International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 08 | Aug - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Refinement of Bio-signal Data from Wearables for Stress Recognition Using Machine Learning and Transparent Artificial Intelligence

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ABSTRACT

This study explores the use of wearable devices for real-time detection of stress and evaluates the impact of meditation audio in alleviating stress following academic activities. It involves the collection of physiological signals specifically Heart Rate Variability (HRV) derived from Interbeat Intervals (IBI), Blood Volume Pulse (BVP), and Electrodermal Activity (EDA) during the Montreal Imaging Stress Task (MIST). To enhance the accuracy of stress classification, the study integrates a Genetic Algorithm with Mutual Information for efficient feature selection by minimizing redundancy. Additionally, Bayesian optimization is employed for fine-tuning the hyperparameters of machine learning models. Experimental results show that combining EDA, BVP, and HRV yields peak classification accuracies of 98.28% for two-level and 97.02% for three-level stress detection using the Gradient Boosting (GB) algorithm. When using only EDA and HRV, the system still performs well, achieving 97.07% and 95.23% accuracy for two- and three-level classifications, respectively. SHAP-based Explainable AI (XAI) analysis further confirms that HRV and EDA are the most influential features in determining stress levels. The study also demonstrates that meditation audio has a measurable calming effect, supporting its potential for stress management. These findings underscore the promise of integrating wearable technologies with machine learning for effective stress monitoring and intervention in academic settings.

Keywords: Wearable devices, Real-time stress detection, Heart Rate Variability (HRV), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Montreal Imaging Stress Task (MIST), Genetic Algorithm, Mutual Information, Feature selection, Bayesian optimization, Machine learning, Gradient Boosting, Stress classification, SHAP, Explainable AI (XAI).

I. INTRODUCTION

In today's fast-paced academic and professional environments, stress has become an increasingly prevalent health concern. Prolonged exposure to stress can lead to a range of physical and psychological issues, including cardiovascular problems, anxiety, and impaired cognitive performance. Early and accurate detection of stress is therefore essential to ensure timely intervention and management. Traditional stress detection techniques often rely on subjective measures like questionnaires or involve complex and obtrusive biomedical instruments such as EEG or EMG, which are not ideal for real-world applications.

With advancements in wearable sensor technologies, it is now feasible to continuously monitor physiological signals such as Heart Rate Variability (HRV), Electrodermal Activity (EDA), and Blood Volume Pulse (BVP) in a non-invasive manner. These biosignals offer valuable insights into the body's stress response mechanisms. The use of wearable biosensors opens new opportunities for real-time stress monitoring, especially in environments like schools and universities where students frequently experience elevated stress levels.

This study explores the effectiveness of using physiological data collected from wearable devices during a stress-inducing task, the Montreal Imaging Stress Task (MIST), to classify stress levels in individuals. It further evaluates the impact of listening to meditation audio as a method for stress alleviation. The research integrates a hybrid feature selection approach using Genetic Algorithm and Mutual Information (GA+MI) to enhance classification accuracy by removing redundant features. Additionally, machine learning models are optimized using Bayesian hyperparameter tuning techniques to improve performance.

To enhance interpretability and trust in AI systems, the study employs SHAP (SHapley Additive exPlanations), an Explainable AI (XAI) method, to identify the most influential features contributing to stress classification. The results of this research underline the potential of combining wearable technology with advanced machine learning techniques to build accurate, explainable, and user-friendly stress detection systems. Ultimately, this contributes to promoting mental wellness and stress management strategies among students through data-driven solutions.

II. RELATED WORK

Stress detection using physiological signals has become a critical area of research, particularly with the rise of wearable technology that allows for real-time, continuous, and non-invasive monitoring. A significant amount of work has been conducted using various biosignals such as EEG, ECG, EMG, Galvanic Skin Response (GSR), and Electrodermal Activity (EDA). These studies have generally employed tasks like the Montreal Imaging Stress Task (MIST) to induce controlled stress in participants and analyze physiological responses.

Minguillon et al. proposed a portable multimodal stress detection system utilizing EEG, ECG, EMG, and GSR. Although EEG alone achieved only 50% accuracy due to its sensitivity to noise and artifacts, integrating multiple physiological signals improved classification accuracy to 86%. This demonstrated the strength of multimodal signal fusion, though it also emphasized the practical challenges of EEG-based systems, such as user discomfort and lack of portability. Setz et al.focused specifically on EDA and tested six classification algorithms, including various kernels of Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). Their results showed that EDA alone could distinguish between cognitive load and stress with an accuracy exceeding 80%, using leave-one- subject-out cross-validation. The study underscored the reliability of EDA as a robust biomarker for stress-related detection.

Zhu et al. extended this line of research by exploring EDA-based stress classification using the SVM classifier, achieving an accuracy of 92.9%. Similarly, Hsieh et al.proposed a novel feature selection strategy based on EDA signals. They demonstrated that EDA features held significant discriminative power and achieved a classification accuracy of 92.38%, reaffirming EDA's role in stress detection.

Han et al. introduced an approach combining ECG and respiratory (RESP) data for stress classification and obtained a high accuracy of 96% using a Random Forest classifier. However, they noted limitations in the reliability of RESP as a stress indicator due to its susceptibility to external factors such as physical exertion, posture changes, and environmental noise. As a result, alternative physiological features like Heart Rate Variability (HRV) and Blood Volume Pulse (BVP) derived from Interbeat Interval (IBI) data have gained attention for their potential in real-time applications.

Despite these advances, most existing studies fall short in several key areas:

They do not implement advanced feature selection techniques like Genetic Algorithms (GA) combined with Mutual Information (MI), which can significantly improve model performance by eliminating redundant or irrelevant features.

Many do not utilize Bayesian Optimization, a powerful tool for hyperparameter tuning that can optimize model configurations more efficiently than grid or random search methods. There is a notable lack of focus on Explainable Artificial Intelligence (XAI). Few existing works address the interpretability of machine learning models, which is crucial for transparency and trust, especially in health- related applications.

In contrast, the current study integrates wearable biosensor data (EDA, HRV, and BVP) with a robust machine learning pipeline that includes GA+MI-based feature selection, Bayesian hyperparameter optimization, and SHAP (SHapley Additive exPlanations) for explainable predictions. Moreover, this study uniquely examines the impact of meditation audio on stress levels post-exposure to MIST, providing insights into potential real-time stress reduction techniques.

Thus, while previous studies have laid the groundwork for physiological stress classification, the proposed work builds upon them by addressing their limitations and advancing the field with an interpretable, optimized, and user-friendly solution tailored for real-world academic environments.

III. METHODOLOGY

The methodology adopted in this research focuses on creating a robust and interpretable stress classification system using physiological data collected from wearable biosensors. The process involves multiple phases, including data collection from participants during stress- inducing and relaxation tasks, preprocessing the raw biosignals to remove noise, extracting relevant features, designing a user-friendly interface for real-time interaction, and finally integrating and testing the complete pipeline.

Data Collection:

Physiological data was collected from college students using wearable sensors capable of capturing Electrodermal Activity (EDA), Interbeat

Interval (IBI)-derived Heart Rate Variability (HRV), and Blood Volume Pulse (BVP). The Montreal Imaging Stress Task (MIST) was employed to simulate a controlled academic stress environment. After the stress phase, participants listened to meditation audio, and the physiological response was recorded again. This dual-phase setup allowed analysis of both stress induction and relaxation.

Preprocessing:

The raw biosignal data often contains noise due to movement artifacts and sensor inconsistencies. Therefore, preprocessing steps such as signal smoothing, filtering, and normalization were applied to clean the data. IBI was derived from raw pulse data to calculate HRV. Missing values were handled through interpolation techniques, and the signals were segmented appropriately for feature extraction. This ensured that only high- quality, noise-free input was passed to the machine learning models.

Information Retrieval:

Once the signals were preprocessed, relevant features were extracted from EDA, HRV, and BVP data. These features were evaluated using a hybrid approach that combined Genetic Algorithm (GA) and Mutual Information (MI) to identify the most informative attributes. The selected features were then stored and retrieved in a structured format for use in training and validating the machine learning models. This phase ensured efficient data flow and storage between components of the system.

User Interface Design:

A minimal and interactive web-based user interface was developed using HTML, CSS, and JavaScript, integrated into a Django- powered Python backend. The interface allows users to upload or monitor real-time biosensor data, visualize stress levels dynamically, and track stress reduction after interventions like meditation. Emphasis was placed on usability, clarity, and responsiveness to facilitate ease of use by students or clinicians.

Integration and Testing:

All system modules — including data acquisition, preprocessing, machine learning inference, and visual output — were integrated into a unified platform. The system was deployed using Django-ORM and MySQL, tested using real participant data, and evaluated through ten-fold cross-validation. Functional, performance, and usability testing ensured robustness, accuracy, and scalability of the solution in real-world academic environments.

3.1 Dataset used

The dataset was generated from experimental sessions conducted with college students, using Empatica E4 wristbands to collect EDA, BVP, and IBI signals during stress (MIST) and relaxation (meditation audio) phases. The sessions were structured to simulate academic stress scenarios. The collected data was labeled according to different stress levels—baseline, stress, and post-meditation—and segmented accordingly for binary (2-level) and multi- class (3-level) classification tasks. The dataset is unique due to its dual-phase structure and real-time nature.

3.2 Data preprocessing

Preprocessing involved cleaning the raw biosensor data through bandpass filtering to eliminate motion artifacts and electrical noise. HRV was computed from IBI intervals, while EDA signals were de-trended and normalized. Each signal was segmented into windows to align with experimental phases. Statistical, temporal, and frequency-domain features were extracted. This clean and well-structured data ensured better model generalization and robustness across varying stress conditions.

3.3 Algorithm used

In this study, multiple machine learning algorithms are used to classify stress levels based on physiological signals collected from wearable devices. One of the advanced models applied is the Graph Neural Network (GNN), which is well-suited for capturing relationships between features such as Electrodermal Activity (EDA), Heart Rate Variability (HRV), and Blood Volume Pulse (BVP). GNN treats each feature as a node in a graph and models their interconnections as edges, allowing the system to understand how various biosignals influence one another during stress conditions. This graph-based approach enables the model to extract deeper patterns in the data, leading to more accurate stress classification. Logistic Regression is also employed as a baseline model in this research. Though simple, it is effective in binary and multi-class classification tasks, especially when feature relationships are mostly linear. It offers high interpretability, allowing researchers to understand how specific physiological parameters contribute to stress prediction. Its efficiency and ease of implementation make it a valuable benchmark against which more complex models are evaluated. Another key algorithm used is the Support Vector Machine (SVM), which is effective in handling high- dimensional data like biosignals. SVM constructs an optimal hyperplane that separates different stress levels with maximum margin. It is especially useful when there are subtle but important differences between classes. By using different kernel functions, SVM can manage both linear and non-linear data distributions, making it a versatile tool in stress detection tasks. The most accurate results in this project were achieved using Gradient Boosting (GB). This ensemble method builds models in stages, with each new model correcting the errors of the previous one. It performed exceptionally well, achieving up to 98.28% accuracy for binary classification and 97.02% for three-class classification. The model's performance was further improved through Bayesian hyperparameter optimization. Gradient Boosting's ability to handle complex patterns in the data and its compatibility with feature interpretation methods like SHAP made it the most effective model in this study. Collectively, these algorithms offer a balanced approach, combining simplicity, interpretability, and high performance to support real-time stress detection and management using wearable technologies.

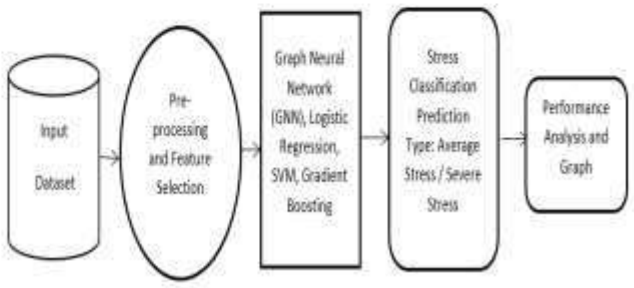

Figure 3.3.1 : System Architecture

3.4 Techniques

A hybrid feature selection technique combining Genetic Algorithm (GA) and Mutual Information (MI) was employed to reduce dimensionality and enhance the relevance of selected features. Bayesian optimization was applied for fine-tuning model parameters. To ensure interpretability, SHAP (SHapley Additive exPlanations) values were calculated, highlighting the contribution of each feature toward the final decision. This use of Explainable AI (XAI) ensures transparency and trust in the system's predictions.

3.5 Flowchart

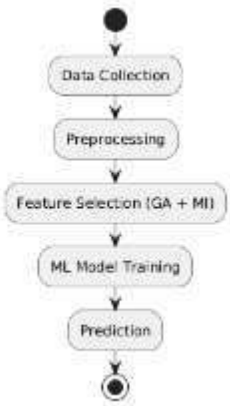

Figure 3.5.1: Flowchart

IV. RESULTS

4.1 Graphs

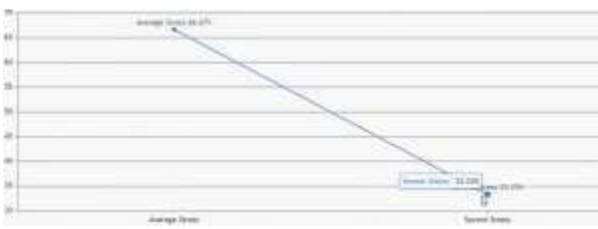

Figure 4.1.1 : Line chart of stress

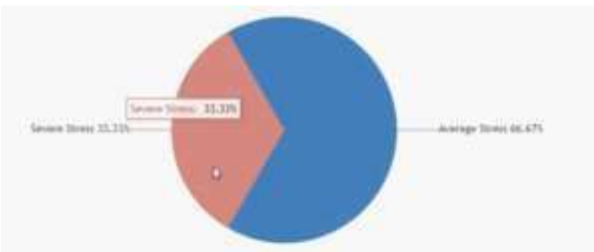

Figure 4.1.3: Pie chart of stress

The Gradient Boosting model achieved the highest accuracy of 98.28% for binary stress classification and 97.02% for three-class classification. Models using only EDA and HRV also performed well, reaching 97.07% and 95.23% respectively. SHAP analysis confirmed that HRV and EDA are the most influential features in stress detection.

CONCLUSION

This research presents an effective and interpretable framework for real-time stress classification using physiological data collected from wearable biosensors. By integrating EDA, HRV, and BVP signals with advanced machine learning techniques, the system achieves high classification accuracy while maintaining transparency through Explainable AI (SHAP). The hybrid feature selection approach using Genetic Algorithm and Mutual Information significantly enhances model performance by eliminating redundant features, while Bayesian optimization ensures fine-tuned hyperparameters for each classifier. The findings confirm that EDA and HRV are the most influential signals for stress detection, and Gradient Boosting outperforms other models in both binary and multi-class classification scenarios. Moreover, the study demonstrates that listening to meditation audio effectively reduces physiological stress responses, reinforcing its value as a simple intervention in academic settings.Overall, this work underscores the potential of combining wearable technologies with intelligent, explainable machine learning systems to monitor, detect, and manage stress in real-world environments. Future work can focus on expanding the dataset, integrating additional biometric signals, and deploying the system for continuous use in educational or workplace scenarios.

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