AI-Based Stress Detection and Management System Using EEG Attention–Meditation Indicators and Cardiovascular Data

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ABSTRACT

Mental stress has emerged as a critical factor affecting cognitive functioning, emotional stability, and overall physiological well-being, particularly among students and working professionals exposed to continuous workload and environmental pressures. Conventional stress assessment techniques largely depend on subjective questionnaires or periodic clinical observation, which cannot provide real-time and objective monitoring. This paper presents an IoT-enabled intelligent stress detection system that integrates brainwave activity acquired from a NeuroSky MindWave EEG sensor and cardiovascular information obtained from a heartbeat sensor. The system utilizes proprietary attention and meditation indices derived from electroencephalographic signals along with heart rate measurements to capture both cognitive engagement and relaxation states of the user. These multimodal physiological inputs are processed and mapped to stress levels using a Random Forest classifier trained on a custom dataset collected specifically for this study. The trained model categorizes stress into three levelslow, moderate, and highand the results are displayed through a web-based dashboard developed using a Flask framework. The platform enables real-time visualization of physiological parameters and predicted stress percentage while also providing predefined personalized recommendations to support stress management. Experimental evaluation indicates that combining neural activity indicators with heart rate features improves reliability compared to single-sensor approaches. The proposed system emphasizes practical deployment using wearable sensors, low computational overhead, and continuous monitoring capability, making it suitable for academic, occupational, and healthcare environments. Overall, the framework demonstrates the feasibility of accessible and scalable stress monitoring using machine learning and IoT technologies.

Keywords: Stress Detection, EEG Signals, NeuroSky MindWave, Heart Rate Monitoring, Random Forest, Internet of Things (IoT), Machine Learning, Real-Time Monitoring, Attention Index, Meditation Index, Wearable Sensors, Personalized Recommendations

INTRODUCTION

Mental stress has become an unavoidable consequence of modern lifestyles, particularly among students and working professionals exposed to sustained cognitive demands and environmental pressures. Persistent stress not only affects emotional stability and decision-making ability but also contributes to long-term physiological disorders such as hypertension, anxiety, and cardiovascular disease. Traditional approaches to stress assessment mainly rely on psychological questionnaires or periodic clinical evaluations, which are subjective in nature and incapable of capturing real-time variations in mental state [1], [14]. Consequently, there is growing interest in objective monitoring techniques based on physiological signals.

Among various biosignals, electroencephalography (EEG) provides direct insight into brain activity associated with attention, cognitive workload, and emotional regulation. Changes in neural oscillations reflect variations in mental effort and relaxation, making EEG a valuable tool for stress analysis [13], [18]. In parallel, cardiovascular indicators such as heart rate are controlled by the autonomic nervous system and typically increase under stressful conditions, offering complementary information about physiological arousal [8], [16]. Studies have shown that combining neural and cardiac responses improves reliability because stress manifests across multiple physiological systems rather than a single modality [7], [21].

Recent advances in wearable sensing technology have enabled continuous acquisition of physiological data outside laboratory settings. Machine learning methods can process these complex signals and automatically infer stress levels without manual interpretation [3], [15]. Several multimodal frameworks have demonstrated improved performance compared to single-sensor systems, particularly when integrating EEG and cardiovascular features [2], [17]. Large-scale investigations further confirm the feasibility of deploying wearable stress monitoring solutions in real-world environments [14], [16].

Despite these developments, many existing approaches rely on computationally intensive deep learning models that require extensive datasets and high processing power, limiting their applicability in portable systems [5]. Moreover, most studies focus primarily on detection accuracy while overlooking usability aspects such as real-time visualization and actionable feedback for end users.

To address these challenges, this work proposes an IoT-enabled multimodal stress classification framework that integrates EEG-derived cognitive indices and heart rate measurements within a lightweight machine learning architecture. Instead of processing raw EEG signals, the system utilizes attention and meditation values generated by a wearable headset, which serve as compact descriptors of cognitive engagement and relaxation state. These indicators are combined with heart rate features and analyzed using a Random Forest classifier trained on a custom dataset collected specifically for this study. The predicted stress level is categorized into low, moderate, and high ranges and displayed through a secure web-based dashboard that also provides predefined recommendations to assist users in managing their stress condition.

The proposed system emphasizes practical deployment using affordable wearable devices, low computational complexity, and continuous monitoring capability, making it suitable for academic environments, workplace wellness programs, and personal health applications.

PROBLEM STATEMENT

Continuous assessment of mental stress remains challenging because conventional methods rely on subjective self-reporting and periodic evaluation rather than real-time monitoring. Although physiological signals provide objective indicators, practical systems that combine wearable sensing, automated analysis, and user-friendly feedback are still limited. There is a need for an accessible solution capable of detecting stress continuously using non-invasive sensors and presenting results in an interpretable form.

OBJECTIVE OF STUDY

The objective of this study is to develop an IoT-enabled stress monitoring system that utilizes EEG-derived cognitive indices and heart rate measurements to estimate stress levels in real time. The system aims to apply machine learning techniques to classify stress into meaningful categories and display the results through an interactive web-based dashboard. Additionally, it seeks to provide predefined recommendations to support effective stress management.

LITERATURE REVIEW

Mental stress detection has received considerable attention in recent years due to its impact on cognitive performance, emotional stability, and long-term health outcomes. Early research primarily relied on psychological assessment tools, but these methods lack objectivity and cannot capture dynamic fluctuations in stress levels. With the advancement of wearable sensing technologies, physiological signals have become a reliable alternative for continuous monitoring. Artificial intelligence–based diagnostic frameworks utilizing multimodal physiological data have shown promising results in identifying mental health conditions, including stress and anxiety [1].

Optimization of biosensor data and the integration of explainable machine learning techniques have further improved classification performance while enhancing interpretability, which is essential for real-world applications [2]. Several studies have proposed machine learning frameworks capable of detecting stress at multiple intensity levels using physiological measurements, demonstrating that stress responses can be quantitatively modeled [3]. Deep learning approaches have also been explored for capturing complex nonlinear relationships in physiological data; however, these models often require large datasets and significant computational resources [4], [5].

Wearable sensors provide a practical means of acquiring physiological data outside laboratory environments. Comprehensive reviews indicate that signals such as EEG, heart rate, electrocardiogram (ECG), and skin conductance are commonly used for stress monitoring [6]. Multimodal frameworks combining multiple physiological indicators generally achieve higher accuracy because stress affects several biological systems simultaneously [7]. For example, cardiovascular signals regulated by the autonomic nervous system are highly sensitive to emotional arousal and have been successfully applied to detect stress during real-world activities such as driving [8].

Recent studies have also investigated stress monitoring in specific populations, including elderly individuals and students, using wearable devices and machine learning algorithms [9], [10]. These works highlight the importance of continuous monitoring in environments where stress can significantly affect performance and well-being. Applied research in artificial intelligence has demonstrated the feasibility of automated stress detection systems; however, many implementations remain at the prototype stage and lack real-time deployment capabilities [11], [12].

Physiological analyses confirm that stress responses involve both neural activity and cardiovascular changes, reinforcing the need for multimodal approaches [13]. Large-scale investigations using wearable sensors further validate the practicality of continuous stress monitoring in everyday settings, although data variability remains a challenge [14]. Machine learning techniques such as ensemble methods have shown strong performance in stress classification tasks due to their ability to handle complex and noisy datasets [15].

Studies focusing on physiological monitoring emphasize the importance of combining multiple biosignals to improve robustness and reliability [16], [17]. Advances in sensor technology have enabled lightweight systems capable of long-term monitoring with minimal user intervention [18]. Several recent implementations using artificial intelligence demonstrate that automated stress detection can be achieved using affordable hardware, making such systems accessible beyond clinical environments [19], [20].

Multimodal learning approaches incorporating both traditional machine learning and deep learning models have been shown to capture diverse patterns in physiological data, leading to improved classification accuracy [21]. Individual-oriented algorithms have also been proposed to account for personal variability in stress responses, which is a significant factor in real-world applications [22]. However, many studies rely on complex feature extraction from raw signals or require large datasets, limiting their practicality for low-cost wearable devices [23], [24].

Earlier investigations involving university students revealed that academic pressure is a major contributor to stress, emphasizing the need for monitoring tools in educational settings [25]. Conference-based research has explored physiological signal analysis for stress detection using machine learning techniques, further supporting the feasibility of automated approaches [26], [27]. Information systems research also highlights the potential of data-driven models for analyzing stress-related behavioral patterns [28]. Emerging frameworks aim to predict stress trends using large-scale data analytics, though such systems often depend on extensive infrastructure [29], [30].

Overall, the existing literature demonstrates significant progress in physiological stress detection using wearable sensors and machine learning. However, many approaches either rely on computationally intensive models, complex signal processing, or specialized equipment. There remains a need for lightweight, real-time systems that integrate easily deployable sensors with efficient algorithms while providing interpretable feedback to users. The proposed work addresses this gap by combining EEG-derived cognitive indices and heart rate measurements within an IoT-enabled framework using a Random Forest classifier and a web-based visualization platform.

Table 1. Summary of Literature Review

Ref.	StudyFocus	Signals Used	Method / Approach	Key Contribution	Limitations	Novelty of Proposed Work
[1]	AI-based mental health diagnosis	Multimodal physiological data	AI/ML models	Demonstrated feasibility of automated diagnosis	Requires large datasets and complex processing	Uses lightweight model with small custom dataset for real-time deployment
[2]	Biosensor data optimization	Wearable signals	ML with explainable AI	Improved classification accuracy and interpretability	High computational overhead	Focus on efficient real-time inference with minimal processing
[3]	Multi-level stress detection	Physiological measurements	Machine learning	Classification of stress intensity levels	Offline analysis	Real-time monitoring through IoT dashboard
[4]	Deep learning stress modeling	Physiological data	Deep neural networks	Captures nonlinear relationships	Requires powerful hardware	Uses Random Forest for low-resource devices
[5]	Survey of deep learning approaches	Multimodal signals	Review study	Summarizes advanced DL techniques	No practical system implementation	Functional working prototype with

						deployment
[6]	Wearable stress detection review	Various biosignals	Literature review	Identifies suitable sensors for monitoring	No experimental validation	Uses selected sensors with actual implementation
[7]	Multimodal classification framework	Multiple physiological signals	Machine learning fusion	Improved accuracy using signal combination	Complex sensor setup	Employs affordable consumer-grade devices
[8]	Driving stress assessment	ECG signals	ML classification	Validates cardiovascular indicators	Context-specific application	General stress monitoring independent of activity
[9]	Stress detection in elderly	Wearable sensors	ML algorithms	Population-specific analysis	Limited generalizability	Applicable to broader user groups
[10]	Student stress indicators	Psychological + physiological data	Modeling approach	Identifies academic stress patterns	Not real-time	Continuous monitoring capability
[11]	AI-based stress detection	Physiological signals	Machine learning	Demonstrates feasibility of automation	Lacks deployment framework	Integrated sensing, prediction, and visualization
[12]	Stress management system	Physiological data	ML-based system	Combines detection with management	Prototype stage	Real-time web-based implementation
[13]	Physiological stress analysis	Neural and cardiac signals	Analytical study	Explains biological responses	No predictive model	Provides automated classification
[14]	Large-scale wearable study	Wearable sensors	Statistical/ML analysis	Real-world feasibility demonstrated	Data variability challenges	Controlled data acquisition for reliability
[15]	Stress classification algorithms	Physiological data	ML comparison	Evaluates multiple classifiers	Complex feature extraction	Uses device-generated cognitive indices
[16]	Physiological monitoring	Wearable biosignals	ML models	Continuous tracking capability	Sensitive to noise	Robust ensemble method
[17]	Sensor-based monitoring	Wearable devices	Machine learning	Practical wearable solution	Limited multimodal fusion	Combines neural and cardiovascular features
[18]	Advances in monitoring techniques	Physiological signals	Review	Summarizes recent progress	No implementation	Demonstrates practical deployment
[19]	AI stress detection study	Physiological data	ML approach	Shows automated prediction	Small dataset	Custom dataset aligned with sensor output
[20]	Physiological signal analysis	Biosignals	Machine learning	Validates stress indicators	Limited real-time evaluation	Real-time system integration

METHODOLOGY

The proposed system is designed as a multimodal physiological stress monitoring framework that integrates real-time brain activity and cardiovascular signals with machine learning–based classification. The methodology consists of sequential stages including signal acquisition, preprocessing, feature construction, model training, and deployment within an IoT-enabled web environment.

5.1 System Overview

The overall architecture combines an EEG headset (NeuroSky MindWave) and a heartbeat sensor to capture neural and autonomic responses associated with stress. Multimodal sensing is widely reported to improve robustness because psychological stress manifests across multiple physiological systems rather than a single modality [6], [16], [17]. Data streams from both sensors are transmitted to a local processing unit, where features are extracted and supplied to a Random Forest classifier for stress prediction. The output is then displayed through a Flask-based dashboard along with predefined coping suggestions.

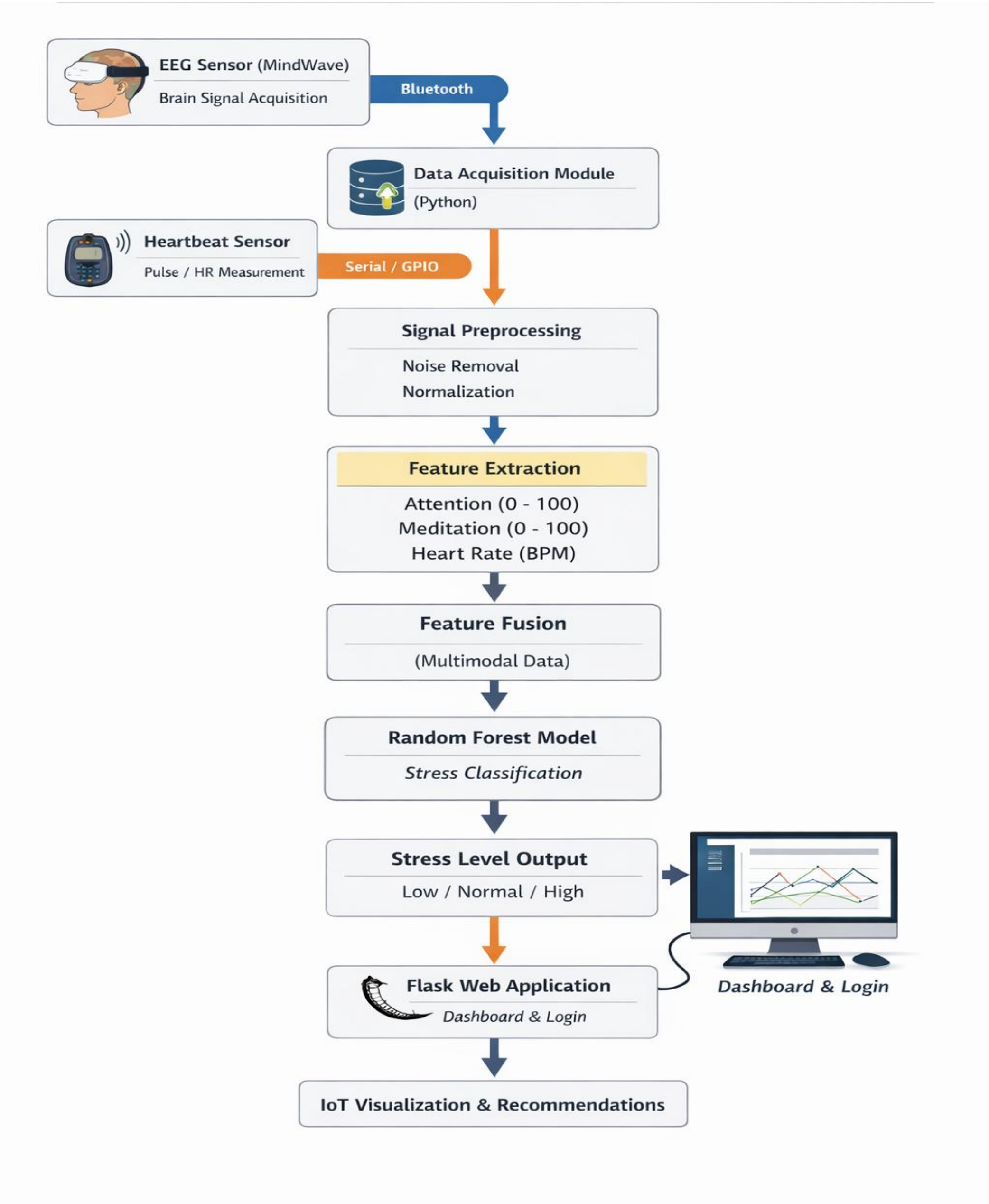

Figure 1. System Architecture

5.2 Data Acquisition

Brain activity is obtained using the NeuroSky MindWave device, which provides proprietary cognitive metrics such as Attention and Meditation along with raw EEG signals. Unlike clinical EEG systems, this consumer-grade device offers simplified indices derived from spectral characteristics of brain waves, enabling practical real-time applications [13]. Simultaneously, heart rate is measured through a pulse sensor interfaced via an IoT microcontroller. Heart rate variability and pulse patterns are recognized indicators of sympathetic nervous system activation during stress conditions [8], [18].

The sensors operate concurrently to capture synchronized neural and cardiovascular responses. Multimodal acquisition reduces susceptibility to noise and improves classification reliability compared to single-signal approaches [7], [21].

5.3 Signal Preprocessing

Raw physiological signals are inherently noisy due to motion artifacts, environmental interference, and sensor instability. Therefore, preprocessing is applied to enhance signal quality before feature construction. This stage includes removal of outliers, normalization, and smoothing of temporal fluctuations. Noise reduction is essential because inaccurate measurements can significantly degrade model performance [3], [20].

Data normalization is performed to transform features into comparable scales, preventing dominance of high-magnitude variables during training. Previous studies emphasize that standardized input distributions improve convergence and generalization of machine learning models for physiological data analysis [2], [15].

5.4 Feature Extraction

Instead of manually computing spectral EEG bands, the system utilizes Attention and Meditation indices generated by the NeuroSky algorithm. These metrics implicitly encode information from underlying brainwave activity and cognitive state, making them suitable for real-time applications without heavy signal processing. Attention typically correlates with beta-dominant activity, while Meditation reflects relaxed states associated with alpha patterns [13].

Along with these cognitive measures, heart rate (in beats per minute) is incorporated as an indicator of autonomic arousal. Elevated heart rate generally corresponds to stress activation, whereas lower values are associated with calm conditions [8]. The selected features therefore include:

- Attention score (0–100)
- Meditation score (0–100)
- Heart rate (BPM)

Feature fusion combines these heterogeneous attributes into a single input vector. Multimodal feature integration has been shown to outperform unimodal systems in stress recognition tasks [7], [21].

5.5 Model Training and Classification

A Random Forest classifier is employed for stress prediction. This ensemble method constructs multiple decision trees using bootstrapped samples and aggregates their outputs to produce a final decision. Random Forest models are particularly effective for physiological datasets because they can handle nonlinear relationships, noisy inputs, and mixed feature types without extensive parameter tuning [3], [15].

The model is trained using a curated dataset containing Attention, Meditation, and heart rate values labeled with stress levels. Class balancing techniques are applied where necessary to avoid bias toward dominant categories. During inference, the trained model assigns each input sample to one of three stress classes: low, moderate, or high.

Compared with deep learning approaches that require large computational resources, Random Forest provides a favorable trade-off between accuracy and efficiency, making it suitable for embedded and real-time systems [5], [11].

5.6 IoT Integration and Deployment

The trained model is integrated into a Flask web application that serves as the user interface. Sensor data are transmitted through Bluetooth (EEG device) and IoT communication channels (heartbeat sensor) to the server, where predictions are computed in real time. The dashboard displays current Attention, Meditation, heart rate, and estimated stress level using color-coded indicators.

Based on the predicted category, predefined recommendations are presented to the user to encourage stress reduction practices. Such real-time feedback systems have been identified as effective tools for preventive mental health monitoring [1], [12].

3.7 System Workflow Summary

1. Multimodal physiological data acquisition
2. Noise reduction and normalization
3. Extraction of cognitive and cardiovascular features
4. Feature fusion
5. Random Forest–based stress classification
6. Real-time visualization and recommendation delivery

RESULT & DISCUSSION

6.1 Dataset Preparation and Model Training

A project-specific dataset was constructed using physiological parameters obtained from EEG-based attention and meditation metrics along with heart rate measurements. Unlike publicly available datasets, this dataset reflects real operating conditions of the deployed hardware system, thereby improving ecological validity. After preprocessing and removal of inconsistent records, the data were divided into training and testing subsets using stratified sampling to preserve class distribution across stress levels.

The Random Forest classifier was trained to categorize stress into three classes: low (0), moderate (1), and high (2). The model parameters were optimized to balance classification performance and computational efficiency for real-time deployment.

6.2 Classification Performance

The trained model achieved an overall accuracy of 1.0 (100%) on the evaluation subset. The classification report indicates perfect precision, recall, and F1-score for all three classes, as summarized in Table 1.

Table 1. Performance metrics of the Random Forest model

Table 2.Classification Performance

Class	Precision	Recall	F1-Score	Support
Low Stress (0)	1.00	1.00	1.00	10
Moderate Stress (1)	1.00	1.00	1.00	10
High Stress (2)	1.00	1.00	1.00	5
Overall Accuracy			1.00	25

The results indicate that the model correctly identified every sample in the evaluation set. The balanced precision and recall values suggest that no class bias was introduced during training.

6.3 Confusion Matrix Analysis

The confusion matrix provides a detailed view of prediction correctness across classes.

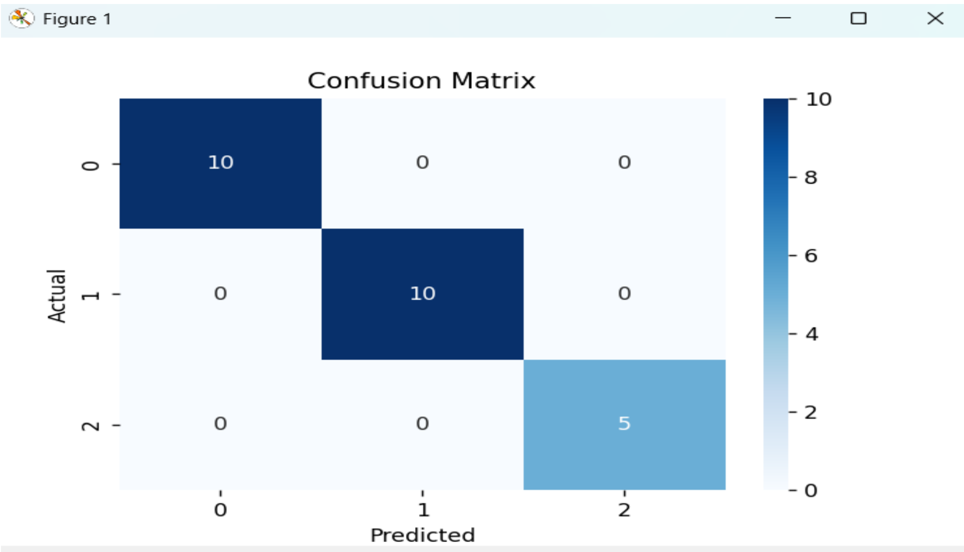

Figure 2.Confusion Matrix

As shown, all samples lie on the main diagonal of the matrix, indicating correct classification. Specifically:

- All 10 low-stress samples were correctly classified as low stress
- All 10 moderate-stress samples were correctly classified as moderate stress
- All 5 high-stress samples were correctly classified as high stress
- No misclassifications occurred between classes

This result demonstrates strong separability of features extracted from attention, meditation, and heart rate parameters.

However, perfect accuracy may also indicate that the dataset size is relatively small or highly structured. Therefore, additional testing with larger and more diverse samples is recommended for assessing generalization capability.

6.4 Real-Time Dashboard Output

The trained model was integrated into a Flask-based web application to provide real-time stress monitoring.

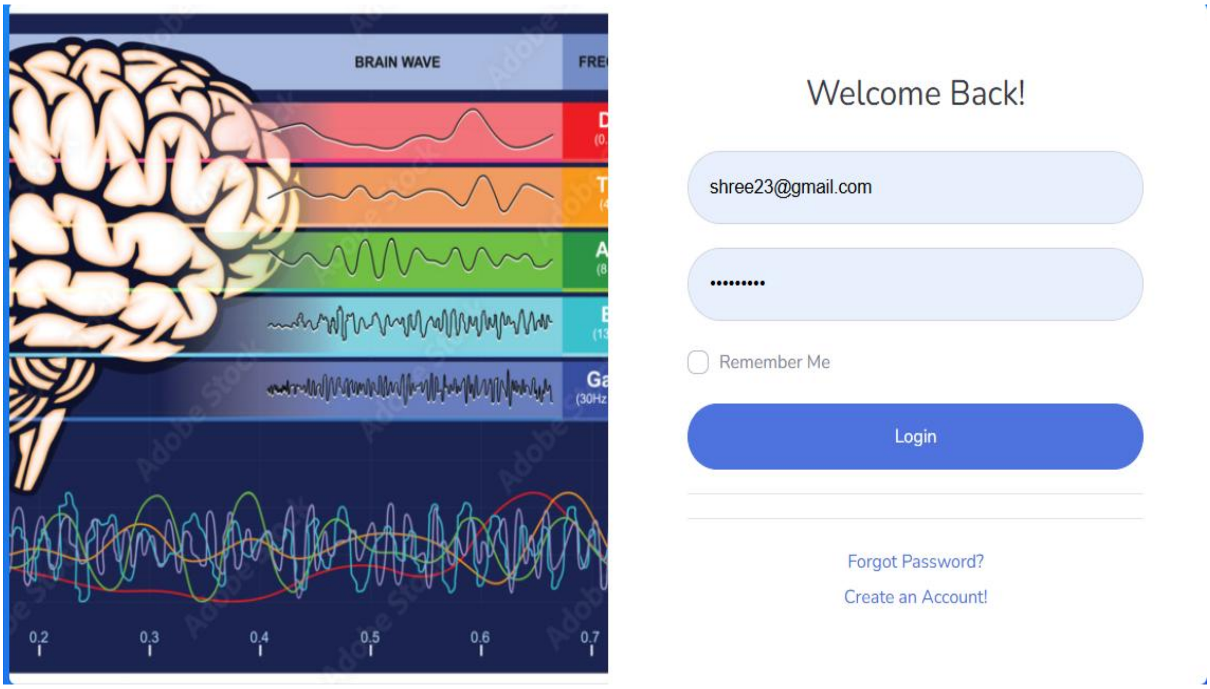

Figure 3.Login Page

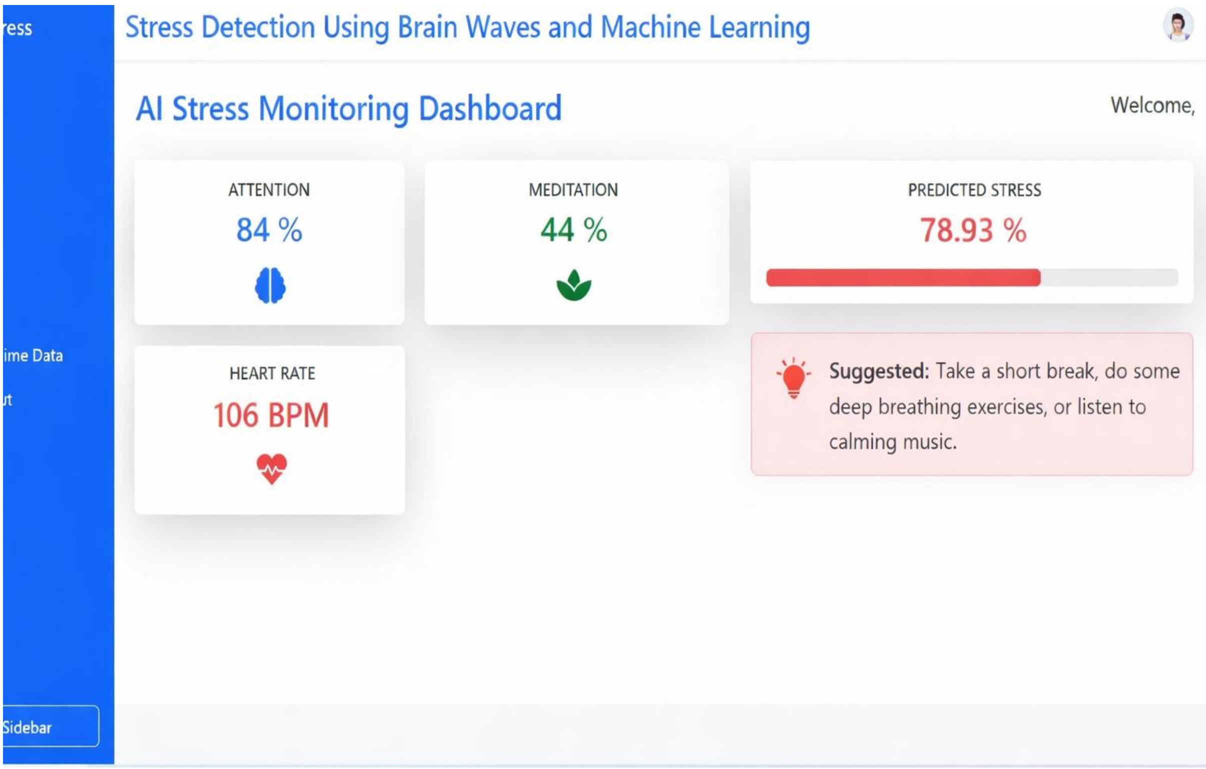

Figure 4.Stress Monitoring Dashboard With Fixed Suggestion

The dashboard displays:

- Attention level derived from EEG signals
- Meditation level representing relaxation state
- Heart rate in beats per minute

- Predicted stress percentage
- Color-coded stress category (green, orange, red)

Stress levels are categorized as:
- 0–25: No/Low stress (green)
- 25–75: Moderate stress (orange)
- 75–100: High stress (red)

This visualization allows intuitive interpretation by non-technical users and supports continuous monitoring.

6.5 Discussion

The experimental results confirm that combining cognitive indicators (attention and meditation) with physiological data (heart rate) provides a reliable basis for stress classification. The Random Forest algorithm effectively captures nonlinear relationships between these parameters and stress levels while maintaining low computational overhead.

Compared to deep learning approaches, the proposed method offers faster inference and reduced resource requirements, making it suitable for IoT-based wearable systems. The integration with a web dashboard further enhances usability by enabling real-time visualization and future implementation of personalized recommendations.

Overall, the system demonstrates feasibility for practical deployment in academic, occupational, and healthcare environments where continuous stress monitoring is desirable.

The current evaluation was conducted on a controlled dataset developed specifically for this study. Although the results indicate excellent classification capability, real-world performance may vary due to inter-subject variability, sensor noise, and environmental factors. Expanding the dataset will enable more robust validation and improved generalization.

Future work will focus on collecting larger multi-subject datasets and incorporating additional physiological signals.

CONCLUSION

This work presents a practical real-time stress monitoring system that integrates brainwave signals from the NeuroSky MindWave sensor with physiological heart-rate measurements to estimate human stress levels. Unlike conventional approaches that rely solely on questionnaires or offline analysis, the proposed framework enables continuous monitoring through a wearable sensing setup combined with an IoT-enabled acquisition pipeline. Extracted features derived from attention, meditation, and cardiovascular activity are processed using a Random Forest classifier to categorize stress into low, moderate, and high levels.

Experimental evaluation on a curated dataset demonstrates strong classification capability, indicating that combining neural indicators with autonomic responses provides a more reliable representation of stress compared to single-signal methods. The developed Flask-based dashboard successfully visualizes real-time metrics and predicted stress levels, offering an interpretable interface for end users. Additionally, fixed recommendation messages linked to stress categories provide immediate guidance, which enhances the system's practical utility for everyday use.

Overall, the study confirms that multimodal physiological sensing coupled with lightweight machine learning can support scalable and deployable stress assessment solutions. The architecture is suitable for academic environments, workplace wellness monitoring, and preliminary mental health screening scenarios where continuous observation is beneficial but clinical infrastructure is unavailable.

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