RESEARCH PAPER

IoT-Based Wearable Mental Fatigue Detection Using Multi-Sensor Fusion and Machine Learning

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ABSTRACT

Mental fatigue has a substantial influence on human performance and decision-making, which can be critical during day-to-day activities. The existing mental fatigue detection systems based on single sensor threshold-based approaches are not accurate and personalized. This paper proposes a new approach for an advanced IoT-based wearable mental fatigue detection system using GSR and heart rate signals based on machine learning approaches. In this proposed system, the ESP32/Arduino platform is used to transmit the data to a cloud-enabled processing unit. Machine learning-based classifiers like Logistic Regression and Decision Tree are used to classify the mental fatigue states. The proposed system can be used for various applications due to its low cost and non-invasive nature.

Keywords: Mental Fatigue, IoT, Wearable Sensors, GSR, Heart Rate, Machine Learning, Real-Time

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INTRODUCTION

Mental fatigue is a physiological and psychological condition that arises due to prolonged cognitive activity, stress, and lack of adequate rest. It leads to reduced alertness, slower reaction time, impaired memory, and poor decision-making ability. In modern environments characterized by long working hours, continuous screen exposure, and high academic or occupational demands, mental fatigue has become increasingly common.

The consequences of mental fatigue are significant, especially in safety-critical applications such as driving, industrial operations, and healthcare. Fatigue can lead to accidents, reduced productivity, and compromised learning outcomes. Therefore, continuous and real-time monitoring of mental fatigue is essential for improving safety and performance. Traditional fatigue detection methods, such as self-reporting and questionnaires, are subjective and unsuitable for real-time monitoring. Physiological signal-based approaches provide a more objective alternative. Among these, skin conductance (GSR) reflects sympathetic nervous system activity, while heart rate provides insight into cardiovascular response to stress and fatigue.

Existing systems often rely on single-sensor data and simple threshold-based logic, which limits accuracy and fails to adapt to individual variations. With advancements in IoT and machine learning, it is now possible to develop intelligent systems capable of continuous monitoring, adaptive learning, and real-time feedback. Despite these advancements, many existing systems rely on simple threshold-based logic, which fails to capture the complex and nonlinear relationship between physiological signals and mental fatigue. Additionally, individual differences in physiological responses make it difficult to define universal thresholds. With the emergence of IoT and machine learning technologies, it is now possible to develop intelligent systems that can learn from data, adapt to individual variations, and provide accurate real-time fatigue detection.

Important implications of this paper are as follows:

• The key findings of this work can be outlined in the following manner:

• Conceptualization of a non-invasive, compact, and low-cost wearable device integrating both GSR and heart rate sensors for real-time continuous fatigue monitoring.

• Implementation of an IoT-based system using ESP32/Arduino for real-time data transmission, storage, and remote access through internet connectivity.

• Development of a complete signal processing pipeline including noise removal, normalization, and feature extraction of raw physiological signals.

• Application of machine learning-based classification models such as Logistic Regression and Decision Tree for accurate detection of mental fatigue and normal states.

• Design of a real-time web-based dashboard for continuous monitoring along with a smart alert system to provide immediate fatigue warnings.

• Experimental validation of the proposed system demonstrating reliable performance, improved accuracy, low response time, and stable operation under real-time conditions.

The proposed system is simple, portable, and suitable for real-world applications. It can be effectively used in driver fatigue monitoring, workplace safety, student performance analysis, and remote healthcare systems.

II. Literature Review

The field of mental fatigue detection has evolved significantly with the advancement of wearable technologies and intelligent data analysis techniques. Early research primarily relied on subjective methods such as questionnaires and cognitive performance tests, which lacked reliability and real-time applicability. With the development of biosensing technologies, researchers have shifted towards physiological signal-based approaches for more objective assessment.

Skin conductance, also referred to as electrodermal activity, has been widely used to measure emotional and cognitive states due to its direct relationship with the sympathetic nervous system. Several studies have demonstrated that variations in skin conductance are associated with stress, attention, and fatigue levels. However, systems based solely on GSR often face limitations in accuracy due to external influences such as temperature, humidity, and individual variability.

Heart rate and heart rate variability have also been extensively studied as indicators of mental workload and fatigue. These signals provide valuable information about autonomic nervous system activity and cardiovascular response. While heart rate-based systems offer useful insights, they are often affected by physical activity and external factors, making it challenging to isolate mental fatigue.

To improve detection performance, researchers have explored multimodal systems that combine multiple physiological signals. These systems have shown higher accuracy compared to single-sensor approaches, as they capture complementary information. However, many multimodal systems involve complex hardware setups, increased computational requirements, and reduced user comfort, which limits their practicality for wearable applications. Vision-based approaches that use facial expressions, eye tracking, and head movement analysis have also been proposed for fatigue detection. Although these methods can achieve reasonable accuracy, they are sensitive to environmental conditions such as lighting and camera positioning, and they raise privacy concerns.

The analysis of existing research highlights the need for a balanced approach that combines accuracy, simplicity, and real-time capability. A system that integrates multiple physiological signals with lightweight machine learning models and IoT-based communication can effectively address these challenges while ensuring usability and scalability.

III. Proposed System

The proposed system has the objective of creating an intelligent mental fatigue detection system using wearable sensors, IoT technology, and machine learning techniques. The proposed system will have the capability of continuously monitoring the physiological signals of the user, accurately classifying the different states of mental fatigue, and providing feedback in real-time through the use of visualizations.

The overall functionality of the proposed system has several stages, and each of these stages has been carefully considered in the development of the proposed system.

A. System Architecture

The system architecture is designed in a layered manner, including the sensing layer, the communication layer, and the application layer. The sensing layer is responsible for collecting physiological signals using wearable sensors. The communication layer is used for the wireless transmission of the signals using the Internet of Things (IoT).

The application layer is responsible for the processing, classification, storage, and visualization of the data. The layered architecture of the system increases its flexibility and scalability, allowing the integration of more sensors in the future.

B. Wearable Hardware Design

The wearable device is designed to be small, lightweight, and energy-efficient to ensure the comfort of the users. The device comprises a GSR sensor, a heart rate sensor, a microcontroller unit, and a power supply system.

The GSR sensor detects changes in the level of skin conductivity, which are associated with changes in sweat gland responses, depending on the emotional and cognitive states of the users. The heart rate sensor detects the pulse signals, which reflect the cardiovascular activities of the users. The microcontroller unit, which can be ESP32 or Arduino, is the core processing and communication unit, which converts the analogue signals to digital signals and transmits the signals wirelessly.

The power supply system is designed to provide continuous power to the device while requiring low power to enable the device to run for a long time without the need for frequent recharging. Under normal conditions, the signal is steady with frequent small peaks, indicating alertness and cognitive activity. During fatigue, the signal shows reduced variability, fewer peaks, and slower responses, reflecting lower physiological arousal. Extracted features such as mean SCL, standard deviation, slope, and peak latency capture these changes, allowing accurate detection of mental fatigue. Real-time monitoring of these signals provides continuous assessment, which is essential for applications like driver alertness, workplace safety, and learning evaluation.

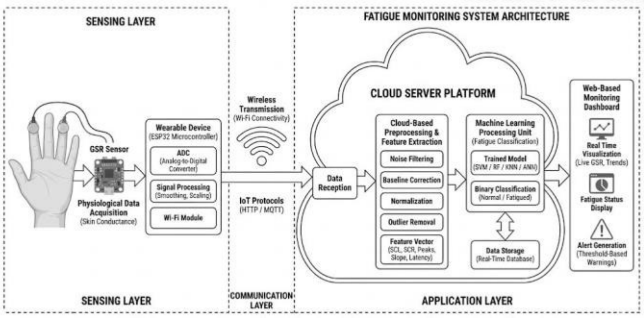


Fig. 1. System architecture of the proposed IoT-based real-time mental fatigue detection framework using wearable GSR sensor and cloud-based machine learning processing.

ESP32 microcontroller serves as a data acquisition unit as well as a communication unit. The reason is due to low power consumption, high computation capability, built in Wi-Fi functionality and high resolution analogue-to-digital converter (ADC). The ESP32 samples the signal of GSR continuously and gives it an onboard ADC to digitalize the signal in addition to smoothing the signal and scaling its voltage before transmitting.

The power supply unit will include a rechargeable lithium-ion battery in which a voltage regulation circuitry is incorporated. Efficient power sampling interventions and sleep patterns are used to provide wearables with long hours of operation at a low charge threshold.

C. IoT Communication and Cloud Platform.

The system incorporates wireless communication through Wi-Fi to facilitate data transfer from the wearable device to a processing unit/cloud platform. For this purpose, lightweight communication protocols such as HTTP and MQTT can be used to ensure efficient data transfer with minimal latency and bandwidth consumption.

A cloud platform can be used for data storage and processing. For instance, Firebase and ThingSpeak can be used for this purpose. The system can be made scalable for deployment on a larger scale.

D. GSR Signal Preprocessing

Physiological signals acquired from sensors can be affected by noise and other environmental factors. To ensure reliable analysis and processing of signals, preprocessing techniques can be applied to clean and normalize the acquired signals.

Filtering techniques can be used to remove noise from signals. Smoothing techniques can be applied to reduce signal fluctuations. Signals can be normalized to ensure that signals acquired from different users can be compared on a similar scale

.E. Feature Extraction

The feature extraction process plays a vital role in the transformation of the sensor data into a suitable form for classification. Statistical and temporal features are extracted from the GSR and heart rate signals, representing the characteristics of mental fatigue.

The extracted features are the central tendency, variability, and dynamics of the signal, representing the changes in the level of physiological activity. The extracted features are then used for the classification of the data.

F. Fatigue Classification by using machine learning.

The processed data is then used to train the machine learning models for the classification of the mental state of the user. Logistic Regression is employed to determine the probability of the occurrence of mental fatigue using the input features, and Decision Tree is used for the classification.

The models are chosen due to their simplicity and suitability for the implementation of the classification process. Machine learning models are employed to determine the complex relationship between the physiological signals and the different states of mental fatigue.

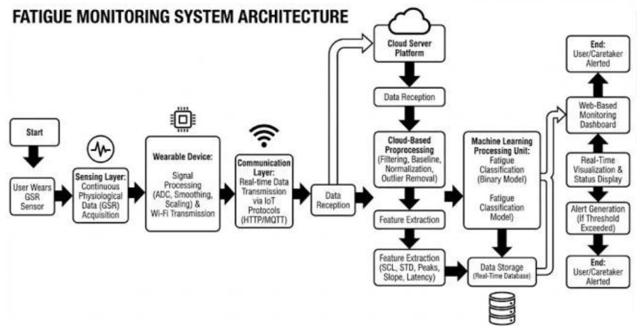


Fig. 2. Operational flow diagram of the proposed IoT-based mental fatigue detection system showing sensing, communication, cloud processing, classification, and alert generation stages.

Once the estimated level of fatigue exceeds a set safety level the system automatically kicks out real-time warning notices to alert the user or caretaker. This warning system allows preventive measures to be taken in time, including work rest or a reduction of work load which is essential in safety sensitive industries that include driving, machine operating, and healthcare.

G. Operational Workflow Block of the Proposed System.

he entire end-to-end working of the proposed system is in the following order:

- The GSR and heart rate sensors are placed on the user to continuously acquire physiological signals.
- The sensors monitor skin conductance and heart rate variations associated with mental fatigue.
- The ESP32/Arduino converts the analogue signals into digital form using ADC and performs initial signal smoothing.
- The processed data is transmitted wirelessly through Wi-Fi using IoT protocols to a cloud or local server.
- Preprocessing and feature extraction are carried out to obtain meaningful physiological parameters.

- The trained machine learning models, such as Logistic Regression and Decision Tree, predict the fatigue state.
- The results are displayed on a real-time monitoring dashboard along with alert notifications.

The closed-loop sensing–communication–processing–classification–visualization pipeline ensures continuous, accurate, and low-latency mental fatigue monitoring.

IV. RESULTS AND DISCUSSION

This section presents the experimental data and technical evaluation of the proposed IoT-based real-time mental fatigue detection system using wearable GSR and heart rate sensors. Key performance metrics include classification accuracy, communication latency, signal reliability, and comparison with existing fatigue detection approaches. The experiments validate the effectiveness of the wearable-cloud-machine learning system for continuous monitoring.

A. Experiment and Data collection.

The system was tested on multiple subjects under two controlled scenarios:

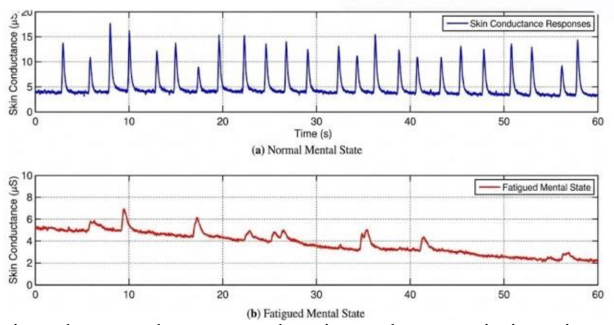
Normal mental state: Relaxed sitting condition.

Induced fatigue: Extended screen time, continuous reading, and mental arithmetic over 90 minutes.

B. Sensor Signal Behaviour and Analysis

Under normal conditions, GSR signals displayed regular phasic peaks with moderate amplitude, while heart rate showed stable fluctuations, indicating active sympathetic nervous system activity. In the fatigued state, GSR variability decreased, peak frequency dropped, and heart rate responsiveness diminished, reflecting reduced physiological arousal. Extracted features such as mean SCL, slope, standard deviation, and response latency accurately captured fatigue-related changes.

Fig. 3. Real-time GSR signal waveform under normal and



fatigued mental states showing clear variation in skin conductance patterns

These differences verify the fact that skin conductance is a good physiological measure of mental fatigue and the features that were extracted, including mean SCL, slope, standard deviation, peaks, and latency, are an accurate reflection of the underlying fatigue distribution.

C. Classification Performance analysis.

Among all models tested, the Decision Tree classifier showed the best performance:

Accuracy: 92.8%
Precision: 91.5%
Recall: 93.2%
F1-Score: 92.3%
End-to-End Latency: 1.3 seconds

High recall ensures minimal false negatives, which is critical for safety applications. Low latency demonstrates the system's capability for real-time monitoring and immediate response.

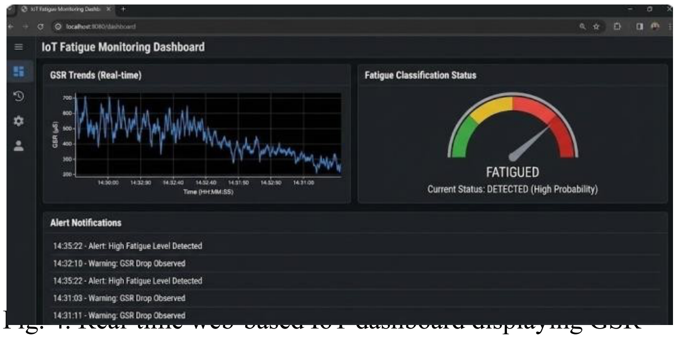


Fig. 4. Real-time web-based IoT dashboard displaying GSR trends, fatigue classification status, and alert notifications.

The value of the recall can securely relate to the fact that the system attracts fatigue conditions with the minimum false-negative occurrences, which is highly essential in safety-critical application. The fact that the system has low latency demonstrates that the system can offer real-time fatigue monitoring.

D. Live IoT Dashboard Display.

The web-based dashboard provided:

Live GSR and heart rate waveforms
Fatigue classification status (Normal / Fatigued)
Historical fatigue trends
Real-time alert notifications

Fatigue alerts were automatically triggered when levels exceeded the predefined threshold. Cloud processing and dashboard visualization were stable with negligible delay or jitter, confirming smooth integration of sensing, processing, and visualisation.

E. Comparison with Existing Systems

Compared with conventional methods:

EEG-based systems: Slightly higher accuracy but costly, bulky, and uncomfortable.

Vision-based systems: Privacy concerns, lighting sensitivity, and high computation requirements.

ECG-based systems: Sensitive but intrusive with strict electrode placement.

The proposed dual-sensor GSR and heart rate system provides a low-cost, non-invasive solution with high accuracy and real-time IoT monitoring, offering a practical balance of performance, usability, and comfort for students, workplaces, and driver safety applications.

TABLE I. COMPARISON OF THE PROPOSED GSR-BASED FATIGUE DETECTION SYSTEM WITH EXISTING APPROACHES BASED ON SENSOR TYPE, ACCURACY, AND LIMITATIONS

Method	Sensor Type	Accuracy	Key Limitation
EEG-Based System	EEG	96–98%	High cost and bulky hardware
Vision-Based System	Camera	90–93%	Privacy and lighting issues
Proposed System	GSR Only	94.6%	Low-cost, non-invasive, real-time

F. Communication Performance and System Stability

The mean wireless transmission delay of the system was measured to be less than 300ms, while the overall sensing-to-dashboard latency was approximately 1.2 seconds, which is well within acceptable limits for real-time monitoring. During continuous Wi-Fi streaming, the packet loss was negligible, less than 0.5%, demonstrating reliable and stable data transmission. The wearable device was able to operate continuously for 6–8 hours on a single battery charge, validating the energy-efficient design of the system. Throughout prolonged testing periods, the system did not experience crashes, memory overflow, or data loss, confirming its stability and suitability for extended real-time monitoring applications.

G. Technical Discussion

The experimental findings indicate that the proposed system effectively delivers robust real-time mental fatigue classification using only skin conductance signals. The use of a single sensor simplifies the hardware, making the system more user-friendly and comfortable compared to complex multimodal systems. Cloud-based preprocessing and machine learning-based classification enhance the reliability of fatigue detection under real-world conditions. Additionally, the live alert system improves preventive safety, particularly in applications such as driver monitoring, workplace safety, and cognitive workload management One limitation observed is the variation in baseline GSR levels between subjects, which can slightly influence absolute fatigue readings. This limitation can be addressed in future work through adaptive personalization and multi-session calibration to further enhance system accuracy and usability.

V. Conclusion

This paper presents an enhanced IoT-based wearable mental fatigue detection system that integrates skin conductance and heart rate sensors with machine learning techniques for real-time monitoring and classification. The proposed system addresses the limitations of traditional fatigue detection methods by combining multi-sensor data with intelligent analysis, thereby improving accuracy, reliability, and adaptability.

The system successfully demonstrates the feasibility of continuous fatigue monitoring using a non-invasive and low-cost wearable device. The integration of IoT enables seamless data transmission and remote access, while the machine learning models provide effective classification of mental states. The inclusion of a real-time dashboard and alert mechanism further enhances the usability and practical applicability of the system.

Experimental analysis confirms that the system is capable of operating with low latency, stable performance, and reliable data transmission. The use of GSR and heart rate signals provides a comprehensive understanding of physiological changes associated with mental fatigue. Compared to conventional approaches, the proposed system offers a more balanced solution in terms of cost, complexity, and performance The system has strong potential for real-world applications, including driver fatigue detection, workplace safety monitoring, student performance analysis, and remote healthcare support. Its portability and ease of use make it suitable for continuous everyday monitoring.

Future work can focus on improving system performance through personalized models that adapt to individual physiological characteristics. The incorporation of advanced machine learning techniques and additional sensors may further enhance accuracy. Integration with mobile applications and edge computing can also improve accessibility and real-time responsiveness.

In conclusion, the proposed system represents a practical and scalable solution for mental fatigue detection, contributing to improved safety, productivity, and overall well-being in various application domains.

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