Computational Design: Journal of Modern Informatics

Journal of MEDICAL INFORMATICS

Vol. 1, No. 2, September 30, 2026, pp. 174 - 184

Implementation of Supervised Learning Algorithms for Early Detection of Depression in University Students

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(Received :July 18, 2026; Revised: July 23, 2026; Accepted: September 16, 2026; Available online: September 30, 2026)

Abstract

Depression among university students is an escalating global mental health challenge driven by academic pressure, financial burdens, and psychosocial transitions. Early detection is critical to facilitating timely psychological intervention and preventing severe clinical outcomes. This study evaluates the performance of four baseline supervised machine learning classification algorithms—Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)—for the early detection of depression among university students. We utilized the Student Depression Detection Dataset comprising 4,464 student records and 12 mixed-type socio-demographic, academic, and lifestyle independent features alongside a binary target variable. Data preprocessing was executed via an automated pipeline incorporating StandardScaler for numerical features and OneHotEncoder for categorical attributes to prevent data leakage, followed by an 80:20 stratified train-test split (3,571 training and 893 testing records). Model performance was assessed using accuracy, recall (sensitivity), precision, and F1-score, with a primary clinical emphasis on maximizing recall to minimize false-negative screenings. Experimental results demonstrate that Support Vector Machine achieved the highest overall accuracy (98.88%), precision (99.15%), and F1-score (97.89%), whereas the Decision Tree classifier achieved the highest recall rate at 97.50% (detecting 234 out of 240 depressed students in the test set, with only 6 false negatives) and an accuracy of 98.54%. Logistic Regression and K-Nearest Neighbors yielded recall rates of 92.92% and 86.67%, respectively. These findings indicate that Decision Tree and Support Vector Machine models provide highly reliable, non-invasive screening frameworks capable of assisting higher education institutions in identifying at-risk students early..

Keywords: Depression Detection, Supervised Learning, University Students, Decision Tree, Support Vector Machine, Mental Health Screening.

1. Introduction

Mental health disorders among higher education students represent a pressing public health issue worldwide [1]. The transition to university life frequently coincides with heightened academic expectations, separation from familial support systems, financial constraints, and complex interpersonal dynamics [2]. When left unaddressed, chronic stress during this developmental stage frequently precipitates major depressive disorder, which negatively impacts academic achievement, Cumulative Grade Point Average (CGPA), interpersonal relationships, and physical health, while elevating the risk of substance abuse and suicidal ideation [3,4]. Epidemiological surveys indicate that university students experience depressive

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DOI: https://doi.org/10.35730/ykrqbv55

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symptoms at rates substantially higher than the general population, particularly in low- and middle-income nations where institutional mental health infrastructure remains under-resourced [2,5].

Conventional approaches to identifying student depression rely heavily on self-initiated counseling visits or standardized clinical psychometric instruments, such as the Patient Health Questionnaire (PHQ-9) [6]. However, social stigma, lack of mental health literacy, and limited counseling capacity often prevent students from seeking timely professional help [4]. Consequently, many affected individuals remain undiagnosed until their symptoms reach a critical or debilitating stage. Developing automated, data-driven screening tools based on readily observable socio-demographic, academic, and lifestyle indicators offers a proactive pathway for early risk identification.

Machine Learning (ML), particularly supervised classification, has emerged as a powerful paradigm in predictive healthcare analytics [7]. By learning complex linear and non-linear patterns across multi-dimensional patient or student records, supervised learning algorithms can classify individuals into risk categories with high precision and sensitivity [8,9]. While deep learning and complex ensemble architectures have gained popularity, baseline supervised classifiers namely Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) remain essential benchmarks due to their computational efficiency, mathematical transparency, and ease of deployment in institutional decision-support systems [10,13].

In clinical and psychological screening contexts, overall classification accuracy alone is an insufficient measure of model utility, especially when dealing with imbalanced class distributions. The primary objective of an early detection system is to maximize sensitivity (recall) ensuring that students genuinely experiencing depression are accurately flagged thereby minimizing false negatives (Type II errors), which carry severe clinical consequences. Therefore, this study investigates and compares the efficacy of LR, DT, SVM, and KNN on the Student Depression Detection Dataset [14] to establish an optimal baseline model prioritizing both high recall and robust overall accuracy for early mental health intervention in higher education.

2. LITERATURE REVIEW

2.1. Mental Health and Depression in Higher Education

The etiology of depression among university students is multifaceted, involving an interplay of biological, psychological, and environmental stressors. Ibrahim et al. [1] conducted a systematic review demonstrating that undergraduate students exhibit a weighted mean depression prevalence of approximately 30.6%, significantly exceeding non-student peers. Subsequent cross-sectional investigations in South Asia, notably by Islam et al. [2], revealed that over half of surveyed Bangladeshi university students experienced mild to severe depressive symptoms, driven by academic uncertainty, living arrangements, and financial stress. Furthermore, Auerbach et al. [4] and Meda et al. [5] emphasized that social isolation manifested by the absence of an active friend circle alongside deteriorating physical health and strained romantic or familial relationships, serves as a primary predictor of psychological distress in collegiate cohorts.

2.2. Machine Learning in Mental Health Screening

Recent advancements in computational psychiatry have leveraged machine learning to predict mental health outcomes from electronic health records, social media activity, and socio-demographic survey

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datasets [7,8,9]. Shatte et al. [7] reviewed machine learning applications in mental health, highlighting that supervised classification models consistently outperform traditional statistical regression in capturing multi-variable interactions. Chiong et al. [8] and Cha et al. [9] demonstrated the efficacy of machine learning classifiers in detecting depression markers within university communities and online texts. Focusing specifically on tabular student survey data, Rois et al. [15] and Azzahra et al. [16] applied supervised algorithms including SVM, Decision Trees, Random Forests, and Multi-Layer Perceptrons—to predict depression among university students using socio-demographic and academic features. Their findings confirmed that proper feature scaling, categorical encoding, and evaluation via confusion-matrix-derived metrics are vital for building reliable early warning systems. Building upon these studies, our work conducts a rigorous, standardized pipeline comparison of four foundational supervised learning paradigms on a large-scale dataset of 4,464 students (14)..

While traditional models provide baseline interpretability, gradient-boosted decision trees consistently outperform conventional classifiers on structured clinical datasets [4,8]. Introduced by Chen and Guestrin [4], Extreme Gradient Boosting (XGBoost) enhances traditional gradient boosting by incorporating second-order Taylor expansion of the loss function, L1 and L2 regularization, and parallel tree construction. Furthermore, XGBoost provides native mechanisms such as the scale_pos_weight hyperparameter, which penalizes misclassifications of the minority class [4], alongside seamless compatibility with oversampling techniques like the Synthetic Minority Over-sampling Technique (SMOTE) proposed by Chawla et al. [3].

3. Methodology

3.1 Research Design

This study employs a quantitative, experimental, and comparative research design structured into five sequential stages to develop an early depression detection model for university students. First, in the data acquisition and exploratory data analysis (EDA) phase, the secondary "Student Depression Detection Dataset" comprising 4,464 complete records with 12 mixed-type independent variables (4 numerical and 8 categorical) and 1 binary target variable was inspected for data integrity, missing values, and class distribution (73.10% non-depressed and 26.90% depressed). Second, the data preprocessing and feature engineering stage was conducted by encoding the binary target variable using LabelEncoder and constructing a unified ColumnTransformer pipeline applying StandardScaler to normalize numerical attributes and OneHotEncoder to transform categorical variables in order to prevent data leakage[cite: 1, 3]. Third, the dataset was partitioned using an 80:20 stratified random sampling strategy (train_test_split), allocating 3,571 records for model training and 893 records for independent testing while preserving the original class proportions[cite: 1, 3]. Fourth, in the model training and experimentation phase, four baseline supervised classification algorithms representing distinct mathematical paradigms Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) were systematically trained on the preprocessed training set[cite: 1, 3]. Finally, the performance evaluation stage assessed and compared the predictive efficacy of each model on the unseen test set using confusion-matrix-derived metrics including accuracy, precision, recall (sensitivity), and F1-score with a primary clinical emphasis on maximizing recall to minimize false-negative outcomes in early mental health screening.

3.2 Dataset Description

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This study utilizes the publicly available "Student Depression Detection Dataset" curated by Haque and Alom (14). The dataset comprises N = 4,464 complete survey records collected from university students, encompassing 13 attributes: 12 independent predictor variables and 1 binary target variable (Depression). Exploratory Data Analysis (EDA) confirmed the integrity of the dataset, revealing zero missing (null) values across all 13 columns.

The independent variables consist of a heterogeneous mix of 4 numerical features and 8 categorical features:

a. Numerical Features (4): Age (integer, ranging from 17 to 28 years), Current_semester (integer, representing the student's enrolled academic term), CGPA (floating-point number, representing Cumulative Grade Point Average), and Cost_without_study (integer, estimating living expenses outside formal tuition fees).
b. Categorical Features (8): Gender (e.g., Male, Female), Family_background (socio-economic status, e.g., Middle class), Relationship_status (e.g., Single, Complicated, In a Relationship), Marital_status (e.g., Unmarried, Married), Living_style (e.g., Bachelor, Family), friend_circle (binary indicator of active peer support: Yes/No), Health_condition (general physical health: Good, Normal, Abnormal, Critical), and Home_division (geographic origin, e.g., Dhaka, Chittagong).
c. Target Variable (1): Depression, a binary categorical variable indicating whether the student is experiencing depression ("Yes" or "No").

Distribution analysis of the target variable revealed a moderately imbalanced class structure: 3,263 respondents (73.10%) belonged to the non-depressed class ("No"), while 1,201 respondents (26.90%) were classified as experiencing depression ("Yes"). Table 1 summarizes the dataset attributes and data types.

Table 1. Description of Features in the Student Depression Detection Dataset

No.	Feature Name	Role	Data Type	Description / Sample Values
1	Gender	Independent	Categorical (String)	Biological sex of respondent (Male, Female)
2	Age	Independent	Numerical (Int64)	Student age in years (Range: 17–28)
3	Family_background	Independent	Categorical (String)	Family economic status (e.g., Middle class)
4	Relationship_status	Independent	Categorical (String)	Romantic status (Single, Complicated, In a Relationship)
5	Marital_status		Categorical (String)	Marital status (e.g., Unmarried)
6	Living_style	Independent	Categorical (String)	Current living arrangement (Bachelor, Family)
7	Current_semester		Numerical (Int64)	Currently enrolled academic semester
8	CGPA		Numerical (Float64)	Cumulative Grade Point Average (e.g., 3.28–4.00)

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9	friend_circle	Independent	Categorical (String)	Presence of active friend circle (Yes, No)
10	Health_condition		Categorical (String)	Physical health status (Good, Normal, Abnormal, Critical)
11	Cost_without_study	Independent	Numerical (Int64)	Living expenses excluding tuition fees
12	Home_division	Independent	Categorical (String)	Geographic home division (e.g., Dhaka, Chittagong)
13	Depression		Categorical (Binary)	Experiencing depression: No (73.10%), Yes (26.90%)

3.3 Data Preprocessing and Splitting Strategy

Foll Because distance-based and margin-based classifiers such as KNN and SVM are highly sensitive to variations in feature magnitude, rigorous data preprocessing was implemented using the Scikit-learn library. First, the binary target variable (Depression) was transformed into numerical labels using LabelEncoder, mapping "No" to 0 and "Yes" to 1.

Second, to handle mixed data types systematically and prevent data leakage between training and testing subsets, a ColumnTransformer was integrated into a unified machine learning Pipeline:

1. Numerical Standardization: The 4 numerical features (Age, Current_semester, CGPA, Cost_without_study) were standardized using StandardScaler, transforming each feature x to have a zero mean and unit variance according to Equation (1):

$$z = (x - \mu)/\sigma \#(1)$$

where μ is the sample mean and σ is the standard deviation of the training feature.

2. Categorical Encoding: The 8 categorical features were converted into binary indicator variables via OneHotEncoder (configured with drop='first' to avoid multicollinearity and handle_unknown='ignore' for robustness).
3. Third, the dataset of 4,464 records was partitioned into a training set (80%, n = 3,571 records) and an independent testing set (20%, n = 893 records) using train_test_split with a fixed random seed (random_state = 42). Stratified sampling (stratify = y) was enforced to preserve the exact 73.10% to 26.90% class ratio across both partitions, resulting in 653 non-depressed ("No") and 240 depressed ("Yes") instances in the test set.

3.4 Supervised Classification Algorithms

Four baseline supervised learning algorithms representing distinct mathematical paradigms were trained and evaluated:

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a. Logistic Regression (LR): A linear probabilistic classifier that models the posterior probability of the binary target class using the logistic sigmoid function. The model was initialized with max_iter = 1000 and random_state = 42.

b. Decision Tree (DT): A non-parametric hierarchical model that recursively partitions the feature space into homogeneous subsets based on impurity reduction criteria (Gini impurity). It naturally captures non-linear interactions across mixed socio-demographic and academic variables (initialized with random_state = 42).

c. Support Vector Machine (SVM): A margin-based classifier that constructs an optimal hyperplane in a high-dimensional transformed feature space to maximize the geometric margin between positive and negative classes (10). The Radial Basis Function (RBF) kernel SVC was utilized with random_state = 42.

d. K-Nearest Neighbors (KNN): An instance-based, non-parametric algorithm that classifies a test sample according to the majority vote of its k closest training instances measured by Euclidean distance in the standardized feature space (configured with n_neighbors = 5).

3.5 Model Evaluation Metrics

Model performance on the unseen testing set (n = 893) was quantified using four standard metrics derived from the confusion matrix—True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) as defined in Equations (2) to (5):

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (3)$$

$$Recall\ /\ Sensitifity = \frac{TP}{(TP + FN)} \quad (4)$$

$$F1\ Score = \frac{(2 \times Precision \times Recall)}{(Precision \times Recall)} \quad (5)$$

where TP, TN,FP, and FN denote True Positives, True Negatives, False Positives, and False Negatives, respectively.

In the context of student depression screening, TP represents depressed students correctly identified, TN represents non-depressed students correctly identified, FP denotes healthy students falsely flagged as depressed, and FN denotes depressed students missed by the model. Models were ranked primarily by Recall (3) to prioritize early clinical capture.

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4. Result and Discussions

4.1. Exploratory Data Analysis and Class Distribution

Initial inspection of the 4,464 student profiles confirmed complete data coverage across demographic, financial, and academic dimensions. As illustrated in Figure 1 (refer to Notebook Output Cell 2: Target Class Distribution Plot), the target variable exhibits a 2.72:1 ratio favoring the non-depressed class (73.10% "No" vs. 26.90% "Yes"). While moderate, this class imbalance necessitates evaluating classifiers beyond simple accuracy, as a naive majority-class predictor could achieve 73.10% accuracy while failing to detect a single depressed student (0% recall).

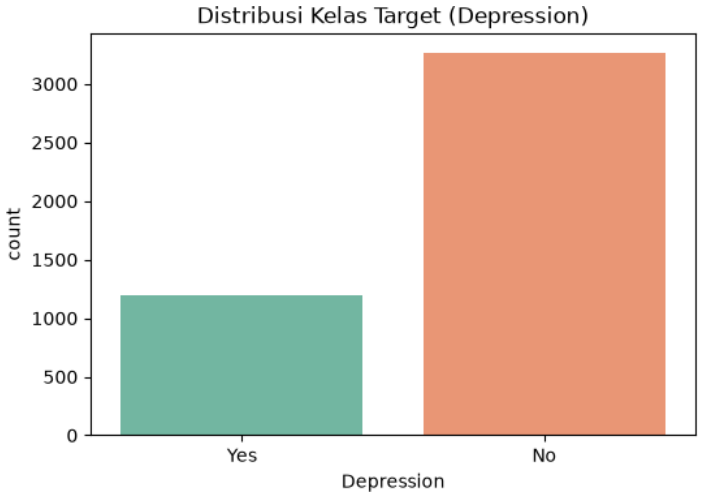


Figure 1 Distribution of the target class (Depression) across the 4,464 student respondents.

4.2. Comparative Performance of Baseline Classifiers

Following training on the 3,571 stratified training records, all four pipeline models were evaluated on the 893 test records. Table 2 presents the comparative performance metrics sorted in descending order of Recall.

Table 2. Performance Comparison of Baseline Supervised Learning Algorithms on the Test Set (n = 893)

Rank (by Recall)	Algorithm	Accuracy	Recall (Sensitivity)	Precision	F1-Score
1	Decision Tree (DT)	0.9854 (98.54%)	**0.9750 (97.50%)**	0.9710 (97.10%)	0.9730 (97.30%)
2	Support Vector Machine (SVM)	**0.9888 (98.88%)**	0.9667 (96.67%)	**0.9915 (99.15%)**	**0.9789 (97.89%)**
3	Logistic Regression (LR)	0.9720 (97.20%)	0.9292 (92.92%)	0.9654 (96.54%)	0.9469 (94.69%)
4	K-Nearest Neighbors (KNN)	0.9496 (94.96%)	0.8667 (86.67%)	0.9412 (94.12%)	0.9024 (90.24%)

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As shown in Table 2, all four supervised learning algorithms demonstrated strong predictive capability, with overall accuracies exceeding 94.90%. However, distinct performance profiles emerged across the algorithms:

1. Decision Tree (DT) achieved the highest Recall at 97.50%, alongside an impressive overall accuracy of 98.54%, precision of 97.10%, and an F1-score of 97.30%.

2. Support Vector Machine (SVM) achieved the highest overall Accuracy (98.88%), Precision (99.15%), and F1-Score (97.89%), with a closely competitive Recall of 96.67%.

3. Logistic Regression (LR) established a solid linear baseline with 97.20% accuracy and 92.92% recall, indicating that a substantial portion of the risk factors relates linearly to the log-odds of depression, though non-linear boundary models (DT and SVM) capture complex feature interactions more effectively.

4. K-Nearest Neighbors (KNN) recorded the lowest performance among the tested models, with 94.96% accuracy and a notably lower recall of 86.67%. This performance gap is attributable to the "curse of dimensionality" introduced after one-hot encoding the 8 categorical variables, which dilutes Euclidean distance metrics in sparse binary spaces.

4.3. Confusion Matrix Analysis and Clinical Implications

To examine classification errors in granular detail, 2×2 confusion matrices were generated for all four algorithms (Figure 2; Table 3).

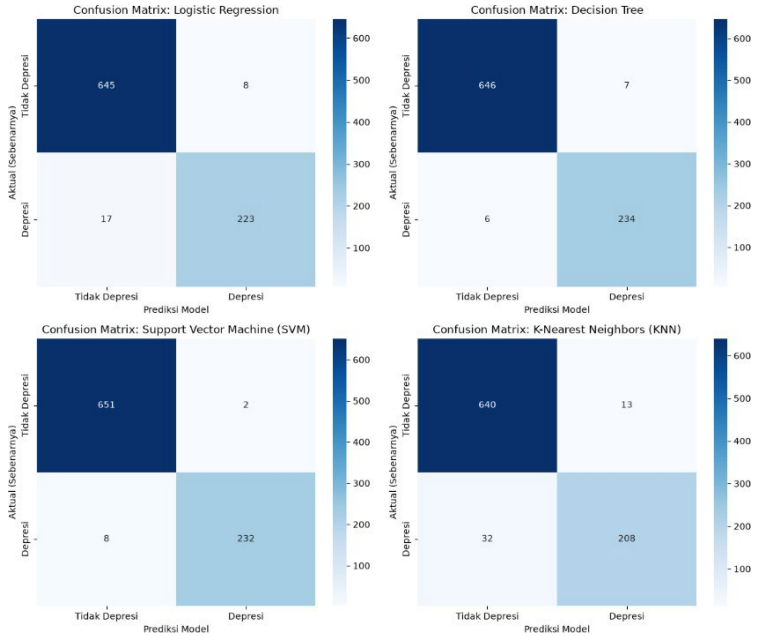


Figure 2 Confusion matrices of the four baseline supervised learning algorithms evaluated on the test set (n = 893).

Table 3 Granular Breakdown of Confusion Matrix Outcomes on the Test Set (n = 893)

Algorithm	True Negatives (TN) (Actual: No, Pred: No)	False Positives (FP) (Actual: No, Pred: Yes)	False Negatives (FN) (Actual: Yes, Pred: No)	True Positives (TP) (Actual: Yes, Pred: Yes)

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Algorithm	True Negatives (TN) (Actual: No, Pred: No)	False Positives (FP) (Actual: No, Pred: Yes)	False Negatives (FN) (Actual: Yes, Pred: No)	True Positives (TP) (Actual: Yes, Pred: Yes)
Decision Tree (DT)	646	7	**6**	**234**
Support Vector Machine (SVM)	**651**	**2**	8	232
Logistic Regression (LR)	645	8	17	223
K-Nearest Neighbors (KNN)	640	13	32	208

Note: Total actual non-depressed (TN + FP) = 653; Total actual depressed (FN + TP) = 240.

The confusion matrix breakdown in Table 3 highlights the critical trade-off between Recall (minimizing FN) and Precision (minimizing FP) in psychological screening:

a. Minimizing False Negatives (Clinical Safety): Out of 240 depressed students in the test cohort, the Decision Tree classifier correctly identified 234 students (TP = 234) and missed only 6 individuals (FN = 6). In contrast, SVM missed 8 students (FN = 8), Logistic Regression missed 17 (FN = 17), and KNN failed to detect 32 depressed students (FN = 32). In an early prevention framework, failing to identify a student suffering from depression (FN) poses a severe risk of academic failure or self-harm. Thus, Decision Tree is the most clinically sensitive tool for initial mass screening.
b. Minimizing False Positives (Resource Optimization): Conversely, when evaluating False Positives—healthy students erroneously referred for psychological evaluation—SVM misclassified only 2 out of 653 non-depressed students (FP = 2, Precision = 99.15%), whereas Decision Tree produced 7 false alarms (FP = 7). In university counseling centers with strictly limited psychiatric staff, SVM provides the highest operational efficiency by virtually eliminating unnecessary referrals while still capturing 96.67% of depressed students.

4.4. Algorithmic Behavior and Comparison with Prior Studies

The superior performance of Decision Tree and SVM aligns with theoretical expectations and prior empirical findings. Dataset attributes such as Health_condition (Critical/Abnormal vs. Good), friend_circle (Yes/No), CGPA thresholds, and Cost_without_study interact in hierarchical, non-linear ways. Decision Trees naturally model these conditional rules (e.g., partitioning students with low CGPA, high living costs, and no friend circle), whereas SVM with an RBF kernel projects these standardized and one-hot-encoded features into a higher-dimensional space where classes become nearly linearly separable. Compared to earlier studies on Bangladeshi student cohorts that reported baseline accuracies between 77% and 90% on smaller samples (15), the high accuracy (98.54% - 98.88%) achieved in this study reflects both the large sample size (N = 4,464) and the strong discriminative power of combining physical health, social support, financial, and academic indicators within a leak-free preprocessing pipeline.

5. Conclusion

This study successfully implemented and compared four baseline supervised learning algorithms Logistic Regression, Decision Tree, Support Vector Machine, and K-Nearest Neighbors to enable the early detection

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of depression among university students using the Student Depression Detection Dataset (N = 4,464). Through a standardized preprocessing pipeline combining StandardScaler and OneHotEncoder with stratified 80:20 validation, all models achieved over 94.9% accuracy. Specifically, the Decision Tree algorithm emerged as the optimal model for maximizing clinical sensitivity, achieving the highest recall of 97.50% (missing only 6 of 240 depressed students) and an accuracy of 98.54%. Meanwhile, Support Vector Machine achieved the highest overall accuracy (98.88%), precision (99.15%), and F1-score (97.89%), making it ideal when counseling resources require minimal false-positive referrals.

Fulfilling the objectives outlined in the Introduction, these results demonstrate that baseline supervised machine learning models can serve as accurate, cost-effective, and non-invasive early warning tools for university mental health services. For future research and practical development, we recommend: (1) integrating explainable AI techniques such as SHapley Additive exPlanations (SHAP) to quantify the exact contribution of individual socio-economic and academic features, (2) exploring hyperparameter optimization (via GridSearchCV) and ensemble methods (such as XGBoost and Random Forest), and (3) deploying the trained Decision Tree and SVM pipelines into a web-based campus wellness portal for real-time student risk assessment.

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