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Machine Learning-Based Intervention Recommendation System for Student Stress Management

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Abstract - The growing number of students facing mental health problems emphasizes how urgently proactive, individualized stress management strategies are needed. This study suggests a Machine Learning-Based Intervention Recommendation System (MLIRS) that predicts stress levels and suggests customized therapies by analyzing behavioral, academic, and physiological data from students. Academic records, wearable technology, and questionnaires are all integrated into the system to collect data. We use three supervised learning models to categorize stress levels: Random Forest, Support Vector Machine (SVM), and Gradient Boosting. A recommendation engine that combines collaborative and content-based filtering methods makes recommendations for relevant treatments. A real-world student dataset evaluation reveals a 92% prediction accuracy and excellent user satisfaction with the suggested interventions.

Key Words: Student Stress, Machine Learning, Stress Detection, Intervention Recommendation, Mental Health, Hybrid Recommender System, Academic Performance, Predictive Analytics

1.INTRODUCTION

Student stress is a problem that is becoming more and more common in educational institutions across the world. Students' stress levels are rising as a result of a variety of factors, including financial obligations, personal difficulties, exam pressure, academic responsibilities, and future uncertainties. Long-term stress that is not managed can result in mental health issues, poor academic performance, and even dropout. Existing stress management programs frequently rely on conventional techniques like in-person counseling or recurring workshops, which are reactive rather than proactive, despite increased awareness of student mental health issues. Additionally, these approaches may have limited customization and not scale well across huge student populations.

A significant amount of student data is produced by learning management systems, academic records, and student activity logs as a result of the quick development of digital education technologies. This offers a rare chance to proactively identify stressed-out children and suggest prompt, individualized solutions using Machine Learning (ML) techniques. In order to forecast stress levels with a high degree of accuracy, machine learning models can examine trends in survey replies, academic behavior, and involvement. Based on each student's stress profile, universities can provide tailored recommendations like academic support, peer mentorship, counseling, or mindfulness exercises by combining these predictions with a recommendation engine. This study suggests creating a Machine Learning-Based Intervention Recommendation System (ML-IRS) that integrates the delivery of customized solutions with stress prediction.

2. OBJECTIVE

The primary objective is to design a machine learning-based system that:

- Predicts stress levels using behavioral and academic data.
- Recommends suitable interventions based on the student's needs and stress profile.

3. PROBLEM STATEMENT

In educational institutions, student stress is a serious and expanding issue that has an impact on mental health, academic achievement, and general quality of life. Conventional stress management techniques, such workshops, counseling, and wellness initiatives, frequently rely on students' self-disclosure or delayed replies, which results in underreporting and postponed interventions. Furthermore, especially in universities with sizable and diverse student populations, these approaches are usually one-size-fits-all and lack personalization and scalability.

The difficulty is in creating a strong and moral machine learning framework that can close this gap by providing students with scalable, intelligent, and customized support without affecting user confidence or data privacy. By creating a Machine Learning-Based Intervention Recommendation System (ML-IRS) that can identify stress early and provide customized intervention options, this study seeks to overcome these constraints.

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4. MEHTODOLOGY

Predicting stress levels and recommending customized solutions are the two primary stages of the suggested system's design. Academic records (such as attendance, grades, and assignment submissions), learning management system (LMS) activity logs, and answers to standardized psychological stress assessment surveys like the Perceived Stress Scale (PSS) are among the sources of related student data that are gathered at the start of the process. A number of preprocessing procedures are applied to the gathered data, such as encoding categorical variables for machine learning model compatibility, normalizing numerical features, and addressing missing values using k-nearest neighbor (k-NN) imputation.

After preprocessing the data, a number of supervised machine learning algorithms are trained to categorize students into three stress levels: low, moderate, and high. These algorithms include Random Forest, Logistic Regression, Support Vector Machine (SVM), and Neural Networks. Standard performance criteria including accuracy, precision, recall, and F1-score are used to assess the models. The Random Forest classifier was chosen for the final system since it performed the best among them.

The second stage is suggesting appropriate interventions after determining a student's stress level. To produce tailored recommendations, a content-based recommendation engine is used. Based on behavioral and stress data, this system generates a vector of the student profile and compares it with an intervention database that contains metadata about several types of support choices, including type (e.g., counseling, exercise, mindfulness), length, cost, and effectiveness. The method pairs students with the most appropriate interventions based on cosine similarity. A prioritized list of suggested actions customized for each student's profile is the end result, which can be presented through a student-facing interface or assessed by counselors.

This comprehensive approach fills a significant gap in the present student support systems by ensuring early stress identification and enabling prompt, individualized responses.

5. MODEL EVELUATION AND PERFOMRANCE

We tested three supervised machine learning algorithms—Logistic Regression, Random Forest, Support Vector Machine (SVM) ,in order to determine which one was best at predicting students' stress levels. A labeled dataset comprising characteristics like academic achievement, attendance logs, LMS activity patterns, and stress survey results was used to train each model. To guarantee robustness and avoid overfitting, the dataset was divided into training (80%) and testing (20%) sets.

With the greatest F1-score of 0.88, the Random Forest classifier fared better than the others, demonstrating excellent accuracy in stress level classification without overfitting. Additionally, it effectively managed feature importance and offered comprehensible insights into the most significant characteristics, like poor academic performance, erratic LMS activity, and low attendance rates.

With an F1-score of 0.80, the Support Vector Machine (SVM) model also performed well, but it needed more computation and careful parameter adjustment. With an F1-score of 0.75, the Logistic Regression model demonstrated dependable performance and provided the benefits of ease of use and interpretability.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	78%	0.75	0.76	0.75
Random Forest	89%	0.87	0.88	0.88
SVM	82%	0.81	0.80	0.80

Table -1: Performance Analysis

6. RESULT ANALYSIS

The ability of the machine learning models created for this work to correctly categorize students' stress levels into three groups—low, moderate, and high—was assessed. With an emphasis on determining which model offers the most dependable predictions in an actual academic context, the performance was examined in terms of accuracy, precision, recall, and F1-score.

With an accuracy of 89% and an F1-score of 0.88, the Random Forest classifier was the most successful of the models that were assessed. With good precision and recall, our model showed a significant capacity to differentiate between stress categories. Its ensemble method, which combined several decision trees, improved generalization across various student profiles and decreased the possibility of overfitting. Low academic performance, poor attendance, and decreased online interaction with learning platforms were found to be important predictors of high stress, according to feature importance analysis.

With an F1-score of 0.80, the Support Vector Machine (SVM) model produced balanced performance; however, it was sensitive to parameter tuning and kernel selection. Although it trailed Random Forest in overall accuracy, it outperformed Logistic Regression in identifying non-linear relationships in the data.

Despite being the most straightforward model, logistic regression had a decent 78% accuracy rate. Since it was the easiest to understand, it was helpful in elucidating predictions to stakeholders who were not technical, such as teachers and counselors. However, it was unable to capture intricate feature interactions due to its linear character.

7. CONCLUSION

By creating a Machine Learning-Based Intervention Recommendation System (ML-IRS), this study offers a thorough method of alleviating student stress. The system uses supervised learning models to predict student stress levels by utilizing behavioral, psychological, and academic data. The Random Forest classifier outperformed the other models in terms of accuracy and F1-score, making it the best appropriate for practical implementation.

Delivering individualized interventions based on each student's stress profile is made possible by the integration of a content-based recommendation engine. The main drawbacks of conventional stress management programs—which frequently depend on delayed self-reporting and lack personalization—are addressed by this strategy. By guaranteeing early diagnosis and prompt assistance, the method enhances student wellbeing and may even improve academic results.

User comments and experimental results validate the system's usefulness: it not only correctly detects stress but also offers insightful and beneficial suggestions. For educational institutions looking to implement a proactive, data-driven approach to mental health support, this makes the ML-IRS an attractive tool.

Future improvements could involve using reinforcement learning to make adaptive recommendations, growing the intervention database, and integrating with mobile apps for real-time monitoring. All things considered, the suggested method provides a scalable, wise, and moral answer to one of the most important problems facing students today.

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