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Work-In-Progress: Optimizing Student Mental Health Support through Biomarker-Driven Machine Learning and Large Language Models

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AI/DRL in low Reynolds number hydrodynamics, Stress Management and Well-being

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Abstract

Mental health challenges among students, particularly within graduate programs, have become a pressing concern for higher education institutions. To address this, a hybrid framework has been developed, integrating wearable technology, physiological biomarkers, and advanced Machine Learning (ML) techniques to monitor and enhance students' stress management and overall quality of life. This framework leverages wearable devices to collect critical physiological data, including electrodermal activity (EDA), metabolic equivalent (MET), pulse rate, respiratory rate, actigraphy counts, and temperature. The above biomarkers are crucial markers to assess stress and mental health states. ML algorithms employed to analyze data can offer precise assessments and predictive insights into students' well-being. In parallel, Large Language Models (LLMs) are incorporated to analyze self-reported data from students, including responses to structured prompts and/or questionnaires. This allows the system to interpret subjective input with greater accuracy while subsequently generating personalized mental health support recommendations. The integration of LLMs with biomarker data can significantly enhance the framework's adaptability and objectivity, thus enabling it to more effectively address students' individual needs. By combining these technologies, the framework can facilitate healthier academic environments using data-driven interventions. This study demonstrates the model's ability to predict stress by highlighting the important role of biomarkers in developing and enhancing mental health interventions. Additionally, the paper discusses the implications of implementing AI-driven solutions in educational settings, offering a strategic perspective on how emerging technologies can be applied to improve mental health support systems within academic settings.

Introduction

Mental health has become a critical issue in academic institutions, particularly within graduate programs where students also working professionals face high levels of stress and pressure. Reports indicate a significant increase in stress-related conditions among graduate students, which negatively impacts their academic performance and quality of life [1]. While traditional mental health interventions have shown effectiveness, they often lack the scalability and personalization needed to address the diverse challenges faced by students [2, 3, 4].

This study introduces a hybrid framework that integrates wearable technology, physiological biomarkers, and artificial intelligence to address these challenges [5]. By combining data collected from wearable devices with insights derived from subjective input, i.e., participants' self-reported prompts [6], the framework seeks to enhance mental health support systems in higher education [7]. The objective is to provide a comprehensive and personalized approach to identifying and mitigating stress among graduate students.

Methods

The framework operates by using wearable technology to gather physiological data, such as electrodermal activity, metabolic equivalent, pulse rate, respiratory rate, actigraphy counts, and temperature. These specific biomarkers are chosen for their well-documented relationship with stress and mental health. For example:

- Electrodermal Activity (EDA) is widely recognized as an indicator of emotional arousal and stress response [8, 9].
- Heart rate variability and respiratory rates have been consistently linked to physiological stress and relaxation states [10, 11].
- Actigraphy counts and temperature changes have been used in sleep and stress studies [12, 13].

Data is collected in real time and stored securely for subsequent analysis. Analytical methods are employed to identify patterns and predict stress levels, using approaches like supervised learning to categorize stress states and unsupervised learning to reveal hidden trends. Time-series analysis further allows the system to track changes over time and detect anomalies.

In addition to physiological data, the framework incorporates self-reported information from students, which is analyzed through large language models. These models process responses to structured prompts or mental health questionnaires to better understand students' subjective experiences. They also perform sentiment analysis to interpret emotional states and generate personalized recommendations for mental health support. By combining these two sources of data, the framework offers a comprehensive view of students' mental health, facilitating proactive and tailored interventions.

To ensure anonymity, all collected data is de-identified before analysis. Students' responses and physiological readings are aggregated to produce class-level insights without revealing individual details. Instructors receive only general reports on the collective stress levels and patterns, enabling them to adapt their teaching strategies without compromising student privacy.

Preliminary Results

Initial experiments with 28 graduate students during the spring semester and 30 during the fall semester demonstrate the framework's effectiveness in predicting stress levels. Preliminary analysis highlights the relative importance of various physiological biomarkers for predicting stress levels [14]. Fig. 1 illustrates the feature importance rankings for targeted data

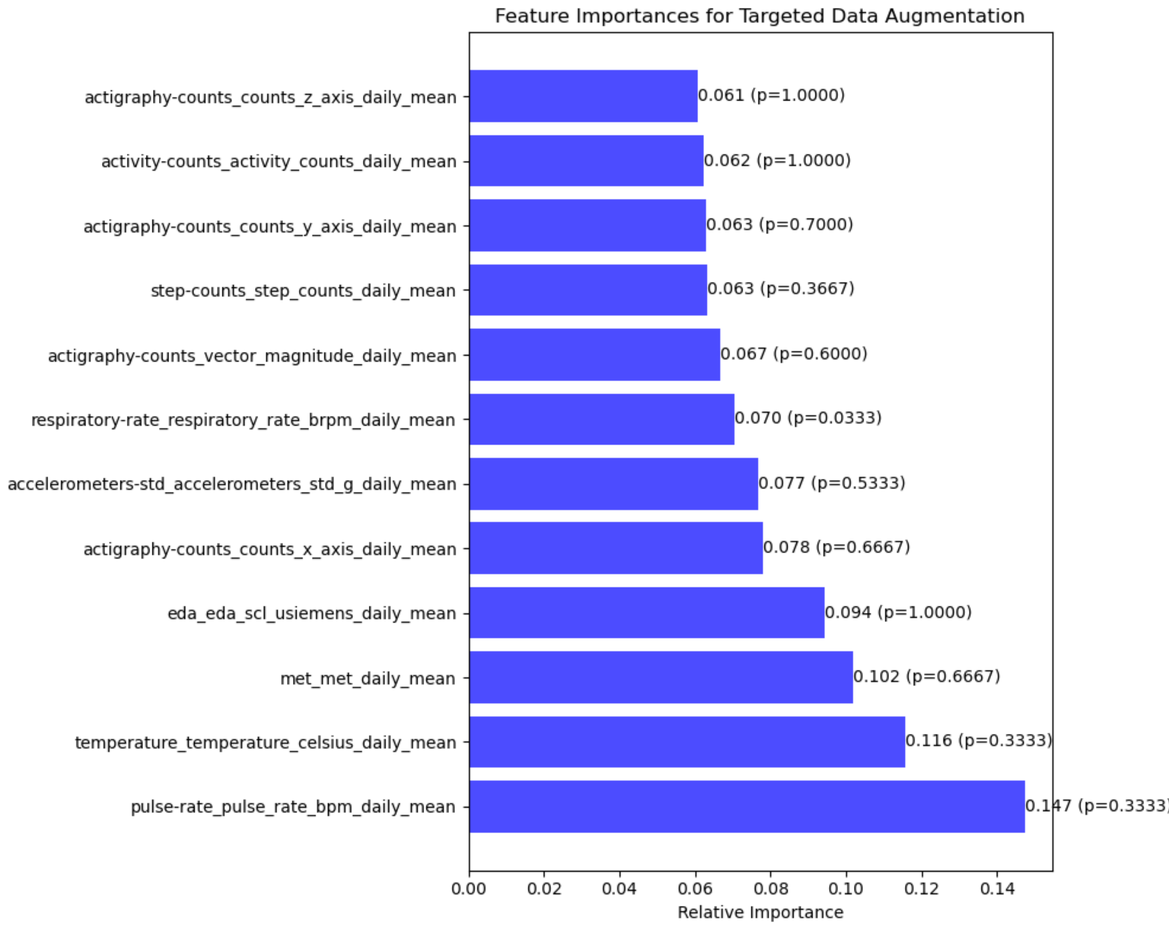

Figure 1: Feature importance rankings for targeted data augmentation. The figure highlights the relative contributions of various physiological biomarkers to stress prediction.

augmentation, with pulse rate, temperature, and metabolic equivalent emerging as the most significant contributors. These findings emphasize the role of multi-dimensional data in understanding stress dynamics.

In addition, model performance for stress prediction is shown in Fig. 2. This comparison evaluates multiple algorithms based on ROC-AUC and accuracy scores, demonstrating that the Random Forest model with selected features achieves the highest performance. These findings provide insights into the framework's potential for accurately predicting stress levels.

Discussion

This study highlights the transformative potential of integrating wearable technology and artificial intelligence to tackle mental health challenges in academic settings. By combining objective physiological data with subjective self-reports, the proposed hybrid system is designed to be both scalable and personalized to individual needs. The incorporation of anonymity protocols ensures that personal data is protected, fostering trust among participants. However, challenges such as

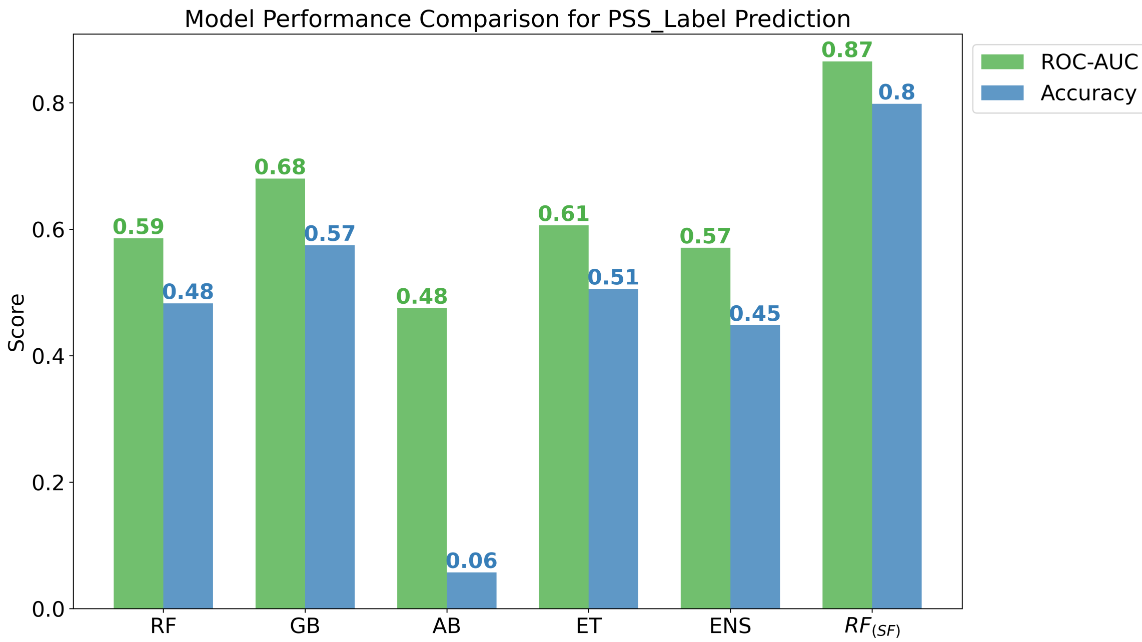

Figure 2: Model performance comparison for Perceived Stress Scale (PSS) label prediction. The chart compares ROC-AUC and accuracy scores across various machine learning models.

ensuring widespread adoption and addressing ethical considerations remain.

The framework provides a forward-thinking approach for academic institutions seeking to implement modern mental health support systems. It offers actionable, data-driven insights that can inform institutional policies and identify students who may be vulnerable to mental health challenges. Moreover, the system's ability to generate personalized recommendations empowers students to take proactive measures to manage stress, fostering academic environments that are healthier and more supportive for all.

Future Work

This paper introduces an innovative framework that combines wearable technology, physiological biomarkers, and artificial intelligence to enhance mental health support for graduate students. Future efforts will prioritize expanding the scope of the dataset, refining the analytical models, and exploring ways to further improve data security and user engagement. By utilizing advanced technologies, this framework has the potential to transform mental health interventions in higher education, promoting environments that are more inclusive and supportive of student well-being.

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