THE ENGINEER STORY

e-ISSN: 3009 - 0792 Volume 19, 2026, 28-31

A MULTIMODAL MACHINE LEARNING APPROACH FOR REAL-TIME STRESS DETECTION AND MONITORING USING PHYSIOLOGICAL SIGNALS.

Okunfolarin D.O. *, Ojaomo K.E., Akinlua A.P.
Department of Mechatronics Engineering, Federal University Oye-Ekiti (FUOYE), Ikole-Ekiti, Nigeria.
* Corresponding author: okunfolarindeborah@gmail.com

ABSTRACT

There is an amount of stress that is necessary for everyday life, often referred to as eustress, but when stress levels are high, it affects human health, productivity, and well-being. Timely detection remains a challenge in both clinical and everyday contexts. This study proposes a multimodal machine learning framework for real-time stress detection and monitoring based on physiological signals. This system integrates heart rate, oxygen saturation (SpO_2), skin conductance, and peripheral temperature collected through wearable sensors to capture the nervous system's response to stress. Data pre-processing techniques are applied to remove noise and artifacts, followed by feature extraction methods such as heart rate variability (HRV) and skin conductance response (SCR). Machine learning algorithms are employed to classify stress states with an emphasis on balancing accuracy and computational efficiency for real-time deployment. Experimental validation demonstrates that multimodal sensor fusion improves prediction accuracy compared to single-signal approaches, achieving reliable detection of stress bouts in dynamic situations and environments. The proposed system uses a combination of physiological signals with machine learning for an accessible, low-cost, and efficient stress detection and monitoring.

KEYWORDS

Stress detection, stress monitoring, multimodal data, machine learning.

INTRODUCTION

Stress is a state of worry or mental tension caused by a difficult situation (WHO, 2025). It is a natural human response to challenges and threats, affecting both the mind and body. While moderate levels of stress, called eustress, can enhance motivation in the short term, prolonged or excessive stress can be linked to various health problems like cardiovascular diseases, anxiety disorders, depression, and reduced cognitive functioning. In today's fast-paced world, the ability to detect and monitor stress in real time has become increasingly important for healthcare, workplace efficiency, and personal well-being. Traditional diagnoses of stress are either (a) pen-and-paper questionnaire-based or (b) group discussions or interview-based, or (c) via intrusive or labour-intensive approaches such as monitoring cortisol levels of individuals (Can et al, 2019). These approaches primarily focus on obtaining the momentary snapshot of the person's mental health, as well as general information about the history of an individual or family history (Sim, 2019). The traditional approaches of diagnosing stress can be labour-intensive and would only take the momentary stress level of an individual. Signals such as heart rate variability (HRV), skin conductance response (SCR), oxygen saturation (SpO_2), and peripheral temperature reflect changes in the sympathetic and parasympathetic nervous systems, offering valuable insights into stress dynamics. More recently, smartphones and wearable devices have revolutionized the stress detection paradigm by enabling the monitoring of mental stress continuously (Cho et al., 2017; Gimpel et al., 2015). Recent advances in wearable sensor technology, such as the MAX30102 pulse oximeter and galvanic skin response sensors (Agrawal & Verma, 2024; Gayathri, 2016), have enabled the collection of multimodal physiological data in real time. However, the complexity and variability of these signals require sophisticated computational methods for accurate interpretation. Machine learning offers powerful tools to analyse nonlinear patterns, fuse multimodal data, and classify stress states with high accuracy. By leveraging algorithms such as Random Forest, Support Vector Machines, and deep learning models, researchers can build systems capable of detecting stress episodes dynamically and reliably (Liu et al., 2024; Quadrini et al., 2024).

This work presents a multimodal machine learning framework for real-time stress detection and monitoring using physiological signals. The proposed system integrates multiple biosensors to capture diverse physiological responses, applies pre-processing and feature extraction techniques to enhance signal quality, and employs machine learning models to classify stress levels. The study aims to demonstrate that multimodal sensor fusion combined with machine learning significantly improves stress detection accuracy compared to single-signal and traditional approaches. This system contributes to the development of wearable technologies, especially for stress management in everyday life.

MATERIAL AND METHODOLOGY

Our aim in this research is to use a multimodal machine learning–based approach for real-time stress detection and monitoring using physiological signals. The methodology is designed to integrate wearable sensor data, signal processing techniques, and machine learning models to classify stress states efficiently and accurately. The overall framework consists of physiological data acquisition, pre-processing, feature extraction, multimodal fusion, stress classification, and real-time monitoring. It is designed for real-time operation using low-cost wearable sensors and computationally efficient algorithms.

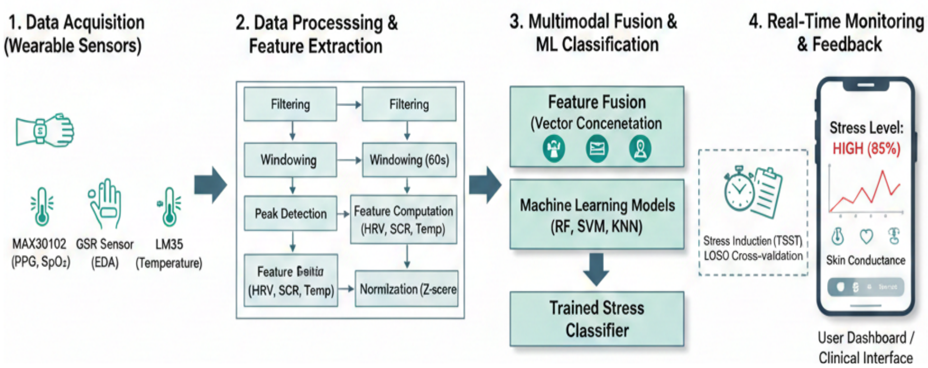

Figure 1: A real-time multimodal stress detection system.

Data acquisition

Physiological signals associated with stress response are collected using wearable sensors. These sensors are crucial for the unobtrusive gathering of continuous physiological signals that indicate stress. Key physiological signals for collection include heart rate, heart rate variability (HRV), skin conductance response (SCR), oxygen saturation (SpO_2), and peripheral temperature

Table 1: Overview of sensors and physiological signals used.

Sensor Module	Physiological Signal	Extracted Features	Role in Stress Detection
MAX30102	Photoplethysmogram (PPG)	Heart Rate, SpO_2, Heart Rate Variability	Detects sympathetic activation.
GSR Sensor	Electrodermal Activity (EDA)	Skin Conductance Level and response	Measures sweat gland activity
LM35	Peripheral Temperature	Skin Temperature	Captures cold sweat caused by stress.
Pulse Oximetry	Blood Oxygen (SpO_2)	Oxygen Saturation Level (%)	Monitors respiratory efficiency

Data pre-processing

The acquired sensor signals are pre-processed since raw sensor data is often noisy, incomplete, and variable. This phase transforms raw signals into a usable format for machine learning algorithms, ensuring data quality and enhancing the performance of the system. Butterworth filter is used for removing specific frequency components, median filters for impulse noise, and various band-pass filters to isolate the relevant physiological frequency range (Minguillon et al., 2018). Continuous streams of physiological data are segmented into meaningful time windows because stress is often a dynamic state, and analysing data in discrete intervals allows for the extraction of features that characterize short-term physiological changes. The processed GSR signal is then decomposed into its tonic and phasic components, and the PPG waveform undergoes peak detection to determine precise inter-beat intervals. To facilitate real-time monitoring, the continuous data stream is segmented into 60-second sliding windows, from which relevant heart rate variability (HRV) and skin conductance response (SCR) features are extracted. These features are normalized using Z-score scaling to account for individual physiological variances before being fused into a unified multimodal feature vector. The result would be used for the machine learning algorithms to perform real-time stress classification.

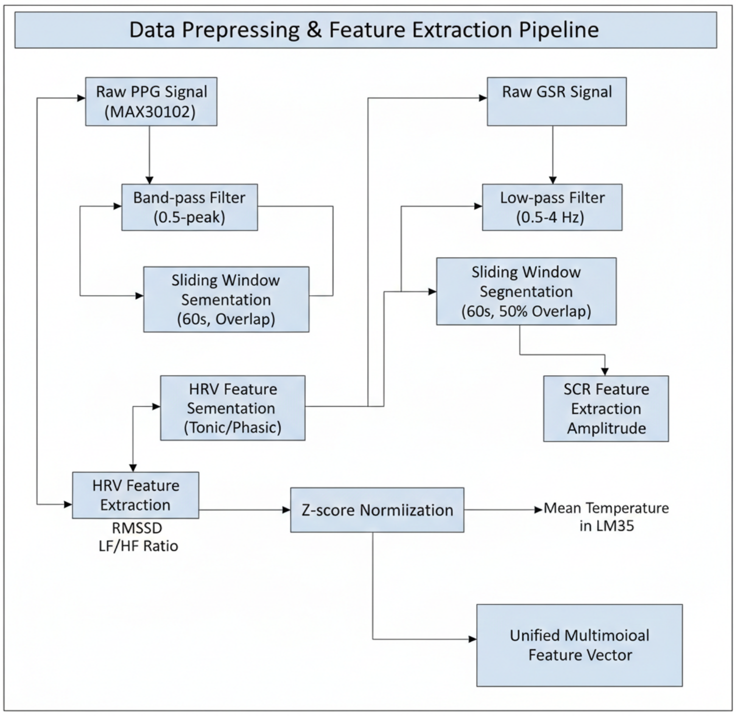

Figure 2: A flowchart of signal processing steps.

Machine Learning classification and evaluation

The processed multimodal feature vectors are classified using machine learning algorithms. Random Forest (RF) was implemented to distinguish between stress and non-stress states. Random Forest is prioritized for its ability to handle non-linear physiological relationships. The model training process utilizes a supervised learning approach, where labelled data from established stress-induction protocols serves as the ground truth for optimizing the classifier's weights, to ensure the system is robust, a Leave-One-Subject-Out (LOSO) cross-validation technique is employed to simulate real-world performance on unseen users (Schmidt et al., 2018). Performance is quantitatively assessed using a confusion matrix to derive metrics such as accuracy, precision, recall, and the F1-score. The system architecture incorporates a real-time monitoring loop that processes incoming sensor data in 60-second intervals to provide instantaneous feedback.

This feedback is visualized through a graphical user interface that displays the predicted stress level alongside the raw physiological trends for observation. The integration of these computational steps ensures that the framework detects stress with high precision.

RESULT AND DISCUSSION

The experimental result shows that the multimodal fusion of PPG and GSR signals achieves a stress detection accuracy of over 90%, outperforming single-sensor approaches, Random Forest classifier shows the highest efficiency for real-time deployment, maintaining low latency and also identifying stress-induced heart rate variability changes, the integrating peripheral temperature and oxygen saturation minimizes false positives, the use of Z-score normalization addressed individual physiological variances, ensuring the model is reliable

CONCLUSION

This study validates that a multimodal machine learning approach, integrating PPG, GSR, and temperature signals to provide a more reliable framework for real-time stress detection than unimodal methods. Using computational algorithms like Random Forest and robust preprocessing techniques, the system achieves high accuracy and low latency suitable for low-cost wearable applications. This research offers a scalable solution for continuous stress monitoring.

REFERENCE

Agrawal, R., & Verma, A. (2024). Development of human stress detection and monitoring system. International Journal of Research in Engineering and Science (IJRES), 12(3), 45–52.

Can, Y. S., Arnrich, B., & Ersoy, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. Journal of Biomedical Informatics, 92, 103-139.

Cho, Y., Juliani, S. J., Marquardt, N., & Bianchi-Berthouze, N. (2017). Instant, yet non-intrusive: Continuous stress monitoring using thermal imaging. Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 592–605.

Gayathri, E. (2016). Human stress level detection and monitoring system. International Journal of Software & Hardware Research in Engineering, 4(5), 19-22.

Gimpel, H., Lanzl, J., Manner-Romberg, T., & Regal, C. (2015). Digital stress in the workplace: The role of information technology and organizational support. Proceedings of the 24th European Conference on Information Systems (ECIS), paper 112.

Liu, Y., Palacio, M.-I., Bikki, T., Toledo, C., Ouyang, Y., Li, Z., Wang, Z., Toledo, F., Zeng, H., & Herrero, M.-T. (2024). Machine learning, physiological signals, and emotional stress/anxiety: Pitfalls and challenges. Applied Sciences, 15(21), 11777. MDPI.

Minguillon, J., Perez, E., Lopez-Gordo, M. A., Pelayo, F., & Sanchez-Carrion, M. J. (2018). Portable system for real-time detection of stress level. Sensors, 18(8), 2504.

Quadrini, M., Capuccio, A., Falcone, D., Daberdaku, S., Blanda, A., Bellanova, L., & Gerard, G. (2024). Stress detection with encoding physiological signals and convolutional neural network. Machine Learning, Springer, 113, 5655–5683.

Schmidt, P., Reiss, A., Duerichen, R., Maraneit, C., & Van Laerhoven, K. (2018). Introducing WESAD, a multimodal dataset for wearable stress and affect detection. Proceedings of the 20th ACM International Conference on Multimodal Interaction, 400–408.

Sim, J. B. (2019). Traditional vs. modern methods of psychological assessment: A comparative review. Journal of Mental Health Technology, 14(2), 112–125.

World Health Organization (WHO). (2025). Stress.