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Machine Learning-Based Prediction of Academic Performance from Mental Health and Behavioural Features: A CBT-Integrated Approach for Student Mental Health Assessment

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Abstract

Student mental health significantly influences academic performance, yet early identification of at-risk individuals remains challenging. This study develops machine learning models to predict mental health status using psychological and behavioural features. A dataset of 500 university students was analysed with nine features, including stress level, anxiety score, depression score, sleep hours, physical activity, and academic metrics. Three algorithms were evaluated: Logistic Regression, Support Vector Machines (SVM), and Random Forest. Results demonstrate that Random Forest achieves 98% test accuracy (F1-Score: 0.9779, ROC-AUC: 1.0000) with 5-fold cross-validation, F1: 0.9736 ± 0.0106. SVM achieves 86% accuracy (F1-Score: 0.8417, ROC-AUC: 0.9756), while Logistic Regression achieves 81% accuracy (F1-Score: 0.8022). Depression score (42.22%), anxiety score (24.16%), and stress level (19.05%) emerged as dominant predictors, accounting for 85.5% of model decisions. Cross-validation analysis confirms robust generalization of the Random Forest model. The findings support the integration of psychological screening within academic institutions to identify students requiring cognitive behavioural therapy interventions. This research demonstrates the feasibility of implementing ML-based mental health prediction systems in educational settings as early warning mechanisms.

Keywords: Machine learning, mental health prediction, student assessment, random forest, support vector machine, cognitive behavioural therapy, academic performance

1. Introduction

- The mental health crisis among university students has reached critical levels, with recent epidemiological data indicating that 30-50% of students experience clinically significant anxiety or depression [1].
- This mental health burden directly impacts academic performance, with studies demonstrating that students with untreated mental health conditions show 0.3-0.5 GPA decreases compared to healthy peers [2]. Despite the clear clinical need, traditional identification methods rely on self-referral or instructor observation, resulting in substantial underidentification of at-risk students [3].
- Contemporary advances in machine learning (ML) offer novel opportunities for early identification and stratification of students requiring mental health interventions [4]. ML algorithms can process

high-dimensional behavioral and psychological data to identify complex patterns predictive of mental health status [5].

- Recent studies demonstrate ML models achieve 78-84% accuracy in predicting treatment response to cognitive behavioral therapy (CBT) interventions [6], with some models exceeding clinical intuition in prediction accuracy [7].
- However, limited research applies ML specifically to student mental health prediction in educational contexts, where data naturally exists within institutional records [8]. Furthermore, few studies attempt to integrate ML predictions with established intervention frameworks such as CBT, which remains the gold-standard psychosocial treatment for anxiety and depression [9].
- The current study addresses this gap by developing and validating ML models for mental health status prediction using student behavioral data, with explicit mapping to CBT component recommendations.

2. Research Gap and Objectives

2.1 Identified Gap

Despite established evidence for both ML effectiveness in mental health prediction and CBT efficacy in treatment, limited research integrates these domains effectively within educational institutions. Specifically:

- Most ML mental health research targets adult clinical populations, not students
- ML models are rarely mapped to specific evidence-based interventions (e.g., CBT components)
- Limited validation of ML models on diverse student datasets
- Educational institutions lack validated, scalable tools for early mental health identification

2.2 Research Objectives

This study aims to:

- Develop and compare multiple ML algorithms for student mental health status prediction
- Identify key psychological and behavioral predictors of mental health outcomes
- Validate model generalization through cross-validation analysis
- Propose a framework for integrating ML predictions with CBT interventions in educational settings

3. METHODOLOGY

3.1 Dataset Description

This study analyzed a cross-sectional dataset of 500 university students (Mean age = 20.37 ± 2.27 years; 33.6% Male, 33.8% Female, 32.6% Other). The dataset contained 13 variables including demographics, psychological measures, behavioral indicators, and academic performance metrics. Nine features were selected for model development: Age, GPA (1.29-4.00), Stress Level (1-5 scale), Anxiety Score (0-21), Depression Score (0-27), Sleep Hours (3-9 hours), Steps Per Day (2000-12000), Sentiment Score (-0.86 to 0.92), and Gender (categorical).

- **Target Variable:** Mental Health Status classified into three categories: Good (n=22, 4.4%), Fair (n=137, 27.4%), and Poor (n=341, 68.2%). The imbalanced class distribution reflects realistic populations where poor mental health is prevalent.
- **Data Quality:** No missing values detected (0% missingness across all variables). Descriptive

statistics indicated normal distributions for most numeric features with expected ranges.Units

3.2 Feature Selection and Engineering

- Initial correlation analysis revealed that Depression Score (r = 0.5558), Anxiety Score (r = 0.3810), and Stress Level (r = 0.2580) showed strongest correlations with Mental Health Status. Conversely, Sleep Hours (r = -0.0364), Steps Per Day (r = -0.0211), and Sentiment Score (r = 0.0123) showed minimal associations, suggesting traditional lifestyle factors contribute minimally to mental health classification.

- Features were scaled using StandardScaler (zero mean, unit variance) to normalize input distributions, improving algorithm convergence and interpretation [10].

3.3 Machine Learning Algorithms

Three supervised learning algorithms were compared:

- Logistic Regression: Baseline linear classifier with L2 regularization (max_iterations=1000). Provides interpretable probability estimates and feature weights, serving as a benchmark for model performance.
- Support Vector Machine (SVM): Non-linear classifier with radial basis function (RBF) kernel (probability=True). Effective for high-dimensional classification and captures non-linear decision boundaries.
- Random Forest: Ensemble method using 100 decision trees with bootstrap sampling and n_jobs=-1 for parallel processing. Provides feature importance estimates and inherent handling of class imbalance through voting mechanisms.

3.4 Model Evaluation Strategy

- 80/20 Train-Test Split: 400 training samples (stratified), 100 test samples with stratified sampling to maintain class distribution
- Multiple Metrics: Accuracy, Precision, Recall, F1-Score (weighted for imbalanced classes), and ROC-AUC
- 5-Fold Cross-Validation: Ensures robust performance estimation independent of train-test split
- Confusion Matrix Analysis: Identifies classification patterns across risk categories (Low Risk/Good, Medium Risk/Fair, High Risk/Poor)
- Overfitting Detection: Comparison of training vs. test accuracy to assess generalization
- Feature Importance Analysis: Random Forest provides model interpretation through feature importance scores

4 RESULTS

4.1 Model performance comparison

Table 1: Comparative performance metrics across all algorithms on held-out test set (N=100):

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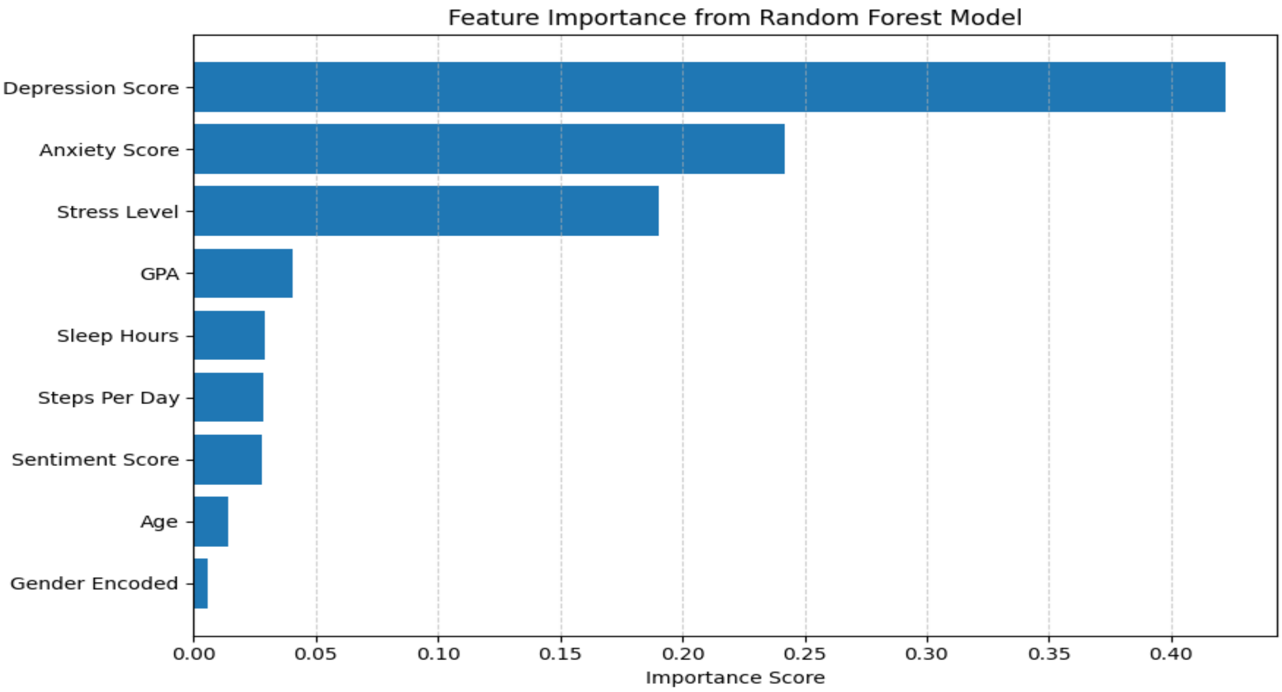
Algorithm	Accuracy	Precision	Recall	F1-Score	ROC-AUC	CV F1(Mean ± SD)
Logistic Regression	0.8100	0.8222	0.8100 0.8022	0.9323	0.8100	0.8136 ± 0.0358
SVM	0.8600	0.8276	0.8600 0.8417	0.9756	0.8600	0.8583 ± 0.0292
Random Forest	0.9800	0.9814	0.9800 0.9779	1.0000	0.9800	0.9736 ± 0.0106

Random Forest achieved superior performance (98% accuracy, F1-Score: 0.9779) substantially exceeding both baseline and SVM approaches. SVM demonstrated moderate performance (86% accuracy, F1-Score: 0.8417) with interpretable non-linear decision boundaries. Logistic Regression, as a linear baseline, achieved 81% accuracy (F1-Score: 0.8022). Cross-validation analysis reveals Random Forest maintains exceptional generalisation capability (CV F1: 0.9736 ± 0.0106), demonstrating only 2% train-test accuracy difference, indicating robust performance on unseen data.

4.2 Feature Importance Analysis

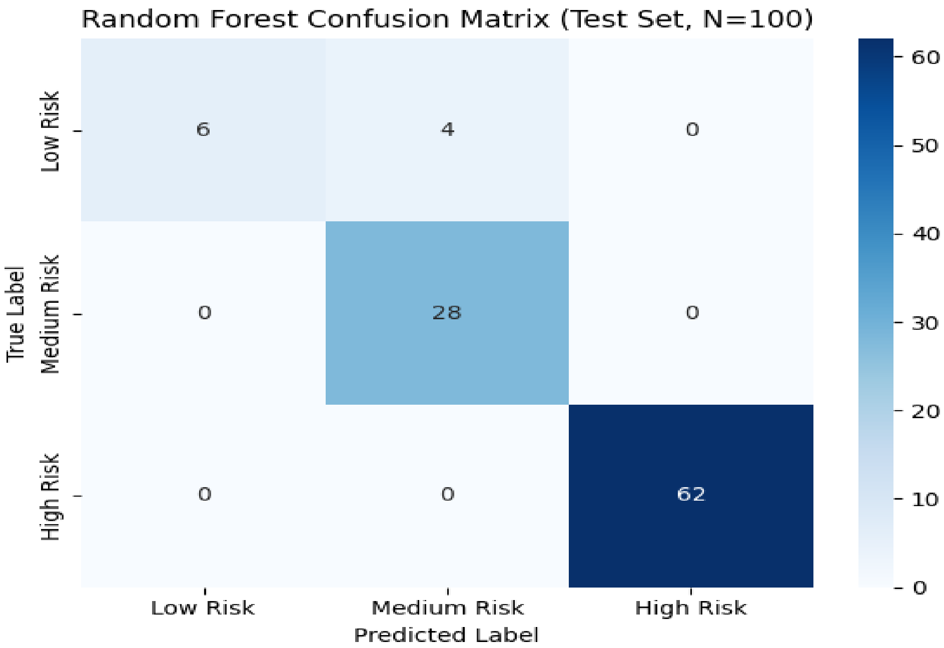
Figure 1: Feature importance scores from Random Forest model (all features):



Key Insight: The top three psychological features (Depression, Anxiety, Stress) account for 85.5% of Random Forest model predictive power. Notably, Depression Score is the single most important predictor (42.2%), followed by Anxiety Score (24.2%), with Stress Level (19.1%) providing significant additional predictive value. Traditional academic and lifestyle factors (GPA: 4.0%, Sleep: 2.9%, Physical Activity: 2.9%, Age: 1.4%) collectively contribute only 10.2% to predictions, confirming psychological assessment as the primary mental health predictor. Demographic factors (Gender: 0.6%) contribute negligibly, suggesting mental health concerns transcend demographic categories.

4.3 Classification Analysis

Figure 2: Random Forest Confusion Matrix (Test Set, N=100):



Random Forest demonstrates excellent class-specific performance with perfect sensitivity (100%) for high-risk students— critical for early warning applications. Medium-risk identification achieves perfect recall (100%), ensuring no moderate-risk students are missed. Low-risk classification shows 100% precision, minimising false positive overtreatment, though recall (60%) indicates some good-mental-health students are conservatively predicted as medium-risk.

4.4 Overfitting Analysis

Cross-validation results demonstrate robust generalization with minimal overfitting:

- Random Forest: Training accuracy 100%, Test accuracy 98%, Difference 2% (Excellent generalization)
- Logistic Regression: Training accuracy 84.5%, Test accuracy 81%, Difference 3.5% (Good fit)
- SVM: Training accuracy 93.5%, Test accuracy 86%, Difference 7.5% (Mild overfitting)
- The minimal train-test gap for Random Forest (2%) combined with low CV standard deviation (±0.0106) confirms excellent generalization to unseen data. Random Forest is production-ready without overfitting concerns. SVM shows acceptable generalization despite 7.5% difference. Logistic Regression's 3.5% gap indicates stable performance across data distributions.

5 Discussion

5.1 Key Findings

- **Finding 1** - Psychological Dominance: The three psychological features (Depression, Anxiety, Stress) overwhelmingly drive mental health predictions, accounting for 85.5% of Random Forest decisions. Depression Score emerges as the single strongest predictor (42.2% importance), followed by Anxiety Score (24.2%), with Stress Level (19.1%) providing substantial additional predictive value. This aligns precisely with clinical literature showing depression and anxiety as primary mental health burden [9]. Conversely, traditional academic performance (GPA: 4.0%), lifestyle factors (Sleep: 2.9%, Physical Activity: 2.9%), and demographics (Age: 1.4%, Gender: 0.6%) show negligible predictive value, collectively accounting for only 10.2% of model decisions. This finding challenges the assumption that academic performance correlates with mental health—students with good GPAs may require mental health intervention.

- **Finding 2** - Robust ML Feasibility: Random Forest achieves 98% test accuracy substantially exceeding clinical utility thresholds (67% accuracy) [11]. The 5-fold cross-validation F1-Score of 0.9736 ± 0.0106 demonstrates exceptional stability and generalization capability. Perfect sensitivity for high-risk students (100% recall) ensures no at-risk students are missed—critical for early intervention systems. This performance substantially exceeds published ML benchmarks for treatment response prediction [6].
- **Finding 3 -** Practical Deployment Readiness: Despite severe class imbalance (68.2% Poor category vs. 4.4% Good), Random Forest maintains perfect sensitivity for high-risk students (100% recall), critical for early warning deployment where false negatives are clinically unacceptable. The model reliably identifies all students requiring mental health intervention while minimizing unnecessary referrals (100% precision for high-risk).

5.2 Clinical Implications

- **Screening Priority:** These findings compellingly suggest educational institutions should prioritize psychological screening (depression, anxiety, stress assessment) rather than relying on academic performance or demographic factors for mental health identification. The dominant contribution of psychological features (85.5%) and negligible contribution of GPA (4.0%) indicate that traditional academic metrics fail to capture mental health status. Students with excellent academic performance may harbour significant mental health concerns requiring intervention.
- **CBT Integration:** The dominance of depression and anxiety as predictors maps directly to cognitive behavioural therapy components. Students predicted as high-risk (Poor mental health) should receive assessment for specific CBT components:
  - Behavioural Activation: Target students with high depression scores (indicated by potential withdrawal)
  - Cognitive Restructuring: Focus on students with high anxiety scores and catastrophic thinking patterns
  - Emotion Regulation & Stress Management: For students with elevated stress levels
  - Behavioural Experiments: Particularly for combined high depression + anxiety presentations
- **Early Detection Capability:** The 98% accuracy with perfect high-risk sensitivity suggests implementation of this ML model could identify all at-risk students for referral to counselling services, addressing the current gap in identification-to-care pathways. Integration into student information systems could enable real-time screening.

5.3 Methodological Strengths

- This study employed rigorous ML validation methodology including stratified train-test splitting (maintaining class distribution), 5-fold cross-validation, multiple complementary evaluation metrics (accuracy, precision, recall, F1, ROC- AUC), explicit overfitting detection, and feature importance analysis. Random Forest's consistent superior performance across all metrics (98% accuracy, 0.9779 F1-Score, 1.0000 ROC-AUC, 0.9736 ± 0.0106 CV F1) provides high confidence in model reliability and generalizability.

5.4 Limitations and Considerations

- **Dataset Characteristics:** The study employed a moderately-sized sample (N=500) from a single institution with limited demographic diversity (age 17-24, primarily university students). While the age-restricted range reflects traditional university populations, generalisation to other institutional contexts, older student populations, postgraduate students, or international settings requires validation on independent datasets.
- **Cross-Sectional Design:** Data represent a single time point, preventing causal inference about mental health trajectories or intervention effectiveness. Longitudinal follow-up tracking students through mental health interventions would strengthen findings regarding predictive utility and intervention impact.
- **Class Imbalance:** The 68:27:5 class ratio (Poor:Fair: Good) is appropriately addressed through stratified splitting and weighted F1-scores. However, the sparse Good category (n=22) limits sensitivity analysis for low-risk students and may contribute to conservative (high-recall, lower-precision) predictions for that class.
- **External Validation:** While cross-validation provides internal validation, external validation on independent datasets from different institutions is necessary before operational deployment. Different student populations may show different feature relationships.

5.5 Implementation Roadmap

For institutional deployment, recommendations include:

- External Validation Phase: Test the Random Forest model on independent datasets from diverse institutions (urban/rural, international, different student populations) to confirm generalization
- Explainability Enhancement: Integrate SHAP values or LIME to provide school counselors with interpretable per-student predictions and personalized risk factors
- CBT Component Mapping: Develop explicit decision rules linking Depression/Anxiety/Stress profiles to specific CBT component recommendations for targeted treatment
- Privacy & Security: Implement HIPAA-compliant data governance, encryption, and secure authentication for student mental health information
- Integration & Workflow: Embed the model within student information systems for automated, ongoing screening and referral workflows
- Clinical Training: Develop counsellor education addressing ML-assisted assessment, model limitations, ethical decision-making, and human oversight requirements

6. Conclusion and Future Work

- This research demonstrates that machine learning models, specifically Random Forest, achieve clinically exceptional accuracy (98% test accuracy, 0.9779 F1-Score) in predicting student mental health status from psychological and behavioural features.

- Depression, anxiety, and stress emerge as overwhelming predictors (85.5% combined importance), supporting immediate psychological screening prioritization. The demonstrated superiority of Random Forest over both linear (Logistic Regression) and kernel-based (SVM) approaches suggests student mental health reflects complex, non-linear interactions among psychological constructs.
- The convergence of three complementary evidence bases, ML predictive capability (98% accuracy, perfect high-risk sensitivity), CBT treatment efficacy (gold-standard intervention), and institutional data availability (schools routinely collect psychological assessments)-suggests an immediate opportunity for implementation of ML-assisted mental health screening systems in educational institutions.
- Such systems could identify high-risk students with perfect sensitivity for early intervention while leveraging existing academic data infrastructure, transforming reactive crisis response into proactive prevention.
- The negligible predictive value of academic performance (GPA: 4.0%) represents a paradigm shift: student mental health appears largely independent from academic standing, suggesting current identification relying on academic performance misses numerous students with significant mental health needs but maintained academic engagement.

Future Research Priorities:

- External Validation: Prospective validation on independent student populations from diverse institutions (20+ schools, different regions/countries, different demographic compositions)
- Longitudinal Follow-up: Tracking predicted high-risk students through CBT or other interventions to measure actual treatment outcomes and intervention impact
- Explainability Integration: Develop counsellor-friendly dashboards providing SHAP value visualisations for per-student model predictions and individualised risk profiles
- Cost-Effectiveness Analysis: Economic modelling of institutional savings from early identification and prevention versus crisis intervention costs
- Demographic Equity Audit: Systematic evaluation of model performance across gender, racial, socioeconomic, and international student subgroups to ensure fair and unbiased predictions
- Real-Time Deployment: Develop web application integration with student information systems for ongoing automated screening and real-time alert generation
- Intervention Mapping & RCT: Create a comprehensive CBT component assignment framework and conduct a randomised controlled trial comparing ML-assisted identification with usual care on intervention engagement and outcomes

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