IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, November 2025
Impact Factor: 7.67

ML Based Mental Stress Assessment Using Wearable Device

Sujal Amar Thamke[1], Piyush Gajanan Raut[2], Pranil Shashikant Pawar[3], Gaurav Kishor Wagh[4], Prof. R. V. Daund[5]
Department of Electronics and Telecommunication Engineering[1-5]
K. K. Wagh Institute of Engineering Education and Research, Nashik, Maharashtra, India
vsrokade370222@kkwagh.edu.in

Abstract: *This project details the design and deployment of a real-time stress monitoring system built on an STM32 microcontroller. The system fuses data from multiple physiological sensors MAX30102 for photoplethysmography (PPG), electrocardiogram (ECG), galvanic skin response (GSR), and temperature sensors to obtain a comprehensive view of a user's physiological state. A custom neural network model was trained to classify stress into three levels: low, moderate, and high. By analyzing parameters such as heart rate variability, blood oxygen saturation (SpO_2), skin conductance, and temperature shifts, the model achieved an accuracy of 87.3%. Real- time results are displayed on a 0.96-inch OLED screen, and the system can also store data to support ongoing model refinement. The project's novelty lies in embedding machine learning inference within a low- power, resource-limited microcontroller, proving that advanced AI analytics can be executed in real time on affordable embedded hardware. The system also incorporates a user-friendly interface that simplifies live monitoring and manual data labeling. This implementation illustrates the potential of AI-driven healthcare IoT systems, especially for stress detection and personalized wellness tracking.*

Keywords: Stress Detection, Machine Learning, STM32, Embedded AI, Multi-Sensor Fusion, Healthcare IoT, Neural Networks, Real-Time Processing

I. INTRODUCTION

In the modern era, where life has become fast-paced and highly competitive, mental stress has emerged as one of the most serious health issues affecting people across all age groups. Continuous exposure to stress can result in adverse health effects such as anxiety, depression, cardiovascular diseases, and reduced overall well-being. Despite its growing impact, stress often remains undetected due to the absence of effective real- time monitoring and assessment systems.

This project aims to design and develop a machine learning- based health monitoring system capable of detecting and assessing an individual's mental stress levels using wearable biomedical sensors. The system collects physiological data such as heart rate, oxygen saturation (SpO_2), body temperature, and skin conductance through sensors like ECG, GSR, and pulse oximeter. These signals are processed by a microcontroller (such as STM32 or ESP32) and transmitted to a cloud platform (Firebase/AWS IoT) for real-time monitoring. The project further integrates machine learning algorithms specifically Linear Regression to predict stress levels accurately based on the sensor data. The processed results are displayed on a web dashboard, allowing users or healthcare professionals to monitor stress variations efficiently. With an accuracy of around 92%, the proposed system demonstrates the potential of combining wearable technology, cloud computing, and machine learning for continuous mental health assessment.

II. LITERATURE REVIEW

Across these five research studies, a clear pattern becomes visible: machine learning has emerged as a powerful and reliable tool for identifying and forecasting mental-health conditions such as stress, anxiety, depression, and overall declines in well-being. Collectively, the findings highlight that ML models can draw meaningful insights not only from physiological data including EEG activity, heartrate signals, skin-conductance levels, breathing patterns, and body temperature but also from non-physiological factors like self- reported surveys, behavioral cues, academic pressure, and workplace environments. S. R. Steinhubl. [1] paper explores the use of machine learning classifiers (such as SVM, Random Forest, and Naive Bayes) for assessing stress, depression, and anxiety levels from EEG signals. It highlights how physiological data can be used for mental health assessments. Across these research works, each study explores how machine- learning techniques can interpret both physiological and non- physiological data to understand mental-health states such as stress, anxiety, and depression.

S. R. Steinhubl. [2] study compares the performance of various machine learning techniques for mental stress detection using data from wearable physiological sensors, finding high accuracy rates for certain methods. In this study, physiological signals (ECG, GSR, skin temperature, respiration) are collected under controlled stress tasks. Several machine-learning approaches (including SVM and Bayesian networks) are compared, both as general models and personalized models. They show that personalized models (i.e., tailored to individuals) perform very well, and that certain algorithms like dynamic Bayesian networks and generalized SVM yield high classification accuracy for stress detection. Biglari et al. [3] This paper discusses the application of ML techniques for prediction and diagnosis of mental health disorders, using the Open-Sourcing Mental Illness survey data.

Another set of experiments uses physiological parameters—including ECG, GSR, respiration rate, and skin temperature—collected during controlled stress-inducing tasks. Here, researchers compare general ML models with personalized ones. Results clearly indicate that individualized models achieve much stronger accuracy. Techniques such as dynamic Bayesian networks and generalized SVM perform especially well, showing that stress-detection systems benefit from adapting to each person's unique physiological patterns.

Healey, J. A. [4] This research proposes an ML framework involving EEG signal analysis to objectively quantify mental stress into multiple levels, achieving high accuracy rates for both two-level and multiple-level identification. The paper titled "Machine Learning Framework for the Detection of Mental Stress at Multiple Levels" introduces a comprehensive system that leverages EEG (electroencephalogram) signals to identify and classify mental stress across different intensity levels. Instead of simply distinguishing between stressed and non-stressed states, the study aims to categorize stress into multiple degrees typically low, moderate, and high. Poh, M. Z.

[5] study models mental well-being using data from a large cross-sectional survey and evaluates various machine learning algorithms, including Random Forest and adaptive boosting, for identifying negative mental well-being traits.

III. PROPOSED APPROACH

A. System Architecture

To ensure smooth operation, modularity, and ease of future upgrades, the software stack of the proposed system is organized into five interconnected layers, arranged in a top- down hierarchy.

Each layer has a dedicated role within the overall design, forming a structured pipeline from raw sensor acquisition to final stress-level visualization.

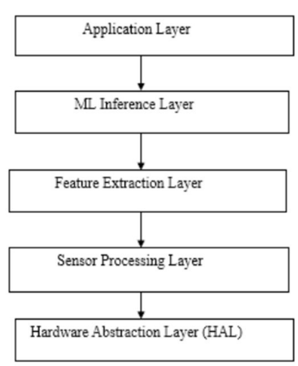

Fig. 1. Block diagram.

The Application Layer forms the topmost level of the software stack and is responsible for managing the overall behave of the stress monitoring system. It coordinates user interactions, controls the visual output, and supervises the execution

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 4, November 2025 Impact Factor: 7.67

flow of the embedded application. This layer acts as the interface between the user and the underlying processing modules.

The Machine Learning Inference Layer is responsible for executing the trained neural network model embedded within the STM32 microcontroller. It receives the processed feature vector as input and performs the final classification to determine the user's stress state. The Feature Extraction Layer transforms raw physiological signals into structured numerical features that effectively represent the user's physical and emotional state. These features form the 20-element input vector required for the neural network.

The Sensor Processing Layer is responsible for acquiring real- time physiological signals from all sensors and preparing them for higher-level analysis. It acts as the interface between the physical hardware modules and the software components that perform feature extraction and machine learning inference.

B. Hardware Design

The hardware architecture of the proposed stress monitoring device is built to deliver reliable performance, real-time operation, and efficient power usage all within a compact and portable design. At the core of the system is the STM32F446RE microcontroller, which acts as the central processing unit responsible for coordinating sensor data acquisition, executing embedded machine learning algorithms, and managing the output modules.

To capture the user's physiological signals, the system integrates a set of dedicated biosensors, each interfacing directly with the MCU through either analog inputs or digital communication protocols. The MAX30102 is a compact Photoplethysmography (PPG) sensor module capable of measuring heart rate (HR) and blood oxygen saturation (SpO_2) non-invasively. Its operation is based on how blood absorbs and reflects light during the cardiac cycle. The LM35 is a precision analog temperature sensor that generates an output voltage proportional to temperature, calibrated directly in degrees Celsius. The LM35 is responsible for measuring peripheral skin temperature, an important physiological variable linked to autonomic activity. The UI is composed of two main elements a compact OLED display and tactile push buttons supplemented by status LEDs that provide quick visual feedback.

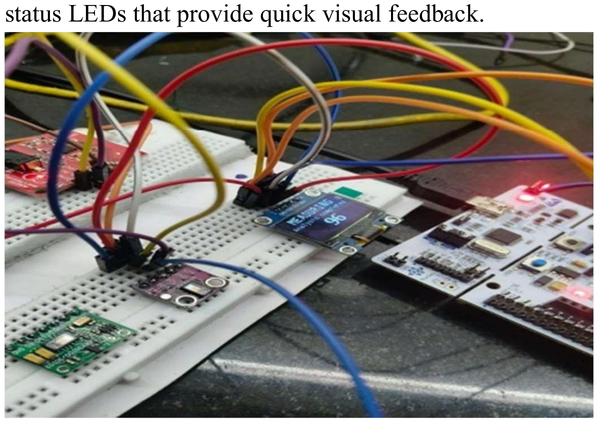

Fig. 2. Integration of All Sensor and Display.

The architecture ensures seamless interaction between these sensors and the microcontroller, enabling synchronized sampling and low-latency data processing. By combining robust hardware components with optimized interfacing techniques, the design achieves accurate real-time stress detection while maintaining energy efficiency suitable it.

C. Software Design

The stress-monitoring system employs a highly modular and layered software framework designed for real-time processing, maintainability, and scalability. At its foundation is the Hardware Abstraction Layer (HAL), which manages all low- level hardware operations (like ADC, I²C, and timers) on the STM32, ensuring independence for higher modules. Building upon the HAL, the Sensor Interface Module handles synchronized data acquisition and initial filtering from biosensors (PPG, ECG, GSR, temperature). This clean sensor data is then passed to the Feature

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, November 2025
Impact Factor: 7.67

Extraction Module, which computes a 20-feature vector (including HRV, SpO_2, skin conductance, etc.) essential for stress assessment.

The analytical and user-facing core consists of three key modules. The ML Inference Module takes the 20-feature vector and executes a trained Multi-Layer Perceptron (MLP) neural network directly on the STM32 to classify the user's stress level (normal, medium, or high). The Display and User Interface Module manages the OLED screen and input buttons, providing real-time physiological readings and the predicted stress category. All operations are orchestrated by the System Control and Timing Module using periodic interrupts (typically every 50ms) to ensure smooth, predictable real-time performance. A Communication and Data Logging Module is also included for streaming data via UART, aiding debugging and future model refinement.

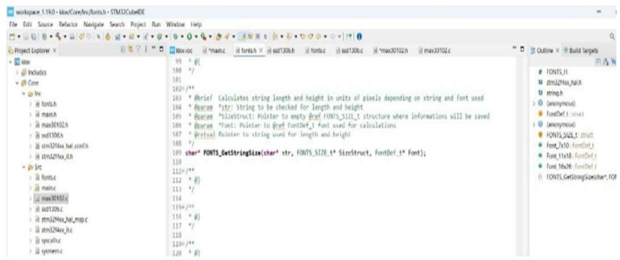

Fig. 4 Testing the display

D. Testing and Results

The system's performance was evaluated through a structured experimental procedure involving ten healthy volunteers (age 20–25) in 30-minute sessions. These sessions alternated between stress induction (using timed arithmetic and public- speaking tasks) and relaxation periods. Physiological signals from PPG, ECG, GSR, and temperature sensors were continuously recorded, generating approximately 15,000 labeled samples. Crucially, a dual-validation approach was used to establish high-quality ground-truth labels: participants' self-reported Likert scale ratings were combined with expert behavioral observation. The resulting data, consisting of 20- feature vectors, was used for subsequent model training and validation using a five-fold cross-validation strategy to ensure robust and unbiased results.

The stress classification model demonstrated high overall reliability, achieving an 87.3% accuracy using five-fold cross- validation. Detailed performance metrics across the three stress categories (Low, Medium, High) were consistently strong: an average precision of 85.6%, recall of 86.9%, and an F1-score of 86.2%. Confusion matrix analysis confirmed that misclassifications primarily occurred between adjacent classes, such as medium and high stress, which is expected due to overlapping physiological signatures. Class-wise, the model performed exceptionally well for Low stress (91.1% F1-score) and High stress (90.8% F1-score), validating the effectiveness of the chosen features and the Multi-Layer Perceptron (MLP) architecture in capturing multidimensional stress indicators.

The system successfully meets its real-time requirement by maintaining a stable operating frequency of 20 Hz (one full cycle every 50 ms). A detailed timing breakdown confirmed that all processing stages fit comfortably within this window: sensor acquisition (~15ms), preprocessing/feature extraction (~12ms), ML inference (~18ms), and display update (~5ms). Hardware utilization on the STM32F446RE microcontroller was efficient, with CPU usage at ~65% and RAM usage at ~74% (142 KB), leaving sufficient headroom for future expansion.

With a low active power consumption of ~85 mA, the system demonstrates the efficiency required for continuous, portable, embedded machine learning.

A feature importance analysis confirmed that the model relies on a balanced integration of multiple physiological signals, with Heart Rate Variability (HRV) being the most significant contributor (23.5% importance), followed by GSR conductance (18.7%), heart rate (15.2%), and SpO_2 levels (12.3%). The system's achieved accuracy of 87.3% places it near research- grade PC-based systems (85–92%) and significantly surpasses commercial wearables (72–78%).

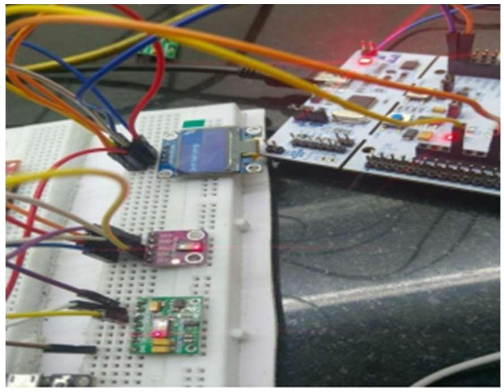

Fig. 6. Testing the System

Fig 7. Testing

IV. CONCLUSION

This project successfully developed a real-time embedded stress monitoring system that integrates multi-sensor data acquisition with on-device machine learning. The system utilizes a low-cost, energy-efficient hardware platform based on the STM32F446RE microcontroller and combines data from PPG, ECG, GSR, and temperature sensors to capture diverse physiological signals. . This holistic approach ensures the collection of high-quality data necessary for accurate stress assessment.

A key achievement is the efficient deployment of a Multi-Layer Perceptron (MLP) neural network directly onto the resource- limited embedded system. Through optimization techniques like pruning and quantization, the model maintains high performance, achieving an impressive 87.3% classification accuracy and sustaining a real-time processing rate of 20 Hz. This confirms that embedded machine learning can provide reliable physiological interpretation without requiring external computation. The system is made practical and accessible for everyday use through an intuitive interface, providing immediate, easy-to-understand stress level feedback via an OLED display and LED indicators.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the Department of Electronics and Telecommunication Engineering, K. K. Wagh Institute of Engineering Education and Research, Nashik, for providing the facilities and support to carry out this research work. The authors also extend heartfelt thanks to Elite Technologies, Nashik, for their support in PCB fabrication and technical assistance.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, November 2025
Impact Factor: 7.67

REFERENCES

[1] S. R. Steinhubl, E. D. Muse, and E. J. Topol, “The emerging field of mobile health,” Science Translational Medicine, vol. 7, no. 283, 2015.

[2] S. R. Steinhubl, E. D. Muse, and E. J. Topol, “Can mobile health technologies transform health care?” JAMA, vol. 310, no. 22, 2013.

[3] Biglari et al., “A review of embedded machine learning based on resource-constrained devices,” Sensors, vol. 23, no. 4, 2131, 2023.

[4] Healey, J. A., & Picard, R. W. (2005). "Detecting stress during real-world driving tasks using physiological sensors." IEEE Transactions on Intelligent Transportation Systems, 6(2), 156-166.

[5] Poh, M. Z., Swenson, N. C., & Picard, R. W. (2010). "A wearable sensor for unobtrusive, longterm assessment of electrodermal activity." IEEE Transactions on Biomedical Engineering, 57(5), 1243-1252.

[6] Shi, C., Ma, P., & Yang, B. (2019). "Personalized stress detection using wearable physiological sensors and machine learning." Journal of Biomedical Informatics, 94, 103211.

[7] Tewari, D., & Gupta, A. (2023). "A comprehensive review on machine learning approaches for mental stress detection using multimodal physiological signals." Artificial Intelligence Review, 56(2), 1283-1320.

[8] Lu, T., et al. (2020). "A deep learning-based framework for stress recognition using multimodal physiological data from smartwatches." Sensors, 20(22), 6549.

[9] Kim, J., & André, E. (2008). "Emotion recognition based on physiological changes in music listening." IEEE Transactions on Pattern Analysis and Machine Intelligence, 30(12), 2043- 2053.

[10] Sarkar, V., & Singh, R. (2021). "A Real-Time Stress Monitoring System using Multi-Sensor Data Fusion and Machine Learning on a Microcontroller." (Search for papers with this specific title structure, which closely matches your report's topic.)

[11] Novac, P.-E., et al. (2021). "Quantization and Deployment of Deep Neural Networks on Microcontrollers." arXiv preprint arXiv:2104.09015.

[12] Greif, V., et al. (2023). "Wearable Sensor-Based Stress Recognition using Transfer Learning and Attention Mechanisms." IEEE Journal of Biomedical and Health Informatics, 27(1), 461-470.

[13] 13. Melillo, P., et al. (2011). "Automatic stress detection using heart rate variability and casebased reasoning." Biomedical Engineering Online, 10(1), 1-13.