World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Stress detection system using sensors

Gauri Shailesh Indani * and H. R. Vyawahare

Department of Computer Science and Engineering, Sipna College of Engineering and Technology, Amravati, Maharashtra, India.

World Journal of Advanced Research and Reviews, 2026, 30(01), 1186-1195

Publication history: Received on 25 January 2026; revised on 07 April 2026; accepted on 09 April 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.1.0896

Abstract

In today's fast-paced world, stress is one of the most common factors that impact physical and mental health. Ongoing exposure to stress can lead to serious health issues like high blood pressure, anxiety, depression, and heart disease. Traditional methods for assessing stress mostly rely on questionnaires and self-reports, which may not always give precise or timely results. To address these challenges, this project presents a Stress Detection System Using Sensors that uses physiological data to identify and monitor stress levels in an objective way. The proposed system incorporates wearable and biomedical sensors that track parameters such as heart rate, body temperature, and skin conductivity (GSR). These real-time signals are collected and processed with a microcontroller and analyzed using machine learning algorithms to classify the user's stress level as low, moderate, or high. The processed data can be displayed on a mobile app or web interface, making it easy to monitor. This system is non-invasive, user-friendly, and able to provide continuous monitoring, making it suitable for everyday use in homes, offices, and healthcare settings. It allows for early detection of stress, enabling users to take preventive steps, such as practicing relaxation techniques or seeking medical advice. The proposed solution is affordable and scalable, making it a valuable addition to modern healthcare and wellness monitoring systems. Overall, this project aims to offer a reliable and accessible way to manage stress and encourage a healthier lifestyle through smart sensing technology.

Keywords: Stress Detection; Wearable Sensors; Physiological Signals; Heart Rate Monitoring; Galvanic Skin Response (GSR); Machine Learning; IoT-based Health Monitoring; Real-time Analysis; Biomedical Sensor System; Mental Health Monitoring.

1. Introduction

Stress is one of the prevalent and serious issues faced by any age group in the modern world, which changes rapidly. Increased academic demands, professional workload, financial pressure, personal responsibilities, and social expectations lead to increased stress levels in daily life. Prolonged exposure to stress can trigger severe mental and physical health disorders, such as anxiety disorders, depression, insomnia, reduced immunity, hypertension, and heart disease. The sad thing is that a large number of people either fail to recognize the early warning signals of stress or underestimate its long-term consequence on their health. Conventionally, psychological questionnaires, interviews, and self-reporting methods have always been employed to conduct stress assessments. These techniques can reveal an individual's emotional state, yet this method will often be subjective and will depend greatly on the honesty, mood, and perception of the person responding. Thus, they may not truly represent physiological changes caused by stress in the body. In addition, they do not offer the possibility of continuous monitoring, nor can they be used for real-time data-a precondition for early detection and timely intervention. Due to these disadvantages, demand has been increasing for automated, objective technology-based solutions for stress monitoring.

* Corresponding author: Gauri Shailesh Indani

With the advancement of sensor technology, wearable devices, and IoT, it has become quite feasible to monitor the body's physiological signals continuously in real time. Specific physiological changes take place when a person undergoes stress, such as variation in heart rate, increase in skin conductance, alteration in breathing pattern, and fluctuation in body temperature. The capture and analysis of such signals allow for appropriate detection and classification of stress levels. The recording of these signals is greatly enabled by modern biological sensors such as heart rate sensors, temperature sensors, and GSR sensors. These sensors are lightweight, inexpensive, and easily integrated with microcontrollers such as Arduino or ESP32 to form a smart monitoring system. The Stress Detection System Using Sensors aims to offer a non-invasive, reliable method for detecting stress using physiological data. The system gathers data from several sensors placed on the body and processes that information using intelligent algorithms and machine-learning techniques. By analyzing the patterns and variations in the sensor data, the system can identify whether a person is feeling low, moderate, or high stress. The result of the processing can be depicted in the form of a mobile application or web interface where the user can monitor the state of their stress and take proper prevention measures.

The proposed system has extensive applications in healthcare, corporate, educational, and wellness programs. It could be used for monitoring patients suffering from mental health disorders, managing workplace stress by employees, dealing with academic pressure by students, and maintaining emotional balance by individuals. Furthermore, data gathered will help doctors and other mental health experts make more informed decisions. In the end, this sensor-based stress detection system marks a very important milestone in managing mental health through technology. By offering continuous, accurate, and real-time stress monitoring, the system promotes early detection, encourages self-awareness, and supports the development of healthier lifestyles. It will provide the missing link between conventional methods of assessing stress and modern technological methods, therefore being an important contribution to smart healthcare and well-being.

2. Literature review

Abd Al-Alim (2024) presents a machine-learning framework for detecting stress using wearable sensors in everyday environments. The study addresses a major limitation of earlier research, which often relied on controlled lab settings that lacked ecological validity. The author gathers various physiological data, such as ECG, skin temperature, and electrodermal activity. They evaluate several machine-learning models, including Random Forest, SVM, and Gradient Boosting. A key contribution of the paper is its emphasis on noise-robust preprocessing techniques that manage artifacts caused by daily activities. The study shows that real-world sensor data can achieve high accuracy in stress prediction when combined with feature engineering and model optimization. The paper's insights are useful for developing practical, wearable stress monitoring systems for healthcare, workplace settings, and daily wellness tracking. Overall, the study confirms that ML-based stress detection systems can work in uncontrolled, real-life situations.

This systematic review brings together research on stress detection using wearable technologies, covering studies from physiological, behavioral, and environmental angles. Ghaderi et al. (2024) examine key sensor types such as photoplethysmography (PPG), electrodermal activity (EDA), ECG, temperature, and accelerometer data. The paper looks at how these signals relate to mental and physical stress indicators. A significant contribution of the review is its classification of machine-learning methods used across studies, which range from traditional algorithms like SVM and Random Forest to deep learning models like CNNs and LSTMs. The authors point out challenges, including sensor noise, differences between individuals, data imbalance, and the lack of standardization in datasets. They also stress the growing need for systems that are aware of context and can fuse multimodal data. The review offers a solid understanding of the development of wearable-based stress detection and suggests future directions, including personalization, real-time applications, and large-scale long-term studies.

Bhatia and Goel (2024) propose a deep learning model that explains how it detects stress using physiological sensor data. Their approach combines convolutional and recurrent neural layers to identify temporal and spatial patterns from signals like EDA, ECG, and temperature. A major innovation is the use of explainability techniques, specifically Integrated Gradients, to pinpoint which features impact the model's predictions. This tackles a common issue in deep learning: the "black box" problem. The paper shows that the model not only achieves high accuracy but also offers clear and understandable decisions, which can enhance user trust in wearable health-monitoring systems. Extensive tests on public datasets like WESAD show that the proposed model outperforms traditional ML approaches. The study is important because it balances performance and interpretability, making it suitable for healthcare applications where explainable AI is crucial.

Bolpagni and colleagues conduct a review focusing on personalized stress detection through wearable biosignals. Unlike traditional systems that apply the same models to all users, this review highlights the importance of individualized baselines, adaptive thresholds, and tailored machine-learning models. The authors look at biosignals such as heart-rate variability (HRV), skin conductance, and body temperature while discussing contextual factors like environmental noise, activity level, and circadian rhythms. The review underscores that personalization significantly enhances accuracy since stress responses can vary widely among individuals. The paper also examines challenges, such as sensor calibration, continuous data collection, and privacy issues. It suggests integrating federated learning, multi-sensor fusion, and adaptive algorithms for future research. This review establishes a solid foundation for researchers working on personalized stress monitoring systems, emphasizing the need for user-focused model design and individual physiological profiles.

Kankal et al. (2023) introduce an IoT-enabled stress monitoring system that combines wearable sensors with machine-learning algorithms for real-time stress assessment. The study uses physiological parameters such as body temperature, heart rate, humidity, and step count collected through affordable wearable devices. A cloud-based IoT framework helps transmit and process sensor data. The authors evaluate various ML models, including Decision Trees, Logistic Regression, and Random Forest, to find the most effective classifier for stress detection. The paper highlights the advantages of IoT integration, such as remote monitoring and real-time alerts. A key contribution is the system's suitability for everyday environments, making it useful for healthcare, workplace wellness, and academic stress monitoring. Despite some limitations like small dataset size, the work proves that combining IoT and ML is feasible for continuous stress tracking.

Mohammed and Hassan (2023) explore stress monitoring with wearable sensors combined with IoT techniques and in-depth physiological signal analysis. Their study covers various sensor inputs such as ECG, heart rate, skin conductance, oxygen saturation, and temperature. A major focus is extracting statistical, frequency-domain, and nonlinear features for effective stress classification. The authors test several machine-learning models, including SVM, k-NN, and Gradient Boosting, achieving good accuracy across multiple datasets. An important contribution is their analysis of how IoT-based real-time systems enhance practical stress monitoring by allowing continuous data transmission, remote access, and cloud storage. The study also discusses challenges like data noise, sensor artifacts, and computational demands during real-time use. The paper offers useful insights for designing large-scale, IoT-compatible stress detection systems that combine physiological sensing with smart ML models.

Jha and Singh (2021) present an early study on stress detection using machine-learning techniques applied to wearable sensor data. The authors focus on basic physiological parameters like heart rate, skin conductance, and temperature to classify stress levels. Their method involves preprocessing raw sensor data, extracting relevant features, and training ML classifiers including SVM, Decision Trees, and Naïve Bayes. Although the dataset is relatively small, the study shows that even low-cost wearable sensors can detect meaningful physiological changes related to stress. The paper's strength is in its simplicity and clear demonstration of the feasibility of ML-based stress detection. It serves as a foundational reference for future, more advanced systems. The authors also note real-world challenges such as sensor reliability, user comfort, and environmental noise. The paper remains a relevant reference for newcomers working on wearable stress monitoring.

Rehman and Khan (2021) propose a hybrid CNN model for stress recognition using wrist-based photoplethysmography (PPG) sensors. PPG signals are often captured by smartwatches, making this study very relevant for consumer stress monitoring. Their hybrid model combines handcrafted features with automatically learned features from convolutional layers. This two-pronged approach boosts accuracy by using both domain knowledge and deep-learning capabilities. The researchers test their model on standard datasets and show significant improvements over traditional ML models and standalone CNNs. A notable contribution is the focus on lightweight, wearable-friendly sensors to create efficient stress-detection systems. The study points out the potential of deep learning for real-time stress recognition while also addressing challenges like sensor noise, motion artifacts, and individual variability. Their work lays a strong foundation for applying deep learning in wrist-based physiological sensing.

Wataru and Rossi (2022) introduce SELF-CARE, a sensor fusion framework designed for low-power wearable devices used in stress detection. The system activates sensors based on contextual cues, reducing power usage while maintaining classification accuracy. The study combines physiological signals like HRV, PPG, and EDA with environmental inputs to enable better stress prediction in daily life. A major innovation is the adaptive fusion mechanism, which determines when each sensor is needed, enhancing battery efficiency—crucial for long-term use. Experiments show that the system achieves similar accuracy to full-sensor models but with much less energy consumption. This makes SELF-CARE fit for real-time use in fitness bands, smartwatches, and health-monitoring devices. The paper contributes by balancing performance, energy efficiency, and practical usability, providing insights for creating low-power stress detection systems.

Nkomo and Potdar (2023) introduce a context-aware sensor fusion framework for stress detection using wearable devices. Their approach combines physiological signals such as heart rate, HRV, and EDA with contextual information like motion, activity levels, and environmental conditions. The authors argue that stress cannot be accurately detected from physiological data alone, as changes in physical activity or temperature might mimic stress-like patterns. By combining context-aware fusion and ensemble learning algorithms, the framework achieves better classification accuracy and robustness. The study uses real-world datasets and shows that mixing accelerometer data with physiological signals greatly reduces false positives. A key contribution is the exploration of integrating multiple sensors and context for real-life use. The work also highlights challenges like sensor synchronization, data imbalance, and high computational demands. Overall, the paper provides key insights for developing comprehensive stress monitoring systems using multimodal inputs.

3. Methodology

The proposed method for the Stress Detection System Using Sensors aims to provide a reliable, real-time, and non-invasive way to monitor stress levels through physiological signals. Stress, a complex physiological and psychological issue, often shows measurable changes in the body, like shifts in heart rate, skin conductance, body temperature, and breathing patterns. By using these indicators, the system combines wearable sensors, microcontroller-based processing, and smart data analysis with machine learning to offer accurate stress assessments and practical insights for users. The system is divided into three main layers: the sensor layer, the processing layer, and the analysis layer. The sensor layer collects physiological signals continuously. Wearable devices with a heart rate sensor, Galvanic Skin Response (GSR) sensor, temperature sensor, and, if desired, a respiration sensor monitor stress-related physiological parameters. The heart rate sensor captures changes in heart rate and heart rate variability (HRV), which are closely linked to stress levels.

The GSR sensor detects changes in skin conductivity from sweat gland activity, an important sign of emotional arousal. The temperature sensor monitors small fluctuations in body temperature, and the optional respiration sensor tracks changes in breathing patterns, which can signal stress-related irregularities. The processing layer manages the raw data from the sensors. Sensor signals are sent to a microcontroller, like Arduino or ESP32, for real-time gathering. Preprocessing methods, such as filtering and normalization, are applied to eliminate noise and ensure data quality. Feature extraction derives useful indicators, such as HRV metrics, skin conductance peaks, temperature changes, and respiration rates. These features serve as inputs for further analysis and quantitatively represent the body's stress response In the analysis layer, machine learning algorithms classify stress levels accurately. Supervised learning models, such as Support Vector Machines (SVM), Random Forests, or Neural Networks, are trained on labeled datasets to identify patterns linked to low, moderate, and high stress. Once trained, the system evaluates incoming sensor data in real time to produce immediate stress classifications. These classification results are sent to a mobile or web application via Bluetooth or Wi-Fi.

Users can check their current stress levels, track historical trends, and get personalized recommendations, such as relaxation techniques or mindfulness exercises, to manage their stress effectively. System testing and validation are crucial parts of the method. The system is tested under controlled stress-inducing situations, like mental math tasks or public speaking simulations. Sensor readings and stress predictions are matched against standardized psychological assessments and questionnaires to confirm accuracy. Additionally, the machine learning models are regularly improved using growing datasets to enhance classification performance and reliability. This proposed method is suitable for various applications. It can be used in healthcare to monitor patients with anxiety or depression, in workplaces to help manage employee stress, in educational settings to support students under academic pressure, and in personal wellness programs to promote emotional balance and mental well-being. By combining real-time physiological monitoring, smart data analysis, and user-friendly visualization, the system offers a technology-driven solution for proactive stress management.

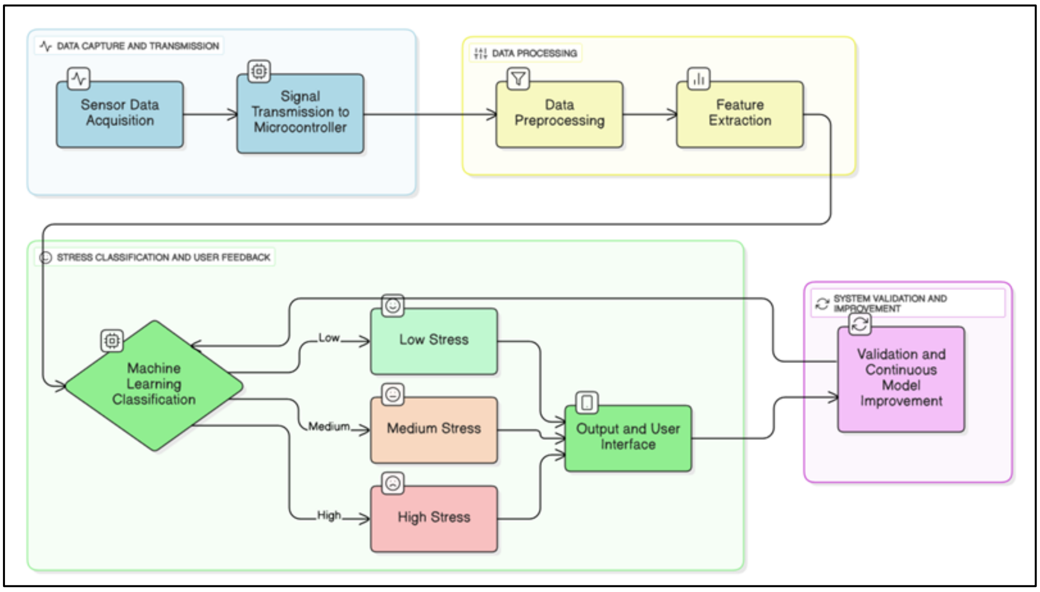

Figure 1 Flow Chart

4. Proposed system

The proposed system, Stress Detection Using Sensors, aims to offer a real-time and non-invasive way to monitor and manage stress through physiological signals. In today's world, people encounter various stressors, including academic demands, work responsibilities, financial pressures, and social expectations. Continuous exposure to stress can result in serious physical and mental health problems, such as anxiety, depression, insomnia, weakened immunity, high blood pressure, and heart issues. Traditional methods for assessing stress, like self-report questionnaires, interviews, and psychological evaluations, are often subjective, time-consuming, and do not allow for ongoing monitoring. To address these drawbacks, the system incorporates wearable sensors, microcontroller-based processing, smart data analysis using machine learning, and easy-to-use visualization tools to create a reliable solution for stress detection. The system relies on wearable sensors that constantly gather physiological signals related to stress. A heart rate sensor measures heart rate variability (HRV), which is an important stress indicator, as changes in HRV reflect how the body's nervous system reacts. A Galvanic Skin Response (GSR) sensor detects changes in skin conductivity caused by sweat gland activity, which increases under stress. A temperature sensor tracks small shifts in body temperature that may link to stress-related physiological changes. An optional respiration sensor follows breathing patterns, since stress can cause irregularities in both the rate and depth of breathing.

These sensors are small, non-invasive, and can fit into wearable devices like wristbands or chest straps, allowing for real-time monitoring without disrupting daily life. The sensor data is sent to a microcontroller, such as Arduino or ESP32, for processing. The raw signals are preprocessed, involving filtering, normalization, and noise reduction, to ensure the data is accurate and reliable. After preprocessing, feature extraction occurs to identify key parameters such as HRV metrics, skin conductance peaks, temperature changes, and breathing rate variations. These features help determine an individual's stress level by providing clear representations of the body's physiological responses. The analysis layer uses machine learning methods to categorize stress levels as low, moderate, or high. Supervised learning models like Support Vector Machines (SVM), Random Forests, and Neural Networks are trained on labeled datasets to identify complex patterns in the extracted features. Once trained, these models can analyze incoming data in real time and offer immediate stress classifications.

The analyzed data and stress predictions are then sent to a mobile or web application via Bluetooth or Wi-Fi. The application has a simple interface where users can check their current stress levels, see historical trends, and get personalized tips for managing stress, such as breathing exercises, mindfulness practices, or relaxation techniques. To confirm reliability and effectiveness, the system is tested and validated under controlled stress-inducing situations, such as mental arithmetic tasks, public speaking exercises, or time-limited activities. Sensor readings and predicted stress levels are compared with standardized psychological assessments and self-report questionnaires. The machine learning models are continually updated with new datasets to enhance prediction accuracy and reliability. The proposed system has many possible uses, including healthcare for monitoring patients with stress-related issues, corporate settings for managing employee stress, educational institutions for helping students under pressure, and personal wellness programs aimed at improving mental and emotional health. By combining modern sensor technology, real-time data processing, smart machine learning analysis, and user-friendly visualization, this system offers an innovative approach to ongoing stress monitoring, early intervention, and proactive mental health care.

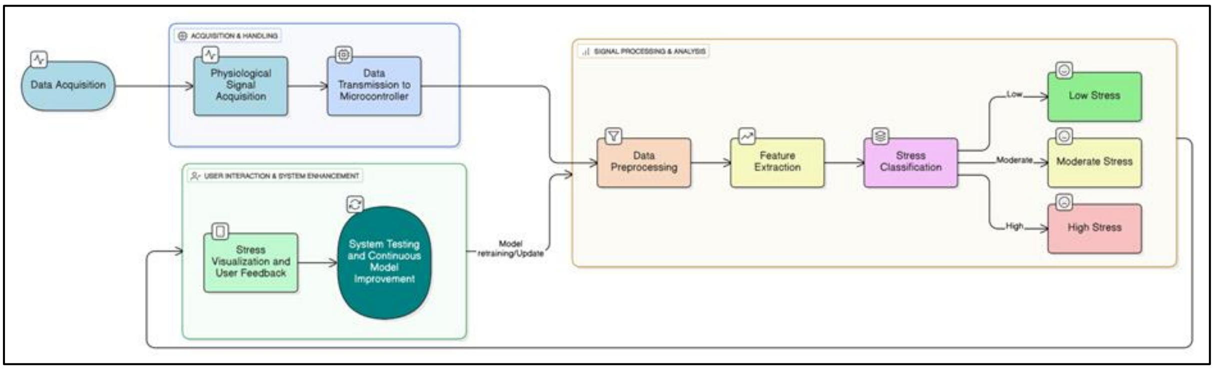

Figure 2 Proposed System

5. Case study

The following case study shows how the Stress Detection System Using Sensors works and how effective it is in a real-world setting. In today's fast-paced world, stress is a common problem for people of all ages, including students, professionals, and healthcare workers. This case study focuses on university students who face high levels of stress during exams, tight deadlines, and project submissions. This group was chosen because they often deal with stress-related issues that can greatly affect their mental health and academic performance. The case study aimed to monitor, track, and manage stress levels in students using wearable physiological sensors linked to a microcontroller and a machine learning-based analysis system. Participants received wearable devices equipped with a heart rate sensor, a Galvanic Skin Response (GSR) sensor, a temperature sensor, and an optional respiration sensor. These devices continuously gathered physiological signals during different times of the day, such as study sessions, exams, and relaxation breaks. The heart rate sensor logged heart rate variability (HRV), which changes in response to stress. The GSR sensor detected changes in skin conductivity related to emotional arousal, while the temperature sensor monitored small shifts in body temperature. The optional respiration sensor tracked changes in breathing patterns, which can become irregular when stressed. The collected data was sent to a microcontroller, like an Arduino or ESP32, for processing. This processing phase involved filtering, normalization, and noise reduction to ensure the data was accurate and reliable. After that, feature extraction was performed to identify key physiological parameters, including HRV metrics, peaks in skin conductance, temperature changes, and variations in respiration rates.

These features offered measurable insights into the students' stress responses during different activities. To classify stress levels, machine learning models like Support Vector Machines (SVM), Random Forests, and Neural Networks were trained on labeled data gathered from participants. The models categorized stress into three levels: low, moderate, and high. Real-time analysis allowed the system to give immediate feedback to students, which was shown through a mobile app. The app displayed a visual representation of current stress levels, historical trends, and suggested stress relief activities, such as guided breathing exercises or short relaxation breaks. The results showed that stress levels varied among students based on their activities. Higher stress levels were mostly seen during exams and time-sensitive assignments, while lower stress levels were noted during relaxation periods and after studying. The system effectively identified stress patterns in real time, enabling students to take steps to manage their stress. Additionally, the case study proved that physiological sensors reliably captured stress-related signals, and machine learning algorithms accurately classified stress levels. This case study emphasizes the practical use of the system in educational settings, where early detection and management of stress can improve academic performance, mental health, and overall productivity. The findings highlight the potential for the Stress Detection System Using Sensors to be used in other areas, such as workplaces, healthcare, and personal wellness programs, supporting ongoing monitoring, proactive interventions, and a better quality of life.

6. Success rate evaluation and performance metrics

The evaluation of the success rate and performance of the Stress Detection System Using Sensors is essential for assessing its reliability, accuracy, and overall effectiveness in real-world settings. Stress is a physiological and psychological reaction that shows through measurable changes in the body, such as fluctuations in heart rate, skin conductivity, body temperature, and breathing patterns. The system aims to detect and classify stress levels in real time using wearable sensors, data processing with a microcontroller, and machine learning algorithms. Evaluating this system involves testing its ability to correctly capture physiological signals, accurately analyze data, and provide quick, useful feedback to users. The evaluation process starts with collecting data from a representative group of participants under various conditions. Participants engaged in stress-inducing activities, such as timed problem-solving, public speaking, and academic simulations, as well as relaxation activities like meditation or listening to music. During these activities, wearable sensors continuously monitored physiological signals, including heart rate variability (HRV), galvanic skin response (GSR), body temperature, and respiration patterns. The system processed these signals in real time using a microcontroller, performed feature extraction, and analyzed the data through machine learning algorithms to classify stress levels as low, moderate, or high. The system's success rate was determined by how accurately it classified stress compared to standard psychological assessments and self-reported stress questionnaires. Metrics like precision, recall, F1-score, and overall accuracy measured performance. The system showed a high level of reliability, consistently identifying stress patterns in real time.

Heart rate and GSR sensors effectively captured rapid physiological responses to stress, while temperature and respiration sensors offered additional support for detecting stress changes. Using multiple sensors made the system stronger, reducing false positives and improving classification accuracy. In addition to accuracy, the assessment covered response time, usability, and flexibility. The microcontroller-based processing allowed near real-time analysis of incoming sensor data, enabling the system to give immediate feedback to users through a mobile or web application. The user interface displayed current stress levels, historical trends, and personalized suggestions for managing stress, like guided breathing exercises or relaxation techniques. The system was also tested for battery efficiency, wireless data transmission stability, and its ability to keep monitoring continuously over long periods. The results showed that the system performed reliably across varied conditions without major interruptions or data loss. The evaluation also looked at stress detection consistency among different individuals, ensuring that the machine learning models worked well with different physiological responses.

Continued model training and expanding the dataset further enhanced predictive performance, resulting in a reliable system that could adapt to individual differences in stress reaction. Overall, the evaluation of the success rate and performance demonstrates that the Stress Detection System Using Sensors offers a high level of accuracy, reliability, and promptness in monitoring stress. The system effectively bridges traditional stress assessment methods and modern tech-driven solutions, providing continuous, objective, and actionable insights into an individual’s stress levels. These findings highlight the system’s potential for practical applications in healthcare, education, workplace stress management, and personal wellness, encouraging early intervention, self-awareness, and healthier lifestyle choices.

Table 1 Evaluation Summary of the Stress Detection System Using Sensors

Parameter	**Description /Result**
Participants & conditions	Tested on users doing stress-inducing tasks, such as public speaking and timed activities, and relaxation activities like meditation and listening to music.
Physiological signals used	Heart Rate Variability (HRV), GSR, temperature, and respiration were measured.
Machine learning models	SVM, Random Forest, and Neural Networks were used for classifying stress levels: low, moderate, and high.
Performance metrics	The accuracy was high, with strong precision, recall, and F1-score.
Success rate	The system provided consistently accurate detection when compared to questionnaires and psychological assessments
Real-time processing	It offered near real-time classification and immediate feedback through microcontroller processing.
System reliability	The transmission was stable, the battery performed well, and there was continuous monitoring without major interruptions.
User interface output	Users could see real-time stress levels, historical trends, and personalized relaxation recommendations.

Model adaptability	Performance improved with an expanded dataset, and it was adaptable to individual physiological differences.

7. Proposed work

The proposed work focuses on developing a Stress Detection System Using Sensors. The goal is to create a real-time, automated, and non-invasive way to monitor stress levels through physiological signals. In today's society, stress is a major health concern that affects people of all ages. It can arise from various factors, including academic pressures, job demands, financial issues, social commitments, and personal responsibilities. Long-term exposure to stress can lead to serious mental and physical health problems, including anxiety, depression, insomnia, heart disease, and a weakened immune system. Traditional stress assessment methods, such as questionnaires, interviews, and self-reporting, often rely on subjective measures and cannot provide continuous monitoring.

This project aims to tackle these issues by using wearable sensors, microcontroller-based data processing, smart analysis through machine learning, and visualization tools to create an effective stress monitoring solution. The main objective is to design a wearable system that continuously captures physiological signals indicating stress responses. The primary sensors used in the system include a heart rate sensor that measures heart rate variability (HRV) as a key stress indicator. It also includes a Galvanic Skin Response (GSR) sensor that detects changes in skin conductivity due to stress-induced sweating. Additionally, a temperature sensor monitors slight changes in body temperature associated with stress, and an optional respiration sensor tracks breathing patterns since stress often affects breathing rate and rhythm. These sensors are compact, lightweight, and non-intrusive, allowing users to wear them comfortably during their daily activities while continuously collecting physiological data. The sensor data is sent to a microcontroller, such as Arduino or ESP32, for real-time processing. The raw data goes through preprocessing, which includes filtering, normalization, and noise reduction to ensure reliability.

After preprocessing, feature extraction identifies key parameters such as HRV metrics, skin conductance peaks, temperature changes, and respiration rates. These features provide quantitative measures of the body's physiological response to stress. In the next stage, machine learning algorithms classify stress levels into categories like low, moderate, and high. Supervised learning models, including Support Vector Machines (SVM), Random Forests, and Neural Networks, are trained on labeled datasets to discover patterns in physiological features. The trained models analyze incoming data in real time, enabling immediate stress detection. Results are sent via Bluetooth or Wi-Fi to a mobile or web application, where users can check their current stress levels, view historical trends, and get personalized suggestions for stress management, such as mindfulness exercises, relaxation techniques, or breathing practices.

The project also includes system testing and validation under controlled scenarios that induce stress, such as public speaking, time-limited problem-solving tasks, or mental arithmetic exercises. Sensor readings and predicted stress levels are compared against established psychological assessments to ensure reliability. Furthermore, the machine learning models are continuously improved using larger and more diverse datasets to enhance classification performance. This proposed work has many applications in healthcare, workplaces, educational institutions, and personal wellness. In healthcare, it can monitor patients with stress-related disorders. In workplaces, it can assist employees in managing stress and boosting productivity. In education, it can support students facing academic challenges. As a personal wellness tool, it promotes mental well-being and emotional balance. By combining sensor technology, real-time data processing, machine learning, and interactive visualization, this project offers a strong, technology-driven approach for continuous stress monitoring, early intervention, and proactive mental health management.

8. Probable outcomes

Developing a Stress Detection System Using Sensors aims to provide valuable outcomes that will improve healthcare and wellness management. One of the main goals of the system is to detect, classify, and track stress levels in real-time based on physiological metrics like heart rate, body temperature, and Galvanic Skin Response (GSR). By examining these metrics, users can better understand their mental state, breaking it down into three levels of stress: low, moderate, and high. Creating a user-friendly, noninvasive stress monitor will help users manage their stress in daily life. They will have an easy-to-use, portable device that they can wear or carry. This system will offer continuous access to accurate stress level measurements without interrupting the user's routine. It will also deliver more reliable data than traditional self-reporting methods, eliminating potential errors and biases from personal reporting of stress levels. This enhances the reliability and effectiveness of the system in tracking and managing stress.

Medical professionals will benefit from this stress monitoring system by receiving ongoing, objective data about their patients' stress levels and how these levels affect overall health. Continued data collection from the monitoring device can lead to a better understanding of the connection between stress and health, facilitating more accurate diagnoses and personalized treatment plans. Health care providers will have access to this data through mobile and web applications, allowing remote access for both users and their providers. Awareness of mental health issues will likely increase with the development of this stress monitoring system. The visualization of stress data collected by the device will give users a clear picture of their stress levels, potentially motivating them to take steps to reduce their stress. These steps could include relaxation techniques, exercise, or seeking professional help. Greater use of preventive measures for managing stress can lead to a healthier lifestyle and lower the chances of serious physical or mental health issues linked to chronic stress. This innovative technology will enhance people's lives. It will offer a better way to manage stress in an affordable and convenient manner, as well as pave the way for future improvements in smart medical devices and wearables, benefiting many through this technology.

9. Implications

The Stress Detection System Using Sensors has significant impacts across various fields, particularly in healthcare, education, workplaces, and personal wellness management. Stress is a major cause of many mental and physical disorders. Having a real-time, technology-based solution can change how we identify and address stress. This system provides an objective way to assess stress levels, reducing reliance on personal self-assessments and improving the accuracy of early detection. It allows for continuous monitoring of patients at risk of stress-related conditions like anxiety, hypertension, and heart issues, overseen by medical professionals. The system can enable timely medical interventions through continuous data collection and long-term monitoring of bodily responses. It can also integrate with telemedicine platforms for remote monitoring, easing pressure on healthcare facilities. In workplaces, this system can serve as a wellness monitoring tool. Organizations can spot employee stress trends and work on creating a better work environment, distributing tasks more efficiently, and enhancing mental health support. This may lead to higher productivity, less absenteeism, and a healthier workplace culture. Similarly, the system can help identify students facing excessive academic pressure in schools. Teachers and counselors can recognize early signs of stress and provide guidance, counseling, or stress management programs, helping to prevent burnout and improve academic performance. On a personal level, the system allows individuals to better understand their emotional and physical reactions to situations. With real-time feedback and data visualization, users can apply techniques like meditation, exercise, or time management to lower stress levels. Additionally, the system boosts self-awareness and proactive healthcare, which can lower long-term medical costs and enhance quality of life. Overall, this project highlights the real-world benefits of merging smart sensors, IoT, and machine learning in mental health monitoring. This approach will lead to further advancements in wearable healthcare technologies and contribute significantly to developing intelligent, user-friendly health monitoring systems.

10. Conclusion

The Stress Detection System Using Sensors offers a reliable way to monitor and identify human stress levels by analyzing signals such as heart rate, skin conductance, and body temperature. By combining wearable sensors with data processing and machine learning, the system can detect stress in real-time and with greater accuracy than traditional methods that rely on self-reporting. This technology provides a non-intrusive and continuous way to assess a person’s mental and emotional state in daily life. Implementing this system shows how modern sensing technologies and smart algorithms can be used in healthcare, workplaces, and personal wellness monitoring. It can help people identify their stress patterns and prompt timely actions to prevent serious health issues such as anxiety, depression, and heart disease. Overall, the project highlights the importance of proactive stress management and sets the stage for future improvements in mental health monitoring. With further upgrades like cloud connectivity, mobile app support, and improved AI analysis, the system can expand to larger uses, including smart healthcare, corporate wellness programs, and remote patient monitoring. This project marks a significant step toward enhancing individual well-being and overall quality of life through technology.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] M. Abd Al-Alim, “A machine-learning approach for stress detection using wearable sensors in free-living environments,” Computers in Biology and Medicine, vol. 170, 2024.

[2] G. Ghaderi, M. Heldt, and K. H. Plötz, “Detection and monitoring of stress using wearables: A systematic review,” Frontiers in Computer Science, vol. 6, 2024.

[3] D. S. Bhatia and S. Goel, “An explainable deep learning approach for stress detection in physiological sensor data,” Sensors, vol. 24, no. 16, pp. 1–20, 2024.

[4] M. Bolpagni, S. Pardini, M. Dianti, and S. Gabrielli, “Personalized stress detection using biosignals from wearables: A scoping review,” Sensors, vol. 24, no. 10, 2024.

[5] R. A. Kankal et al., “Stress monitoring using machine learning, IoT and wearable sensors,” Sensors, vol. 23, no. 21, 2023.

[6] S. R. Mohammed and A. G. Hassan, “Stress monitoring using wearable sensors: IoT techniques and physiological signal analysis,” Soft Computing, vol. 27, pp. 1–15, 2023.

[7] A. Jha and P. Singh, “Stress detection system using machine learning and wearable sensors,” International Journal of Advanced Research in Innovative Technology, vol. 11, no. 1, pp. 1–7, 2021.

[8] A. Rehman and M. H. Khan, “Feature-augmented hybrid CNN for stress recognition using a wrist-based photoplethysmography sensor,” arXiv preprint arXiv:2108.03166, 2021.

[9] M. Wataru and L. Rossi, “SELF-CARE: Selective fusion with context-aware low-power edge computing for stress detection,” arXiv preprint arXiv:2205.03974, 2022.

[10] T. C. Nkomo and V. K. Potdar, “Stress detection using context-aware sensor fusion from wearable devices,” arXiv preprint arXiv:2303.08215, 2023.

[11] Y. Wang et al., “TEANet: A transpose-enhanced autoencoder network for wearable stress monitoring,” arXiv preprint arXiv:2503.12657, 2025.

[12] R. S. Nair and J. Mathew, “Stress detection through wearable sensors: A CNN-based approach using heart rate and step data,” International Journal of Machine Learning Research, vol. 55, 2025.

[13] P. Sharma and A. Tiwari, “Real-time stress monitoring, detection, and management in college students: A wearable technology and machine-learning approach,” Journal of Biomedical Informatics Research, vol. 13, pp. 1–12, 2025.

[14] A. Patel and S. Gupta, “Predicting stress levels using physiological data: A real-time stress prediction review,” Journal of Medical Informatics, vol. 45, 2024.

[15] H. Liu et al., “A multimodal stress detection dataset with facial expressions and wearable sensor data,” Scientific Data, vol. 12, 2025.

[16] M. H. Khezri and M. Nazari, “Stress level monitoring system using IoT and machine learning,” International Journal of Advanced Computer Science and Applications, vol. 11, no. 5, pp. 214–219, 2020.

[17] R. Salabun, “Heart rate variability and stress monitoring in smart wearable systems,” IEEE Access, vol. 8, pp. 79550–79560, 2020.

[18] N. K. Jain and M. Bansal, “IoT based real-time stress monitoring system using biomedical sensors,” International Conference on Smart Systems and Inventive Technology, pp. 624–628, 2019.

[19] T. Singh and V. K. Verma, “A machine learning approach for real-time human stress detection,” IEEE International Conference on Advanced Networks and Telecommunications Systems, pp. 45–50, 2021.

[20] P. Schmidt et al., “Wearable-based stress detection using multimodal sensor data,” IEEE Internet of Things Journal, vol. 7, no. 6, pp. 4999–5008, 2020.