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Strezzlah: An AI-Powered Stress Classification System for University Students using Machine Learning

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ABSTRACT

University students face increasing mental health challenges, with limited access to professional counseling services. This paper presents Strezzlah, an AI-powered web application that classifies student stress levels using machine learning algorithms. The system utilizes the standardized DASS-21 (Depression, Anxiety, and Stress Scale) questionnaire combined with Random Forest and XGBoost classifiers to provide real-time stress assessment and personalized recommendations. Implemented using Flask framework, the system achieved 87.41% accuracy with weighted F1 score of 87.02%. The platform serves students, counselors, and administrators through role-based interfaces, enabling early intervention and scalable mental health support. Results demonstrate the effectiveness of ML-based approaches for automated stress detection in educational environments.

1. Introduction

Mental health challenges among university students have intensified in recent years, driven by academic pressure, social transitions, financial concerns, and uncertainty about future careers. Despite the growing need for psychological support, traditional counselling services often struggle to meet demand due to limited availability, high costs, and persistent stigma surrounding mental health care [1].

Digital solutions powered by artificial intelligence (AI) and machine learning (ML) offer promising alternatives for scalable and accessible mental health support. These tools enable automated stress detection, personalized feedback, and continuous monitoring, helping bridge the gap between students and professional care [2,3].

To address these challenges, this paper introduces *Strezzlah***,** a web-based counsellor assistance system designed to classify student stress levels using ML algorithms. The system integrates the

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standardized DASS-21 (Depression, Anxiety, and Stress Scale) questionnaire (public domain) [4] with Random Forest and XGBoost classifiers to provide real-time stress assessment and actionable recommendations. *Strezzlah* features role-based interfaces for students, counsellors, and administrators, enabling early intervention and data-driven decision-making. By combining psychological assessment with intelligent automation, *Strezzlah* aims to enhance mental health support in academic environments, offering a proactive, accessible, and scalable solution for student well-being.

2. Related Work

2.1 AI in Mental Health Support

AI has become a transformative tool in mental health care, especially within university settings where demand often exceeds available resources. AI-powered platforms offer scalable, accessible, and personalized interventions that help bridge the gap between students and professional support.

Chatbots like Wysa and Woebot have shown promise in delivering cognitive behavioural therapy (CBT) techniques through conversational interfaces, offering immediate assistance and reducing barriers to care [5,6]. These tools can disseminate mental health information, monitor behavioural patterns, and flag early warning signs using predictive analytics.

Recent studies highlight the potential of AI to personalize treatment plans based on individual characteristics, enabling proactive outreach and tailored interventions [7,8]. However, limitations persist. AI chatbots often lack emotional depth, contextual understanding, and ethical decision-making capabilities. Concerns around data privacy, algorithmic bias, and over-reliance on automation remain critical [9].

Ethical reviews emphasize the need for transparency, accountability, and safeguards—especially in crisis scenarios [10]. Scholars argue that AI tools should complement, not replace, human therapists, particularly when addressing complex psychological conditions [11].

2.2 Machine Learning for Stress Detection

Machine learning has demonstrated strong capabilities in classifying psychological stress, particularly when paired with standardized assessments such as the DASS-21. A variety of ML algorithms, including Support Vector Machines (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost), have been successfully applied to predict mental health conditions with high accuracy.

Ghorpade-Aher *et al*., [12] showed that ensemble methods like AdaBoost combined with SVM achieved up to 96% accuracy on large-scale DASS-21 datasets, underscoring the reliability of ML in psychometric analysis. In a separate study, Quadrini *et al*., [13] proposed a novel approach that encodes physiological signals into image representations for stress classification using convolutional neural networks (CNNs), outperforming traditional ML models on benchmark datasets such as WESAD and NEURO. Xiang *et al*., [14] further advanced this field by integrating time- and frequency-domain features from wearable sensor data into a multi-modal deep learning framework, achieving over 91% accuracy in stress detection.

These models are particularly effective in handling structured and physiological data, offering robustness against noise and overfitting. Random Forest is widely appreciated for its interpretability and feature importance ranking, while XGBoost is recognized for its speed, scalability, and regularization capabilities [15]. The integration of ML into stress detection systems enables real-time classification, early intervention, and personalized recommendations, making it a powerful tool for mental health monitoring in academic environments.

3. Methodology

3.1 System Architecture

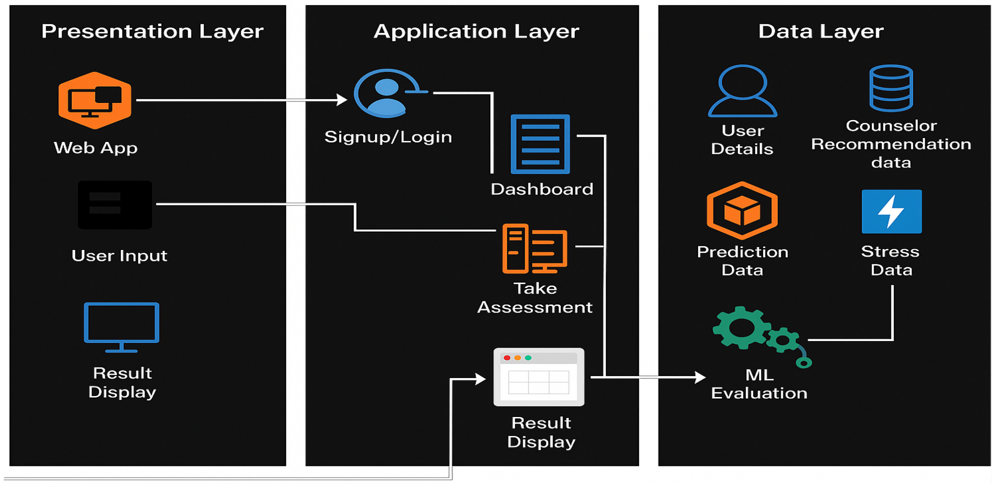

Fig. 1. *Strezzlah* architecture

The *Strezzlah* system is structured into three primary layers, as in Figure 1. It consists of the presentation layer, application layer, and data Layer, where each is responsible for distinct functions that collectively enable stress classification and mental health support.

The presentation layer serves as the user-facing interface, allowing students, counsellors, and administrators to interact with the system. It includes a web application interface, where the user accesses the system via a browser-based platform. Through user input, the students complete the DASS-21 assessment and submit responses. The result could be viewed through the result display. After processing, users receive feedback on their stress levels. It can be seen that this component retrieves results directly from the ML evaluation module in the application layer, ensuring that the displayed output reflects the latest machine learning analysis.

The application layer handles the core logic and processing tasks. The authentication and Navigation component allows users to sign up, log in, and access personalized dashboards. Assessment handling lets the system collect and route DASS-21 responses for analysis. ML Processing will then preprocess the submitted data and pass it through trained machine learning models (Random Forest and XGBoost). ML evaluation module interprets model outputs and generates stress classifications. It pulls necessary data from the prediction data and stress data repositories in the data layer, ensuring accurate and context-aware evaluation.

The data layer manages all stored information required for system operation and analysis. User Data includes profiles, login credentials, and role-based access. Assessment records consist of stored historical DASS-21 responses for each user. Stress data contains labelled datasets used for training and evaluating ML models. Prediction data holds model outputs and intermediate results used during evaluation. Counsellor recommendations will provide standardized advice based on stress levels, which can be displayed to users or flagged for counsellor review.

This layered architecture ensures modularity, scalability, and secure data flow. By separating user interaction from processing and storage, *Strezzlah* maintains performance and reliability while supporting real-time stress classification and personalized mental health support.

3.2 Data Collection and Preprocessing

Multiple datasets were integrated from Kaggle, as in Table 1, including stress-related psychological indicators. The DASS-21 questionnaire provides standardized measurements across depression, anxiety, and stress dimensions. Preprocessing steps include missing value treatment, feature normalization, and label encoding for categorical variables and an 80-20 train-test split.

Table 2
Source of datasets

Dataset	Source
1	https://www.kaggle.com/datasets/jeyasrisenthil/input-data
2	https://www.kaggle.com/datasets/samyakb/student-stress-factors
3	https://www.kaggle.com/datasets/swadeshi/stress-detection-dataset
4	https://www.kaggle.com/datasets/qiriro/ieee-tac
5	https://www.kaggle.com/datasets/laavanya/stress-level-detection

3.3 Machine Learning Models

The *Strezzlah* system incorporates a stress detection model built using two robust machine learning classifiers: Random Forest and XGBoost. The Random Forest algorithm operates by aggregating multiple decision trees, which enhances predictive accuracy and reduces the risk of overfitting. It is particularly effective in handling both categorical and numerical data, making it suitable for diverse survey inputs. XGBoost, on the other hand, is a gradient boosting framework optimized for structured data. It includes built-in regularization and automatic handling of missing values, contributing to its efficiency and high performance.

Both models are trained using labelled data derived from the DASS-21 questionnaire. The training process follows a supervised learning approach, where the models learn to classify stress levels, ranging from normal to extremely severe, based on numerical responses. To ensure optimal performance, cross-validation and hyperparameter tuning are applied during model development. Unlike natural language processing models that rely on textual input, *Strezzlah* exclusively utilizes numerical scores from standardized assessments. These scores are analysed to identify patterns indicative of psychological stress. The methodology ensures interpretable and reliable predictions, which are continuously evaluated and refined through iterative testing.

3.4 System Implementation

The *Strezzlah* system is implemented using the Flask web framework, which provides a lightweight and flexible foundation for building web applications. Flask enables the creation of RESTful API endpoints that facilitate real-time communication between the user interface and the machine learning models. When a user submits responses to the DASS-21 assessment, the system processes the input through trained classifiers: Random Forest and XGBoost, and returns the predicted stress level.

The results are rendered dynamically using HTML templates, ensuring a responsive and user-friendly experience. The system supports role-based access control, allowing differentiated functionality and data visibility for students, counselors, and administrators. Students can complete assessments and view their stress history, counselors can monitor student progress and access detailed evaluations, while administrators manage user accounts and oversee system operations (Figure 2).

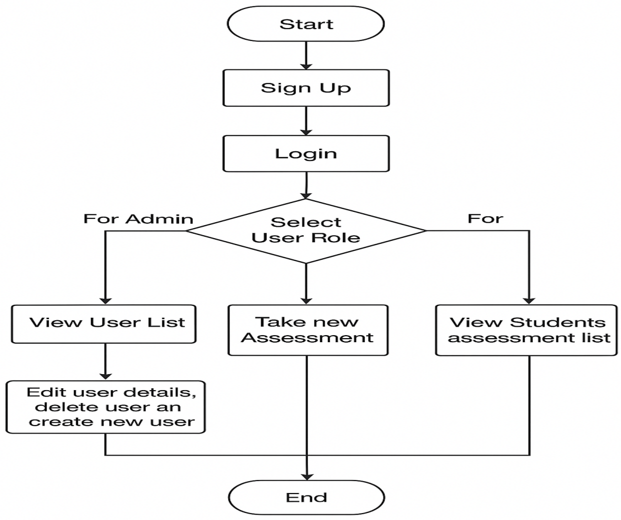

Fig. 2. *Strezzlah* flowchart

This modular implementation ensures scalability, maintainability, and secure data handling, laying the groundwork for future enhancements such as persistent storage, real-time alerts, and expanded analytics capabilities

4. Results
4.1 Model Performance

The trained machine learning models in the Strezzlah system demonstrated strong classification performance in detecting stress levels based on DASS-21 survey data. The Random Forest and XGBoost classifiers achieved an overall accuracy of 87.41% with a weighted F1 score 0f 87.02% and a macro F1 score of 86.40%. These metrics indicate consistent predictive capability across both balanced and imbalanced class distributions. In addition to performance, feature importance analysis was conducted to identify the most influential variables contributing to stress classification. This interpretability is particularly valuable in mental health applications, as it enables counsellors and administrators to understand the underlying factors driving predictions and supports informed decision-making in student support strategies.

4.2 The Strezzlah System

The *Strezzlah* system is a web-based system. In this subsection, we highlight some features in the web-based system. Figure 3 presents an informational page within the system that explains the purpose and structure of the DASS-21 questionnaire. It highlights the three emotional dimensions assessed: depression, anxiety, and stress. It also outlines the benefits of using DASS-21 for students, such as early detection. Figure 4 shows the actual interface where students respond to the DASS-21 questionnaire. It includes a Likert scale for each question, allowing users to rate how much each statement applied to them. Figure 5 displays a sample of students' historical assessment results, including stress severity levels and AI-generated recommendations. It shows users how to track their mental health over time and receive tailored advice.

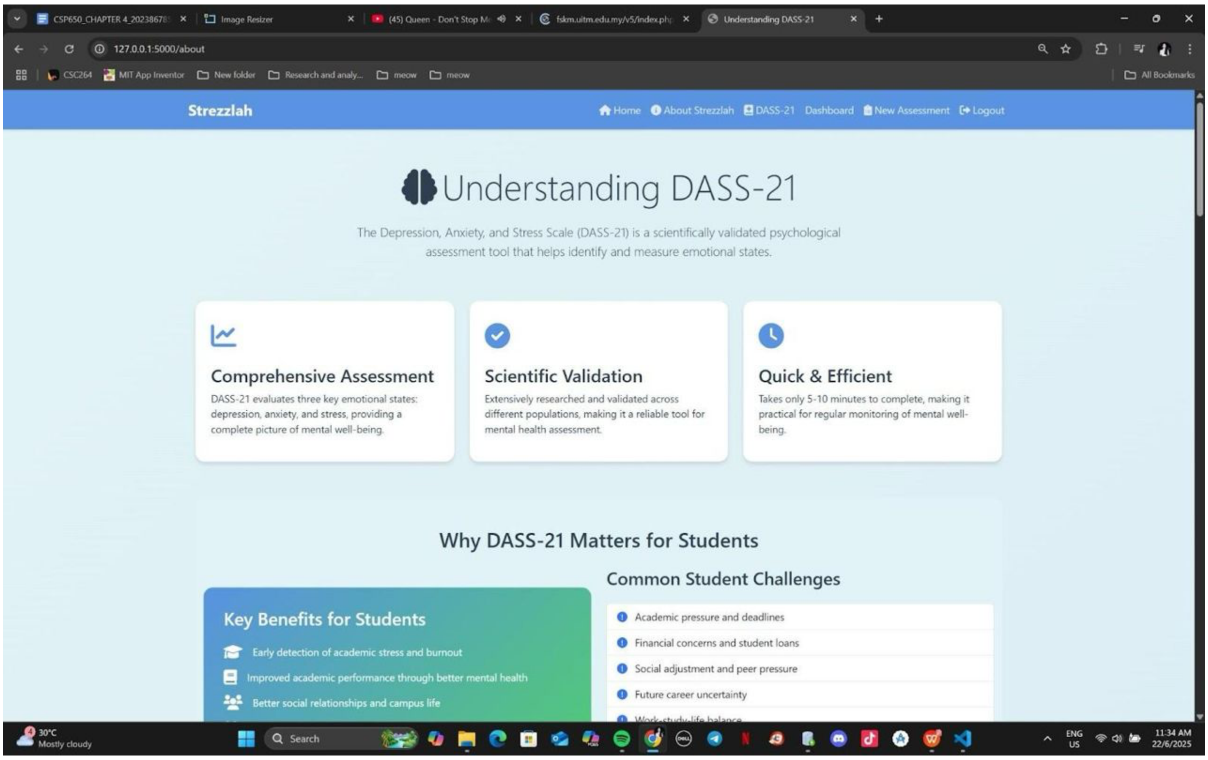

Fig. 3. About DASS-21

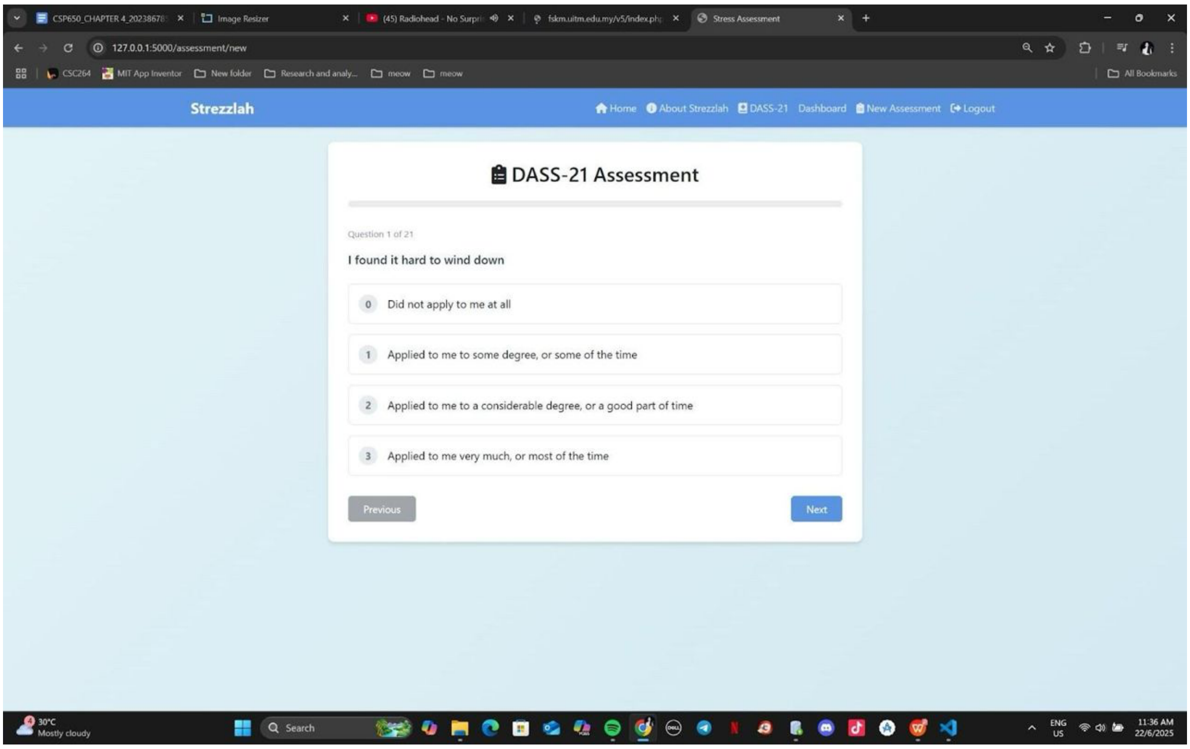

Fig. 4. The student view on the DASS-21 questions

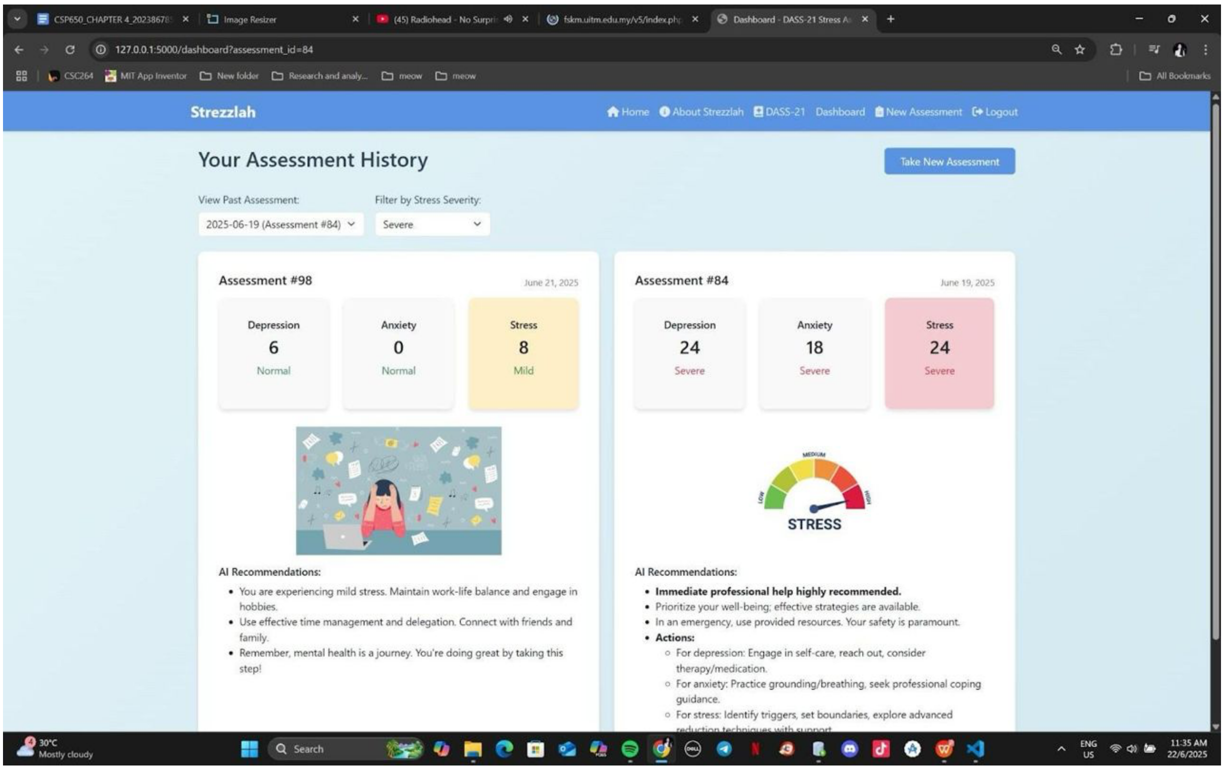

Fig. 5. The assessment history

5. Discussion

The *Strezzlah* system offers several advantages over traditional mental health support approaches. Its 24/7 accessibility ensures that students can engage with the platform at any time, regardless of location, removing geographical and scheduling barriers. The system's scalability allows it to serve a large number of users simultaneously, significantly reducing the workload on counsellors by automating routine assessments and feedback. By utilizing standardized tools such as the DASS-21 questionnaire, *Strezzlah* promotes objectivity in stress evaluation, minimizing the influence of subjective bias. Furthermore, the system supports early detection of psychological distress by proactively identifying students at risk, enabling timely intervention and support.

One notable limitation of the current system is the absence of real-time notification capabilities. In its present form, *Strezzlah* does not automatically alert counsellors or administrators when a user exhibits high or critical stress levels. This gap reduces the system's responsiveness in urgent scenarios, where immediate intervention could be crucial. Implementing real-time alerts, such as email or in-app notifications, would significantly enhance the system's ability to support timely mental health interventions and improve overall safety for at-risk students.

6. Conclusion

The *Strezzlah* demonstrates the potential of AI-powered systems for mental health support in educational environments. By combining standardized psychological assessment with machine learning classification, the system provides accessible, objective stress evaluation while supporting human counsellors with data-driven insights. The 87.41% accuracy achieved validates the effectiveness of ensemble methods for mental health classification tasks. While limitations exist, particularly regarding data persistence and generalizability, the system establishes a foundation for scalable mental health intervention in university settings. Future iterations incorporating persistent storage, enhanced user interfaces, and expanded datasets could transform *Strezzlah* into a comprehensive mental health support platform, bridging the gap between technological innovation and human-centred care.

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