Student Wellness Monitoring System

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ABSTRACT

Stress among students is a growing concern, affecting their mental health, academic performance, and overall well-being. Through this project, we focus on building a system that will provide stress reports and indicators, along with actions and recommendations to manage it. We implement database-based predictions using the Kaggle Student Stress Dataset by employing machine learning models to predict stress levels based on psychological, physiological, and environmental factors. The system includes an interactive dashboard for students and parents to monitor stress levels, view trends, and receive actionable recommendations. With this system, we aim to empower users with data-driven insights to foster proactive mental health management and develop a healthier and supportive educational experience.

1 INTRODUCTION AND MOTIVATION

Stress and mental health challenges have become critical issues among students, impacting their academic performance, social interactions, and overall well-being. With increasing academic pressure, societal expectations, and digital engagement, students often struggle to maintain a balance between their academic and personal lives. Studies reveal that stress can lead to significant long-term psychological and physical health concerns, underscoring the urgent need for effective monitoring and intervention strategies.

The motivation for this project arises from the realization that while mental health awareness is growing, tools for early detection and proactive intervention remain limited. Educational institutions often lack comprehensive systems that combine technology with mental health management, leaving students and parents without actionable insights to address these challenges.

The decision to focus on student wellness stemmed from the need to address a growing societal issue with practical, technology-driven solutions. Initially, the project explored monitoring systems for astronaut and firefighter wellness, but the lack of relevant datasets shifted our focus to students' wellbeing.

Students represent a demographic significantly affected by stress, and addressing their well-being has a profound impact on their academic journey and future success. Furthermore, the accessibility of student data allows for robust analysis, making this topic both impactful and feasible. By focusing on student stress prediction, this project contributes to addressing an urgent societal need while laying the groundwork for future enhancements such as real-time monitoring through sensors and teacher-based insights.

Our project aims to have a tool for students to track their wellness, and take preemptive care while also making it interesting to keep track. By using tools that are affordable or already available to the student we aim to make wellness accessible to the average student.

2 METHODOLOGY AND RESULTS

This project focuses on creating a prototype for Student Wellness Management. By leveraging the Kaggle Student Stress Dataset, the system predicts stress levels based on psychological, physiological, and environmental factors. It also provides an interactive dashboard for students and parents, enabling them to monitor stress trends, understand triggers, and access personalized recommendations for stress relief.

2.1 Process

- **Sensor Reading** - Sensors collect data. For blood pressure sensors it's a score, for motions sensors it's movement or lack of movement, and for the cameras it's emotion recognition.
- **Database** - The real-time data would be stored in a SQLite3 database, this data will be represented as different graphs and charts but will also be run through our stress predictor algorithms.
- **Predicting Algorithm** - Once we start collecting data, we can use our stress predicting algorithm Random Forest to analyze the data and see if there are any potential stress possibilities.
- **Alert Trigger** - If the algorithm predicts stress, the dashboard will generate alerts, suggestions for actions and also notify parents/guardians of possible risk. It will continue to alert students and parents until an action is taken, and the stress prediction diminishes.
- **Dashboard** - The dashboard will present the information in a way that's easy to understand to the user.

2.2 Dataset and Sensors

The dataset contains around 20 features that create the most impact on the Stress of a Student. The features are divided into 5 major factors –

- Psychological Factors – anxiety_level, self_esteem, mental_health_history, depression
- Physiological Factors - headache, blood_pressure, sleep_quality, breathing_problem
- Environmental Factors - noise_level, living_conditions, safety, basic_needs
- Academic Factors - academic_performance, study_load, teacher_student_relationship, future_career_concerns
- Social Factors - social_support, peer_pressure, extracurricular_activities, bullying

"**Stress_Level**" is the target variable with 0 indicating low stress, 1 – medium stress and 2 – high stress.

The possibility of sensors is limitless as the information we want to collect, however we chose three to consider the most accessible for the purpose of our project.

- Blood Pressure Sensor/Monitor - Blood Pressure was one of the top predictors for stress. These sensors are readily available to most people, and while there is a limit on the wearable technology efficacy in monitoring blood pressure; students can check their pressure using a standard bp monitor on a frequent basis.
- Motion Sensors - Passive Infrared Sensors (PIR) motion sensors can monitor restlessness during sleep as well as inactivity during study time. Sleep quality was the top predictor for stress, indicating that apart from surveying the student for sleep related issues. Monitoring restless via wearable technology and motion sensors can help note patterns particularly if there are behaviors leading up to things like tests or assignments due.
- Cameras - Emotion recognition via cameras in students screens can help confirm stress indicators, through emotion detection the dashboard can monitor facial queues to suggest breaks or track moods. OpenCV can be used and trained to detect relevant emotions.

2.3 Prediction Model

This project leverages machine learning and explainable AI (XAI) to analyze a wide range of factors impacting student stress, such as self-esteem, mental health history, social dynamics, and academic pressures. Unlike traditional models, which may offer limited interpretability, our approach prioritizes transparency, enabling us to pinpoint the most influential predictors of stress in a clear, interpretable manner. By uncovering these key stress drivers, this research aims to provide valuable insights for educational institutions to develop targeted interventions and foster a more supportive learning environment for students.

2.3.1 Feature Selection

We applied ANOVA (Analysis of Variance) and the Chi-Square Test to identify the most significant features associated with the target variable, stress_level. Both tests assess the relationship between each feature and the target, with higher scores indicating stronger associations.

The results from both tests highlighted sleep quality and blood pressure as the most significant features. These two variables showed the highest scores, suggesting they are strongly correlated with stress levels in the dataset.

2.3.2 Predictive Modeling Assessment

We assessed the performance of three models—Linear Regression, Decision Tree Regressor, and Random Forest Regressor—using R-Squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics were applied to the actual and predicted results from each model.

The Linear Regression model achieved an R^2 value of 0.67, with a MAE of 0.33, an MSE of 0.22, and an RMSE of 0.47. While the model explained 67% of the variance in the target variable, the error metrics indicated that it was not as effective in predicting stress levels compared to the other models.

The Decision Tree Regressor delivered a stronger performance, with an R^2 of 0.82, a MAE of 0.14, an MSE of 0.12, and an RMSE of 0.35. These results suggested that the Decision Tree model was much better at capturing the complexity of the data, showing improved accuracy over Linear Regression in all metrics.

The Random Forest Regressor showed similar results to the Decision Tree Regressor, with an R^2 value of 0.82, a MAE of 0.14, an MSE of 0.12, and an RMSE of 0.35. These results reinforced the robust predictive power of the Random Forest model, which is well-suited for handling more complex datasets due to its ensemble learning approach.

In conclusion, both the Decision Tree Regressor and Random Forest Regressor outperformed Linear Regression in terms of predictive accuracy, with Random Forest slightly edging out Decision Tree in general robustness. Given the similar performance between Decision Tree and Random Forest, either could be used, with Random Forest offering the added benefit of being less prone to overfitting

2.3.3 SHAP (SHapley Additive exPlanations)

This section delves into SHAP (SHapley Additive exPlanations) analysis, uncovering how individual features impact our models' predictions. SHAP values serve as a unified measure of feature importance.

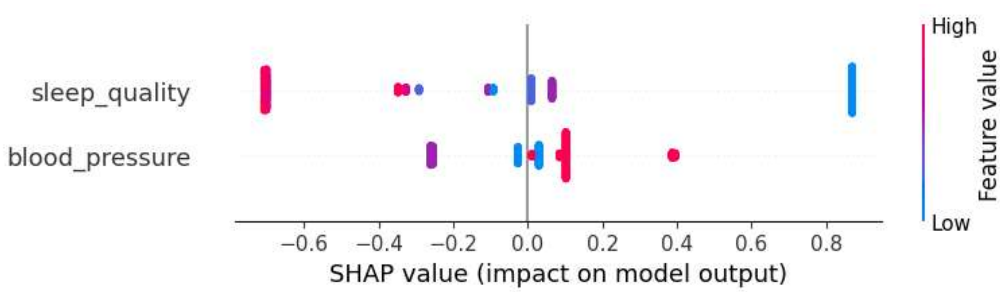

Figure 1 SHAP impact of sleep quality and blood pressure on model performance.

This SHAP summary plot shows the impact of sleep_quality and blood_pressure on the model's predictions. Each point represents a data instance, with the x-axis indicating SHAP values (feature impact on the prediction) and color showing feature values (blue for high, pink for low). For sleep_quality, high values generally push the prediction higher, while low values decrease it. The effect of blood_pressure is more varied, with both high and low values affecting the prediction in mixed directions. Overall, sleep_quality has a more consistent influence, while blood_pressure shows a more distributed impact across different SHAP values.

2.4 Dashboard Features

- Monthly stress level and sleep quality statistics.
- Stress level vs. Productivity insights
- Factors contributing to stress level increase.
- Notification system for students and parents when stress levels are critically high, recommending immediate actions. For example: -
  - Perform a 3 to 5-minute guided deep breathing exercise (e.g., inhale for 4 seconds, hold for 4 seconds, exhale for 6 seconds).
  - A short physical break (stretching, walking, light yoga).
  - Journaling.
- For parents - Dashboard data to guide healthier habits, such as reducing screen time or maintaining a balanced routine.
- For students - Gamified prompts to keep student engaged

3 USE CASES

3.1 Student Use Cases

Here are two case scenarios showing how students can benefit from the stress monitoring system:

3.1.1 Use Case 1: Managing Academic Stress

Scenario: Preparing for Final Exams

- Situation:
  - The dashboard shows increasing stress levels a week before final exams, correlated with reduced sleep hours and irregular meal patterns.
  - Recommendations highlight mindfulness exercises and a balanced schedule.
- Action Taken by the Student:
  - Follows personalized suggestions to practice short mindfulness sessions before study sessions to enhance focus and reduce stress.
  - Adjusts meal timings to include healthy snacks, ensuring sustained energy levels.

3.1.2 Use Case 2: Coping with Social Stress

Scenario: Anxiety Before a Class Presentation

- Situation:
  - The dashboard detects a significant rise in stress levels a day before a scheduled class presentation, based on self-reported inputs.
  - The system offers personalized strategies like breathing exercises and confidence-building techniques.
- Action Taken by the Student:
  - Uses the dashboard’s guided breathing exercises to calm nerves before the presentation.
  - Tracks stress patterns after the presentation to reflect on areas of improvement for future events.

3.2 Parents Use Case

Scenario: Screen Overload

- Situation: Stress and sleep patterns indicate excessive late-night screen time affecting sleep quality.
- Parental Action:
  - Set boundaries on screen use, particularly before bedtime, and introduce device-free zones in the house.
  - Provide alternative activities like reading or meditative apps to wind down.
  - Lead by example by reducing their own screen time.

4 CHALLENGES

- **Topic Evolution**: The project began as a Space Care Monitoring System for astronaut wellness. However, the lack of datasets and the complexity of simulation redirected us to focus on firefighters' wellness. Because of limited data, we pivoted to **Student Wellness Monitoring**, a pressing and accessible issue with relevant datasets.
- **Integration on sensors**: A primary challenge for our project was sensor integration. Conceptually we knew that the ideal dashboard would have access to plenty of real time sensors. However, since we were working with students we had to be reasonable about the tools available to the average student. We considered blood pressure monitors and computer integrated cameras as the most readily available sensors. Affordable sensors like PIR motion detectors built on small dev boards like QTPy can easily be integrated into upgraded versions of our dashboard with minimal cost to the user.

5 TEAM CONTRIBUTION

Delia Castrejon - Delia organized team efforts and facilitated communication among members. In addition, she focused on sensor integration, looking for the most cost-effective and user-available sensors and tools. She worked on the feasibility of adapting real-time sensors to the dashboard and the tools needed to incorporate them. She also started working on hardware elements like building PIR sensors and using CNN and OpenCV to build an emotion detection model.

Riya Bhutada - Riya focused on extensive search of the dataset, literature survey, outlined potential future work to guide subsequent research efforts to further enhance our project's impact. She also organized the presentation and documentation work.

Elizabeth Soto - Elizabeth led the dashboard user interface design, ensuring that the user interface is intuitive and user-friendly. She worked on creating visual representations of the data collected, allowing users to easily access and interpret their health metrics. Additionally, she explored feature selection methods and supervised learning models, with which we trained our dataset with.

6 CONCLUSION AND FUTURE WORK

This project demonstrates the feasibility of using machine learning to monitor and predict student stress levels. The system provides personalized insights via an interactive dashboard, empowering students and parents to take actionable steps to improve well-being. Despite its success, the absence of real-time sensor data and limited dataset diversity highlight opportunities for further enhancement.

Future Considerations:

- **Sensor Integration** - Integrating real time data collection using sensors. Introducing facial expression and posture analysis using cameras, voice sentiment analysis, thermal cameras for self-esteem level, depression, headache.
- **Teacher Dashboard** - Expand dashboard features for teachers to view anonymized aggregated stress data for planning interventions.
- Link **well-being modules (e.g., stress management tutorials) with academic courses in the LMS**.

- **Recommendation system** using AI and database for stress management insights. Personalized suggestions based on the user's stress history (e.g., "You tend to stress more during exams; try this breathing exercise").
- **Gamification**: Introduce badges, challenges, or rewards for **engagement**.
- **Trust-Building Features**: Provide clear explanations for recommendations and predictions.
- **Mobile Application**: Develop a mobile app for increased accessibility.

With this, we conclude that this project has potential scalability for broader educational and institutional use.

7 REFERNCES

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