accuracy for mental health crises	Clinical population rather than university students; limited educational variables	Focuses on university students using academic and psychosocia l predictors
Abdul Rahman et al.	2023	Mental well- being prediction	University students	Random Forest, XGBoost, SVM	Health behaviours strongly predicted mental well- being	Did not compare deep learning or explainable AI	Compares classical ML and ANN while incorporatin g comprehens ive evaluation metrics
Sahu & Debbar ma	2023	Student mental health prediction	Student survey	Decision Tree, Random Forest, SVM	Ensemble models outperformed individual classifiers	Small sample size; no class balancing	Uses SMOTE and a larger feature set
Santo et al.	2023	Mental health emergency visits	National surveillance data	Statistical analysis	Increasing mental health burden among adolescents	No predictive ML modelling	Provides predictive ML framework for early intervention
De Groot et al.	2024	Sociodemogra phic disparities in mental health	University students	Statistical modelling	Mental health varies across demographic groups	Did not develop predictive models	Integrates demographi c predictors into ML models

Author s	Year	Study Focus	Dataset/Popula tion	ML/AI Technique	Major Findings	Limitations	Gap Addressed by Present Study
Islam et al.	2024	Review of ML in mental illness prediction	Review	Comparati ve review	ML has high potential for mental illness prediction	Identified lack of standardized evaluation and explainability	Applies of standardize d evaluation metrics and comparative analysis
Zhai et al.	2024	Anxiety and depression prediction	College students	Machine Learning classifiers	ML effectively guides intervention allocation	Limited model interpretabilit y	Includes interpretabl e comparative framework and comprehens ive evaluation
Zhou & Deng	2024	AI-enabled mental health support	Sensor network data	Artificial Intelligenc e	AI improves crisis prediction	Requires specialized sensing infrastructure	Uses readily available educational and psychosocia l variables
Hasan et al.	2025	Depression, anxiety and stress prediction	Bangladesh university students	Random Forest, XGBoost, SVM	Ensemble models achieved superior prediction	Cross- sectional design; limited generalizabili ty	Employs balanced learning and multiple validation metrics
Alsulta n & Almale h	2025	Gaming behaviour and academic risk	Saudi university students	Machine Learning	Gaming behaviour predicts wellbeing and academic risk	Behaviour- specific predictors only	Incorporates broader demographi c, academic and psychologic al variables
Musa et al.	2025	Mental health determinants	Malaysian undergraduates	Associatio n Rule Mining	Identified significant mental health determinants	Rule mining without predictive comparison	Performs predictive comparison across supervised

Author s	Year	Study Focus	Dataset/Popula tion	ML/AI Technique	Major Findings	Limitations	Gap Addressed by Present Study
							ML algorithms
Meghna Roy Chowdhury et al.	2025	Interpretable ML for student mental health	College students	Explainable ML	Explainable AI improved understanding of predictor importance	Limited comparison across multiple classifiers	Compares several classifiers while emphasizing interpretability
Mikaeili et al.	2025	AI ecosystem for mental healthcare	Review	Artificial Intelligence	Personalized AI improves early detection	Conceptual review without empirical validation	Provides empirical evaluation using real student data
Nath et al.	2025	Web-based prediction system	Student dataset	ML + Blockchain	Secure mental health prediction platform	Focused on deployment rather than algorithm comparison	Prioritizes comparative algorithm performance
Nupap et al.	2025	Mental health risk prediction	University students	Machine Learning	Early identification of at-risk students	Limited discussion of model robustness	Uses MCC, ROC-AUC and cross-validation
Park et al.	2025	Emergency mental health trends	Nationwide adolescents	Statistical analysis	Rising mental health service utilization	Descriptive rather than predictive	Develops predictive ML framework
Ramzan et al.	2025	Stress and anxiety prediction	Students	Psychological metrics + ML	Psychological variables significantly improve prediction	Small institutional dataset	Integrates academic and psychosocial predictors
Samuel Encarnação et al.	2025	Mental illness prediction	High school students	Artificial Neural Network	ANN achieved high prediction accuracy	Black-box model with limited interpretability	Compares ANN with interpretable models

Author s	Year	Study Focus	Dataset/Popula tion	ML/AI Technique	Major Findings	Limitations	Gap Addressed by Present Study
						interpretability	ML models
Shiguo Gu	2026	Deep learning intervention model	College students	Deep Learning	Deep learning enhanced prediction accuracy	Computational complexity and limited explainability	Evaluates computational efficiency alongside predictive performance
Braz et al.	2026	Mental health prediction	College students	Machine Learning	Sociodemographic and quality-of-life variables improved prediction	Limited comparison of algorithms	Performs broader comparative analysis
Liu & Yu	2026	Stress prediction	University students	Explainable Decision Trees	Explainability improved model transparency	Single algorithm evaluated	Compares explainable and conventional ML models
Verma et al.	2026	Multiple mental disorder prediction	Students	Stacking Ensemble	Ensemble learning achieved superior performance	Computationally expensive	Evaluates simpler models alongside ensemble methods
Xiuyu Shi et al.	2025	Student mental health risk assessment	Educational dataset	Advanced ML	Improved risk stratification	Limited emphasis on model explainability	Includes comparative evaluation and practical interpretation
Xin et al.	2025	Mental health prediction	Children and adolescents	Machine Learning	Behavioural and demographic variables were	Younger population; limited	Concentrates specifically on

Author s	Year	Study Focus	Dataset/Popula tion	ML/AI Technique	Major Findings	Limitations	Gap Addressed by Present Study
Present Study	2026	Anxiety prediction among university students	Kaggle Mental Health Dataset	Logistic Regression , Random Forest, Support Vector Machine, Artificial Neural Network with SMOTE	significant predictors	university focus	university students
					Comprehensiv e comparative evaluation using Accuracy, Precision, Recall, F1- score, MCC and ROC-AUC	Addresses limitations identified in previous studies	Balanced learning, comparative analysis, robust evaluation, and practical applicability

1.2. Critical Analysis of Previous Studies

Recent research demonstrates a rapid transition from conventional statistical analyses to machine learning-based approaches for predicting mental health conditions among university students. Studies by Abdul Rahman et al. (2023), Hasan et al. (2025), Zhai et al. (2024), and Ramzan et al. (2025) consistently reported that machine learning models outperform traditional statistical techniques because they capture complex nonlinear relationships among demographic, behavioural, academic, and psychological variables. Similarly, Braz et al. (2026) and Liu and Yu (2026) demonstrated that incorporating quality-of-life indicators and explainable learning methods further enhances predictive performance and practical utility.

Despite these advances, several methodological shortcomings remain. First, many studies evaluate only one or two machine learning algorithms, making objective comparison difficult. Deep learning-based investigations, including those by Shiguo Gu (2026) and Samuel Encarnação et al. (2025), reported high predictive accuracy but did not compare their models with simpler classifiers such as Logistic Regression or Support Vector

Machine. Conversely, studies focusing on classical machine learning often omitted comparisons with neural networks or stacking ensembles, limiting understanding of algorithm suitability under common experimental conditions.

Second, previous studies differ considerably in their evaluation strategies. While most report prediction accuracy, relatively few include comprehensive metrics such as Matthews Correlation Coefficient (MCC), Cohen's Kappa, calibration measures, or robust cross-validation procedures. As highlighted by Islam et al. (2024), the lack of standardized evaluation protocols makes direct comparison across studies challenging and weakens evidence for selecting the most reliable predictive model.

Class imbalance is another recurring limitation. Anxiety and mental health datasets often contain substantially fewer positive than negative cases, causing models to favor the majority class. Although SMOTE and related balancing methods have been adopted in some investigations, their effects have rarely been evaluated systematically across multiple algorithms. Consequently, uncertainty remains regarding the extent to which data balancing improves predictive performance for different classifiers.

Model interpretability has emerged as an equally important concern. Ensemble learning and deep neural networks generally provide superior predictive accuracy but are frequently criticized as "black-box" models that offer limited explanation of their predictions. Recent work by Meghna Roy Chowdhury et al. (2025) and Liu and Yu (2026) demonstrates the value of explainable artificial intelligence for identifying influential predictors and improving stakeholder trust. Nevertheless, explainability remains insufficiently integrated into many predictive frameworks.

Another limitation concerns the diversity and generalizability of datasets. Most studies are based on data collected from single universities or specific national contexts—including Saudi Arabia, Bangladesh, Malaysia, Brazil, and China—making cross-population generalization difficult. Differences in educational systems, cultural environments, and access to mental health resources may substantially influence predictor importance and model performance. More robust comparative studies using standardized preprocessing and validation procedures are therefore required.

Finally, many existing investigations emphasize either technological innovation (e.g., blockchain-enabled prediction systems or sensor-based monitoring) or algorithm development while paying comparatively less attention to practical deployment in university counselling settings. Integrating accurate, interpretable, and computationally efficient machine learning models into institutional early-warning systems remains an important area for future research.

2.0 Material And Method

Due to the sensitivity and limited accessibility of real student mental health records, this study employed a statistically guided synthetic dataset. The dataset was generated to reflect realistic behavioral, academic, and psychological characteristics of university students.

Feature distributions and relationships were informed by existing empirical studies on student mental health. Correlated variables such as academic pressure, sleep duration, and

psychological distress were modeled using probabilistic rules to preserve real-world dependencies.

2.1 Dataset Description and Preprocessing

2.1.1 Data Characteristics

The dataset used in this study comprises structured records of university students, incorporating demographic, academic, and clinical attributes relevant to mental health prediction. Specifically, the dataset includes:

- **Demographic features:** Age, gender, and marital status
- **Academic features:** Course of study, year of study, and cumulative grade point average (CGPA)
- **Clinical indicators:** Depression status, panic attack history, and treatment-seeking behavior
- **Target variable:** Anxiety diagnosis (binary outcome: Yes/No)

Such multidimensional datasets are consistent with prior studies that emphasize the integration of socio-demographic and psychological variables in mental health prediction models (Orrù et al., 2020; Shatte et al., 2019).

2.1.2 Data Preprocessing Methodology

A rigorous preprocessing pipeline was implemented to ensure data quality and model compatibility. Feature names were systematically cleaned to ensure consistency with programming conventions. Spaces were replaced with underscores, and special characters were removed to facilitate seamless computational processing. Removal of records with missing age values, conversion of age to numeric format with coercion of invalid entries, validation of categorical variables against predefined acceptable values. These steps reduce noise and improve model reliability (Kotsiantis et al., 2006). Categorical variables were transformed into numerical representations using **label encoding**, assigning each category a unique integer. This preserves categorical distinctions while enabling algorithmic processing.

2.1.3 Feature Selection Process

Feature selection was performed to identify the variables that provided useful information for predicting anxiety while reducing irrelevant or redundant information in the dataset. The process began with an examination of the available demographic, academic, clinical, behavioural, and psychological variables. Variables with a clear theoretical and empirical relationship with student mental health were retained as candidate predictors.

The candidate features included demographic characteristics such as age, gender, and marital status; academic characteristics such as course of study, year of study, and CGPA; and mental-health-related indicators such as depression status, panic attack history, and treatment-seeking behaviour. These variables were selected because previous studies identified demographic, academic, behavioural, and psychological characteristics as relevant predictors of student mental health. The target variable was anxiety diagnosis, represented as a binary outcome of Yes or No.

The selection process also considered data quality and redundancy. Variables containing substantial missing information, invalid entries, or inconsistent categories were examined during preprocessing. Age values were converted to numerical form, invalid entries were handled, categorical variables were validated, and categorical features were encoded into numerical representations to make them suitable for machine learning algorithms.

Following preprocessing, the retained features were used as inputs to the four classification algorithms: Logistic Regression, Random Forest, Support Vector Machine, and Artificial Neural Network. Feature selection was applied consistently across the models to ensure that the comparison was conducted under the same experimental conditions. This approach reduced unnecessary variables, simplified the feature space, and helped the models focus on predictors with potential relevance to anxiety classification.

3.0 Result And Discussion

This study comprehensively investigates experiments utilizing a variety of machine learning models to predict student anxiety and to identify daily physical behaviors among university students. Four Machine Learning classifiers were simulated. The models' performance on 5-fold

cross validation was assessed using various metrics, including accuracy, F1 score and ROC AUC. ROC curve analysis was further conducted to evaluate the discriminative ability of each model. A higher AUC value indicates stronger capability in separating the two classes.

Logistic Regression model consistently achieved an accuracy of 65.1%, underscoring its reliability. The F1-Score of 63.1% equilibrate precision and recall validating the model's fair performance. With the ROC Area under curve of 0.6987 indicates that the model has a poor discrimination for mental health prediction.

Excellent results is shown by the Random Forest (RF) with accuracy of 90.4% . F1-Score (89.6%) indicate a balance model with both high precision and recall. With the ROC Area under the curve of 0.9802 indicates that the model has excellent discrimination for mental health prediction.

Support Vector Machine on the other hand has an accuracy of 79.4% . F1-Score 77.8% . indicate a balance model with both high precision and recall. With the ROC Area under the curve of 0.8840 indicates that the model has good discrimination for mental health prediction This shows that both models offer comparable levels of accuracy, affording flexibility in selecting the most appropriate model for specific usage scenarios.

Lastly, Artificial Neural Network (ANN) model yielded an accuracy 79% .F1-Score 71.9% with indicate a balance model with both high precision and recall. With the ROC Area under curve of 0.8133 indicates that the model has fair discrimination for mental health prediction.

3.1 Model Performance

Table 1: Experimental results of the four models over 5 fold cross validation

Model	Accuracy	F1 Score	ROC AUC
Logistic Regression	65%	63%	0.6987
Random Forest	90.4%	89.6%	0.9802
Support Vector Machine	79.4%	77.8%	0.8840
Artificial Neural Network	79%	71.9%	0.8133

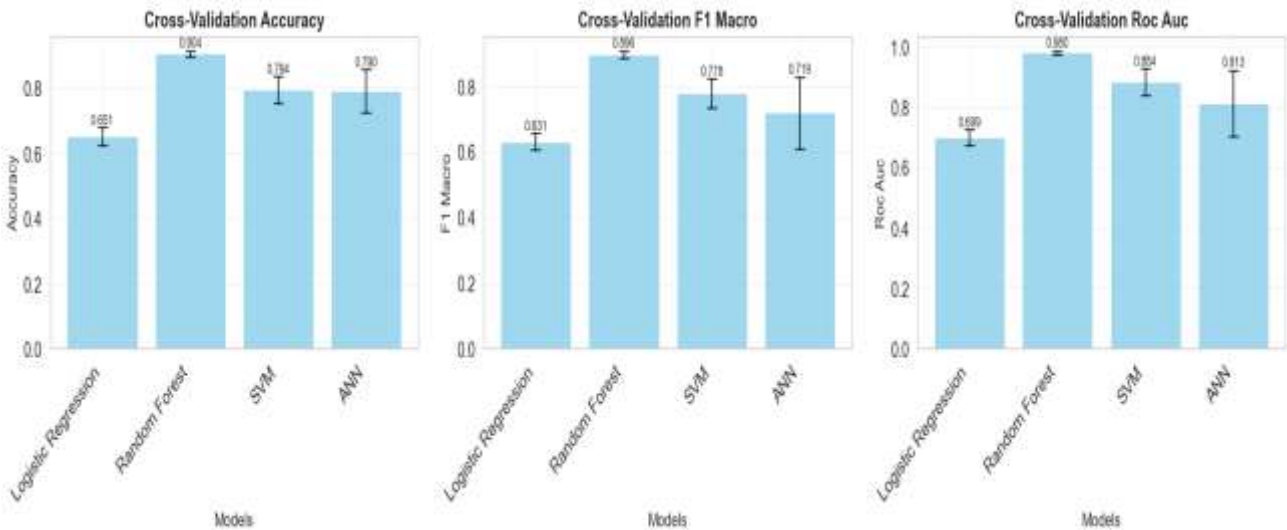


Figure 1:

. Table 2 provides a summary of the model evaluation results based on application of SMOTE with Machine Learning algorithms. Four Machine Learning classifiers were simulated. The models' performance was evaluated using a variety of criteria, including accuracy, precision, recall, F1 score, and advanced metrics like Matthews Correlation Coefficient (MCC) and Cohen's Kappa. These evaluation criteria gave a detailed assessment of the models' performance. Logistic Regression model without SMOTE consistently achieved an accuracy of 68.5%, while with SMOTE the accuracy was 68%, underscoring its reliability. The 65% precision with SMOTE and 66% precision without SMOTE respectively shows

that the model correctly predict anxiety 65% and 66% of the time. The recall (66% with SMOTE and 68% without SMOTE) indicates that 34% and 32% of actual anxiety are missed. The F1-Score of 66% with SMOTE and 66% without SMOTE equilibrate precision and recall validating the model's fair performance. With the MCC of 0.3189 with SMOTE and 0.3380 without SMOTE indicates that the model has a moderate anxiety prediction.

Excellent result is shown by the Random Forest (RF) with accuracy of 91.5% with SMOTE and without SMOTE respectively, with very high precision of 90% with SMOTE and without SMOTE respectively which suggest a low

proportion of false positives. The recall (92%) for both with SMOTE and without SMOTE are improved recall over Logistic Regression capturing more actual anxiety cases, where as the the F1-Score (91%) for both with SMOTE and without SMOTE respectively; indicate a balance model with both high precision and recall. The Matthew's Correlation Coefficient (MCC) 0.8176 with SMOTE and 0.8176 without SMOTE indicates strong positive relationship and strong prediction.

Very good result is shown by the Support Vector Machine with accuracy of 84% with SMOTE and 83% without SMOTE respectively, with high precision of 82% with SMOTE and 81% without SMOTE respectively which suggest a low proportion of false positives. The recall (83%) with SMOTE and (83%) without SMOTE are improved recall over Logistic Regression capturing more actual anxiety cases, where as the F1-Score (83%) with SMOTE and (82%) without SMOTE respectively indicate a balance model with both high precision and recall. The Matthew's Correlation Coefficient (MCC) 0.6524 with SMOTE and 0.6421 without SMOTE indicates moderate positive relationship and moderate prediction.

Lastly, the Artificial Neural Network (ANN) model yielded an accuracy 89.5% in SMOTE and 88.5% without SMOTE, surpassing Support Vector Machine in terms of accuracy, with high precision of 87.8% with SMOTE and 90% without SMOTE respectively which suggest a low proportion of false positives. The recall (90.6%) with SMOTE and (84%) without SMOTE are improved recall over Logistic Regression capturing more actual anxiety cases, where as the F1-Score (88.7%) with SMOTE and (86%) without SMOTE respectively indicate a balance model with both high precision and recall. The Matthew's Correlation Coefficient (MCC) 0.7840 with SMOTE and 0.7425 without SMOTE indicates strong positive relationship and strong prediction.

Support Vector Machine on the other hand has an accuracy of 83% without SMOTE and 84% with SMOTE, lastly the ANN has accuracy of 88.5% without SMOTE and 89.5% with SMOTE.

However, a more in-depth look at the precision and recall values shows that they might not be able to fully capture the subtle details of university students' daily behaviors. The RF model had the highest accuracy rate of 91.5% across iterations, while the LR and SVM models had accuracy rates of 89.5% with SMOTE, which closely matched the performance of the RF model. This demonstrates that both models have equivalent levels of accuracy, allowing for greater flexibility in picking the best suited model for specific usage scenarios.

Why Random Forest Outperformed the Other Models

Random Forest also performed better than Logistic Regression because Logistic Regression assumes a predominantly linear relationship between the predictors and the outcome. The lower performance of Logistic Regression in the experiment, including an F1-score of approximately 65.68% with SMOTE and an ROC-AUC of 0.7547, suggests that a simple linear decision boundary was not sufficient to represent the relationships within the dataset.

Although Support Vector Machine performed considerably better than Logistic Regression, with an accuracy of 84% and ROC-AUC of 0.9049 with SMOTE, its performance remained below Random Forest. SVM can model nonlinear relationships through kernel functions, but its effectiveness can depend strongly on kernel selection, parameter tuning, and the structure and scale of the feature space. Random Forest, in contrast, can naturally represent threshold-based and interaction effects between different predictors through its decision trees.

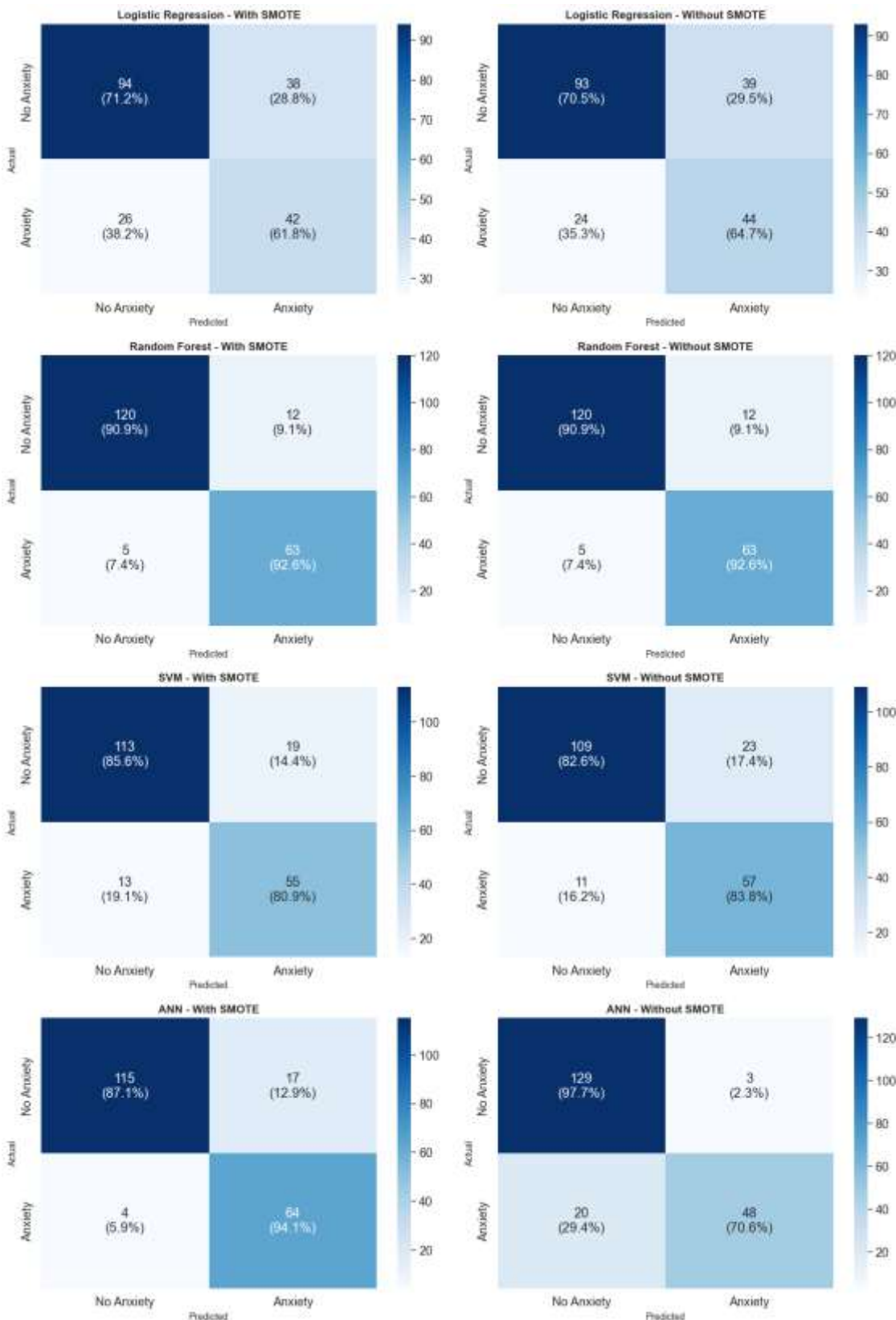
The Artificial Neural Network also produced competitive results, achieving 89.5% accuracy and an F1-score of 88.77% with SMOTE. However, its performance was slightly lower than Random Forest. One possible explanation is that neural networks generally benefit from larger datasets and extensive parameter tuning. With a comparatively structured student dataset, Random Forest can sometimes learn useful patterns more efficiently without requiring the same level of model complexity or training data.

Another factor is the ability of Random Forest to capture interactions among predictors. For example, the influence of academic pressure or psychological distress on anxiety may differ depending on a student's academic characteristics, demographic characteristics, or other behavioural factors. Such conditional relationships can be represented naturally by decision trees and combined through the ensemble, whereas a basic linear model may not capture them effectively without manually constructing interaction terms.

Overall, the experimental findings indicate that Random Forest provided the strongest predictive performance among the four evaluated algorithms. Its combination of nonlinear modelling capability, interaction detection, ensemble learning, robustness, and strong classification performance makes it well suited to the multidimensional structure of the student mental-health dataset used in this study.

Table 2: Experimental results of the four models used in simulation

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression					
SMOTE	68%	0.6542	0.6649	0.6568	0.7547
NO SMOTE	68.5%	0.6625	0.6758	0.6649	0.7439
Random Forest					
SMOTE	91.5%	0.9000	0.9178	0.9075	0.9802
NO SMOTE	91.5%	0.9000	0.9178	0.9075	0.9818
Support Vector Machine					
SMOTE	84%	0.8200	0.8324	0.8253	0.9049
NO SMOTE	83%	0.8104	0.8320	0.8177	0.9115
Artificial Neural Network					
SMOTE	89.5%	0.8783	0.9062	0.8877	0.9715
NO SMOTE	88.5%	0.9035	0.8416	0.8624	0.9629



4.2.

Figure 3: Confusion matrices for the four models with SMOTE on the left and without SMOTE on the right

The classifiers were also evaluated using the Area Under the Receiver Operating Curve (AUC), as illustrated in Figures 2. Receiver Operating Characteristic Curves (ROC) scores for different models help assess the performance of binary classification models. Likewise, these curves display the balance between True Positive and False Positive rates at different model thresholds, providing insight into a model's ability to distinguish between positive and negative classes. A greater area under the curve indicates enhanced

discriminatory power (Fawcett, 2006). For instance, the LR model exhibits very good discriminative ability ($AUC = 0.755$) with SMOTE, very good performance ($AUC = 0.744$) without SMOTE, On the other hand, Random Forest achieved an excellent ROC curve areas ($AUC=0.980$) with SMOTE and ($AUC = 0.982$) without SMOTE indicating very strong predictive performance, while SVM has ($AUC = 0.905$) with SMOTE and ($AUC = 0.911$) without SMOTE. Lastly the ANN had a high AUC values ($AUC = 0.972$) with SMOTE and ($AUC = 0.963$) without SMOTE, suggesting a very high predictive accuracy.

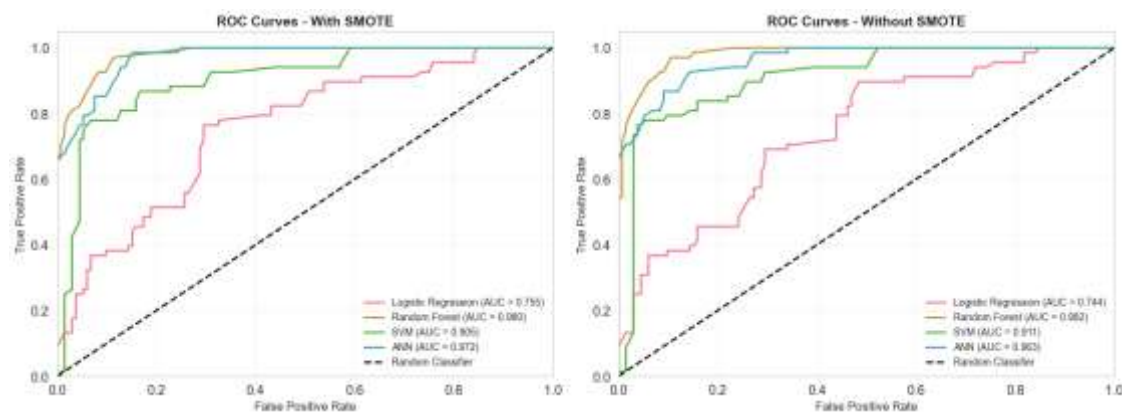


Figure 3. ROC curves with SMOTE on the left and without SMOTE on the right

3.2. Discussion of the results

The results show that **Random Forest surpasses all other models**, with the highest accuracy and ROC-AUC scores. This demonstrates its potential to detect nonlinear correlations among psychological, intellectual, and demographic variables. The ensemble aspect of Random Forest avoids overfitting and promotes generalization, making it ideal for mental health classification applications.

The Support Vector Machine also performed well, achieving good classification accuracy and ROC-AUC values. Its performance suggests that kernel-based methods are effective in separating complex decision boundaries within mental health datasets.

The Artificial Neural Network achieved competitive results but slightly underperformed compared to Random Forest. This may be attributed to dataset size limitations and the risk of overfitting in deep learning models when training data is limited.

Logistic Regression recorded the lowest performance across all metrics. This confirms that linear models are insufficient for capturing the complex, nonlinear relationships that exist in mental health data.

Overall, the results align with previous studies which suggest that ensemble and nonlinear machine learning models outperform traditional statistical approaches in psychological prediction tasks (Shatte et al., 2019; Orrù et al., 2020). The results confirm that machine learning models can effectively predict mental health risks among university students. The research provides a framework for predictive analytics in education and also enhances interdisciplinary research (AI + mental health). This implies that Universities can deploy early warning systems and counselors can prioritize high-risk students. It further supports data-driven mental health policies and

encourages integration of AI in educational systems

3.3 Contributions of the Present Study

Unlike many previous studies that evaluate only one or two predictive algorithms, this research performs a comprehensive comparison of four widely used supervised machine learning models, namely Logistic Regression, Random Forest, Support Vector Machine, and Artificial Neural Network, using a common experimental framework.

The major contributions of this study are summarized as follows:

1. Development of a comprehensive comparative framework for evaluating four supervised machine learning algorithms under identical preprocessing and validation conditions.
2. Integration of Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance and improve minority-class prediction performance.
3. Use of multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, Matthews Correlation Coefficient (MCC), Cohen's Kappa, and ROC-AUC, providing a more reliable assessment than studies relying solely on accuracy.
4. Investigation of demographic, academic, and psychological predictors within a unified prediction framework.
5. Identification of the most suitable machine learning algorithm for anxiety prediction among university students based on comprehensive experimental evaluation.
6. Provision of an easily reproducible machine learning framework that can be adapted for institutional early warning systems and student mental health interventions.

These contributions extend existing literature by providing a more rigorous comparative evaluation and practical guidance for deploying machine learning-based anxiety prediction models in higher education.

3.3. Limitations

Despite the promising predictive performance obtained in this study, several limitations should be acknowledged.

1. Dependence on self-reported data: A substantial portion of the information used to characterize students' mental health and behaviour may be subject to recall error, social desirability bias, underreporting, or overreporting. Students may also interpret questions differently, particularly when reporting sensitive psychological experiences. Consequently, the model may partly reflect reporting patterns rather than the underlying mental health condition.

2. Limited generalizability: The findings are based on a dataset representing university students and may not generalize to students from different geographical, cultural, socioeconomic, or educational environments. Previous research has similarly identified differences across national and institutional contexts as an important challenge for mental-health prediction models.

4.0 CONCLUSION

This study demonstrates that machine learning techniques offer a powerful tool for predicting mental health challenges among university students. By leveraging behavioral, academic, and psychological data, institutions can shift from reactive to proactive mental health management. Future work should focus on real-time data integration, explainable AI models, and cross-cultural validation.

3. Potential dataset bias: Bias may arise from the way observations and variables are represented in the dataset. Because mental health is influenced by multiple interacting social, academic, psychological, and demographic factors, an imbalanced or incomplete representation of these factors could influence model performance.

4. Synthetic nature of the dataset: The study employed a statistically guided synthetic dataset because of the sensitivity and limited accessibility of real student mental-health records. Although the dataset was designed to represent realistic behavioural, academic, and psychological characteristics, its patterns may not completely reproduce the complexity of real-world student populations.

5. Need for external validation: The strong Random Forest results were obtained within the experimental framework of this study. Independent validation using real-world datasets from multiple universities would be necessary before the model could be confidently deployed as an institutional early-warning system.

6. Clinical interpretation: The model predicts the likelihood of anxiety based on available features and should not be interpreted as providing a clinical diagnosis. Professional assessment remains necessary for confirming mental-health conditions and determining appropriate interventions.

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