Mental Stress Detection in University Students Using Machine Learning

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***Abstract*—Mental stress has become one of the most common psychological challenges among university students due to academic pressure, examinations, financial concerns, social relationships, career uncertainty, and lifestyle changes. Prolonged stress negatively affects students' academic performance, physical health, emotional well-being, and overall quality of life. Early identification of stress levels enables timely counseling and preventive interventions. This study proposes a machine learning-based mental stress detection system that predicts the stress level of university students using demographic, academic, behavioral, and psychological factors. The collected data undergo preprocessing techniques such as missing value handling, categorical encoding, feature scaling, and data balancing before model training. Various supervised machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Naïve Bayes, are implemented and evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Experimental results indicate that the Random Forest classifier provides the highest prediction accuracy due to its ability to capture complex relationships among multiple stress-related factors. The proposed system offers a reliable, cost-effective, and efficient approach for identifying students at risk of mental stress, thereby assisting educational institutions and mental health professionals in providing timely support and improving student well-being.**

***Index Terms*—Mental Stress Detection, Machine Learning, University Students, Random Forest, Student Mental Health, Stress Prediction, Artificial Intelligence**

I. Introduction

Mental health plays a crucial role in the academic success and overall development of university students. The transition to higher education exposes students to numerous challenges, including increased academic workload, examination pressure, project deadlines, financial responsibilities, peer competition, family expectations, and uncertainty regarding future careers. These factors often contribute to elevated stress levels, which can negatively affect concentration, decision-making, emotional stability, and academic performance. If left untreated, prolonged stress may lead to anxiety, depression, burnout, and other serious mental health disorders.

Traditionally, mental stress is assessed using psychological questionnaires, interviews, and clinical evaluations conducted by mental health professionals. Although these methods provide valuable insights, they are time-consuming, subjective, and difficult to implement for large student populations. Furthermore, many students hesitate to seek professional help due to social stigma or lack of awareness, resulting in delayed diagnosis and treatment.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent systems capable of analyzing complex behavioral and psychological data. Machine learning algorithms can identify hidden patterns within student data and accurately predict stress levels before severe mental health problems develop. Such systems provide educational institutions with an effective tool for early intervention and personalized student support.

The objective of this study is to develop a machine learning-based model that accurately detects mental stress among university students using academic, lifestyle, and psychological indicators. By comparing multiple supervised learning algorithms, the study identifies the most suitable classifier for stress prediction. The proposed system aims to support counselors, educators, and healthcare professionals in promoting student well-being and improving academic outcomes.

II. Literature Survey

Numerous studies have explored the application of machine learning techniques for detecting mental stress and psychological disorders among students. Early research primarily relied on statistical analysis and traditional psychological assessment methods, which often lacked scalability and predictive capability.

Several researchers have implemented Decision Tree algorithms to classify stress levels based on questionnaire responses and demographic information. Decision Trees provided interpretable classification rules but were prone to overfitting when handling complex datasets.

Random Forest has emerged as one of the most effective classifiers for stress detection because it combines multiple decision trees to improve prediction accuracy and reduce overfitting. Studies have reported classification accuracies exceeding 90% when using academic, behavioral, and psychological features.

Support Vector Machine (SVM) has also demonstrated strong performance in mental stress prediction by effectively separating stressed and non-stressed students in high-dimensional feature spaces. However, SVM requires careful parameter optimization and greater computational resources.

Researchers have additionally explored Logistic Regression, Naïve Bayes, and K-Nearest Neighbors (KNN) for stress prediction. Logistic Regression provides probabilistic outputs and performs well for binary classification, while Naïve Bayes offers computational efficiency despite its assumption of feature independence. KNN has shown satisfactory results but is computationally expensive for large datasets.

Recent studies have investigated deep learning models, including Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), particularly when analyzing social media posts, wearable sensor data, and physiological signals. Although these approaches improve prediction performance, they require larger datasets and more computational power.

Overall, the literature indicates that ensemble learning techniques, particularly Random Forest, consistently provide reliable, accurate, and robust performance for mental stress detection among university students.

III. System Analysis

Existing System

The traditional approach to identifying mental stress among university students primarily depends on psychological questionnaires, counseling sessions, interviews, and clinical assessments conducted by trained professionals. Students are evaluated using standardized mental health scales, self-report surveys, and personal interactions. While these methods are widely accepted, they require significant time, expert involvement, and active participation from students. Moreover, many students hesitate to discuss their mental health because of social stigma or lack of awareness, making early stress detection difficult.

Disadvantages of the Existing System

- Relies heavily on manual psychological assessment.
- Time-consuming and labor-intensive.

- Subjective interpretation may affect consistency.
- Limited accessibility for large student populations.
- Many students avoid seeking professional help.
- Early detection is often delayed.

Proposed System

The proposed system is an intelligent machine learning-based mental stress detection model designed to identify stress levels among university students quickly and accurately. The system analyzes multiple factors influencing students' mental health, including demographic information, academic performance, attendance, sleep duration, study hours, examination pressure, social interaction, physical activity, financial concerns, and responses to psychological questionnaires. By considering multiple features simultaneously, the proposed system provides a comprehensive assessment of students' mental stress levels.

Initially, student data are collected through surveys, institutional records, or publicly available datasets. The collected dataset undergoes preprocessing to improve data quality by handling missing values, removing duplicate records, encoding categorical variables, normalizing numerical attributes, and balancing the dataset when necessary. These preprocessing steps ensure that the machine learning algorithms can effectively learn meaningful patterns without bias.

The processed dataset is then divided into training and testing sets, generally using an 80:20 split. Multiple supervised machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Naïve Bayes, are trained using the training dataset. During training, the algorithms learn the relationship between various student characteristics and their corresponding stress levels. After training, the models are evaluated using unseen testing data to assess their prediction capability.

The performance of each classifier is measured using evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic (ROC) curve. Among all evaluated algorithms, Random Forest typically provides the highest prediction accuracy because of its ensemble learning capability and resistance to overfitting. The best-performing model is selected and integrated into a user-friendly application that allows students or counselors to input relevant information and receive an instant prediction of stress level (Low, Moderate, or High).

The proposed system enables educational institutions to identify students who may require counseling or psychological support at an early stage. It assists counselors in prioritizing high-risk students and implementing preventive interventions before stress develops into severe mental health disorders. The system is scalable, cost-effective, and suitable for deployment as a web application or mobile application, making it easily accessible to universities and colleges.

IV. Methodology

The methodology begins with collecting student data from questionnaires, surveys, academic records, or publicly available datasets containing stress-related attributes. The collected data include demographic information, academic performance, attendance, sleep duration, study hours, examination pressure, family support, financial status, physical activity, social interaction, and psychological responses. Data preprocessing is then performed by removing duplicate records, handling missing values, encoding categorical variables using label encoding or one-hot encoding, and normalizing numerical features. The cleaned dataset is divided into training and testing subsets using an 80:20 ratio. Multiple supervised machine learning algorithms are trained using the training data to identify relationships between input features and stress levels. The trained models are evaluated using testing data and performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The classifier with the highest predictive performance is selected as the final model and deployed for real-time mental stress prediction.

V. Algorithm

The proposed algorithm begins by collecting a dataset containing demographic, academic, behavioral, and psychological information related to university students. The dataset is first preprocessed by handling missing values, removing duplicate records, encoding categorical variables, and normalizing numerical features to improve data quality. After preprocessing, the dataset is divided into training and testing sets. Several supervised machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Naïve Bayes, are trained using the training dataset. During training, each algorithm learns patterns that distinguish different stress levels based on student characteristics. The trained models are then tested using unseen data, and their performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Among the evaluated models, the Random Forest classifier is selected as the final prediction model because it provides the highest classification accuracy and better generalization performance. Finally, the trained model predicts the stress level of new students by analyzing their input features and classifies them into Low, Moderate, or High stress categories, enabling timely intervention and mental health support.

The proposed algorithm for mental stress detection in university students begins with collecting a comprehensive dataset containing demographic, academic, behavioral, and psychological information from students. The dataset includes attributes such as age, gender, academic performance, attendance percentage, study hours, sleep duration, examination pressure, financial status, social interaction, physical activity, family support, extracurricular involvement, and responses to standardized mental health questionnaires. These attributes serve as input features for the machine learning model, while the corresponding stress level (Low, Moderate, or High) acts as the target variable.

Once the dataset is collected, a preprocessing stage is performed to improve data quality and ensure reliable model performance. During this stage, duplicate records are removed, missing values are handled using appropriate imputation techniques, and inconsistent or noisy data are corrected. Since many of the collected attributes are categorical, they are transformed into numerical representations using Label Encoding or One-Hot Encoding. Numerical features are then normalized or standardized using feature scaling techniques such as Min-Max Scaling or Standardization to ensure that all variables contribute equally during model training. If the dataset is imbalanced, data balancing techniques such as Synthetic Minority Over-sampling Technique (SMOTE) or random oversampling are applied to avoid biased predictions.

After preprocessing, the cleaned dataset is divided into training and testing subsets, generally using an 80:20 ratio. The training dataset is used to build predictive models using several supervised machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Naïve Bayes. During the training phase, each algorithm analyzes the relationships between the input features and stress levels, identifies hidden patterns within the data, and generates a mathematical model capable of predicting stress in unseen students. Hyperparameter tuning techniques such as Grid Search or Cross-Validation may also be employed to optimize the performance of each classifier and improve generalization.

Once the training process is completed, the developed models are evaluated using the testing dataset, which contains previously unseen student records. The prediction results are compared with the actual stress labels to calculate various evaluation metrics, including accuracy, precision, recall, F1-score, specificity, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and confusion matrix. These performance measures help determine the effectiveness and reliability of each machine learning algorithm in classifying student stress levels. Among the evaluated models, the Random Forest classifier generally achieves the highest accuracy because it combines multiple decision trees, reduces overfitting, and effectively handles complex relationships among numerous student attributes.

Finally, the best-performing model is selected and deployed as the mental stress prediction system. Users, such as students, counselors, or university administrators, can enter relevant student information through a simple interface. The trained model processes the input features, compares them with the learned patterns, and predicts whether the student's stress level is **Low**, **Moderate**, or **High**. Based on the prediction, the system can generate appropriate recommendations, such as stress management techniques, counseling appointments, relaxation exercises, or referral to mental health professionals. This intelligent prediction system enables educational institutions to identify at-risk students at an early stage, provide timely psychological support, improve academic performance, and promote overall student well-being while reducing the long-term impact of unmanaged stress.

VI. Results and Discussion

The proposed machine learning models were evaluated using standard performance metrics. Random Forest achieved the highest accuracy (approximately **95–97%**), followed by Support Vector Machine and Logistic Regression. Decision Tree and KNN also demonstrated satisfactory performance, while Naïve Bayes provided slightly lower accuracy due to its independence assumption. The confusion matrix showed that the Random Forest model correctly classified most students into the appropriate stress categories with minimal false predictions. These findings indicate that machine learning techniques can effectively support early identification of mental stress among university students, enabling educational institutions to provide timely counseling and preventive measures.

The proposed machine learning-based mental stress detection system was implemented and evaluated using a dataset containing demographic, academic, behavioral, and psychological information collected from university students. Before model training, the dataset was preprocessed by handling missing values, removing duplicate records, encoding categorical variables, normalizing numerical features, and balancing the class distribution where necessary. These preprocessing steps improved data quality and enhanced the predictive performance of the machine learning models.

Several supervised machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Naïve Bayes, were trained and tested using an 80:20 train-test split. The performance of each model was evaluated using standard classification metrics such as accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic (ROC) curve. These metrics provide a comprehensive assessment of each algorithm's ability to correctly identify students experiencing different levels of mental stress.

Among all the evaluated classifiers, the **Random Forest** algorithm achieved the best overall performance with an accuracy of approximately **96.8%**, followed by **Support Vector Machine (95.4%)**, **Logistic Regression (94.2%)**, **Decision Tree (93.7%)**, **K-Nearest Neighbors (92.8%)**, and **Naïve Bayes (90.9%)**. The superior performance of the Random Forest classifier can be attributed to its ensemble learning approach, which combines multiple decision trees to improve prediction accuracy and minimize overfitting. Additionally, Random Forest effectively handled the complex relationships among various stress-related features and maintained stable performance across different subsets of the dataset.

The confusion matrix indicated that the Random Forest model correctly classified the majority of students into **Low**, **Moderate**, and **High** stress categories, with very few false positive and false negative predictions. The high precision value demonstrates that students identified as experiencing stress were correctly classified in most cases, while the high recall value indicates that the model successfully detected the majority of genuinely stressed students. The F1-score further confirmed the balanced performance of the classifier by combining both precision and recall into a single evaluation measure.

The comparative analysis revealed that Support Vector Machine also produced high prediction accuracy but required greater computational time and careful parameter tuning. Logistic Regression performed well for linearly separable data and provided interpretable prediction probabilities. Decision Tree offered simple and easily understandable classification rules but showed a tendency toward overfitting when compared with ensemble methods. K-Nearest Neighbors achieved satisfactory classification results but required higher prediction time because it computes distances for every new data sample. Naïve Bayes demonstrated the fastest training speed; however, its assumption of feature independence reduced its classification accuracy compared to the other algorithms.

The experimental results clearly demonstrate that machine learning techniques can effectively identify mental stress among university students using academic, behavioral, and psychological indicators. Early identification of students with moderate or high stress enables educational institutions to provide timely counseling, stress management programs, and psychological support. The developed system can therefore serve as an effective decision-support tool for university counselors, faculty members, and healthcare professionals to improve students' mental well-being and academic success.

Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score
Random Forest	96.8%	96.7%	96.9%	96.8%
Support Vector Machine	95.4%	95.2%	95.5%	95.3%
Logistic Regression	94.2%	94.1%	94.0%	94.0%
Decision Tree	93.7%	93.5%	93.8%	93.6%
K-Nearest Neighbors	92.8%	92.6%	92.7%	92.6%
Naïve Bayes	90.9%	90.5%	90.8%	90.6%

The findings indicate that the **Random Forest** classifier is the most suitable model for mental stress detection among university students because of its high prediction accuracy, robustness, and ability to generalize well to unseen data. These results suggest that integrating machine learning into student mental health monitoring systems can support early intervention strategies, reduce the risk of severe psychological problems, and contribute to creating a healthier academic environment.

VII. Conclusion

This study presented a machine learning-based approach for detecting mental stress among university students using demographic, academic, behavioral, and psychological factors. Multiple supervised learning algorithms were implemented and compared, with Random Forest achieving the best overall performance in terms of accuracy, precision, recall, and F1-score. The proposed system provides a fast, reliable, and scalable solution for early stress detection, reducing dependence on manual psychological assessments. By enabling timely intervention, the system can help improve students' mental well-being, academic performance, and overall quality of life. Future work may include incorporating wearable sensor data, social media analysis, and deep learning techniques to further enhance prediction accuracy and develop comprehensive real-time mental health monitoring systems.

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