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IoT-Based Mental Health Monitoring Headband using ECG, PPG, and GSR

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Abstract

At the moment, the world is experiencing an increase in case of mental health disorder such as stress, anxiety and mental exhaustion caused by academic and work-related issues, in addition to lifestyle changes. Conventional mental health state monitoring methods are either subjective and objective nature and involve methods such as assessments. However, with recent innovations in wearable technologies and IoT systems, it has become possible to develop wearable devices that could continuously monitor physiological parameters associated with mental health status.

In this project, we suggested the design and implementation of an IoT-Based Mental Health Monitoring Headband using various sensors such as Electrocardiogram (ECG), Photoplethysmogram (PPG), and Galvanic Skin Response (GSR) to monitor stress levels and mental health states. The proposed system includes an ESP32 Microcontroller to conduct real-time experiments on the extraction of physiological features such as heart rate variability (HRV), pulse characteristics, and electrodermal responses using various machine learning techniques to classify mental states such as relaxed, neutral, and stressed.

The proposed system can be considered cost-effective, non-invasive, and wearable, thus enabling the users to have a comfortable experience while being monitored at the same time. The results from the experimental tests conducted in controlled environments have proved the possibility of the proposed system in the reliable acquisition of signals, as well as the differentiation of stressed and relaxing states. The proposed system proves the possibility of the Internet of Things in the preventive mental health of the user as well as personalized wellness.

Keywords: Mental Health Monitoring; Internet of Things; Wearable Headband; Electrocardiography; Photoplethysmography; Galvanic Skin Response; Stress Detection.

How to Cite This Article

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Introduction

Mental health is an essential part of any individual's overall well-being; it tugs directly at cognitive performance, emotional stability, and physical health. Global health studies suggest that a majority of the population is suffering from stress-related disorders, which can only be clinically diagnosed when they result in acute psychological or physiological conditions. The conventional techniques for mental health assessment are essentially episodic, subjective, and self-reported; hence, these methods are not suitable for continuous monitoring or early detection.

Physiological signals under the control of the Autonomic Nervous System (ANS) often offer objective measures of the user's emotional and stress states. ECG signals represent the electrical activity of the heart under the control of the ANS, PPG offers measures of blood volume changes that are sensitive to the pulse signal from the ANS, whereas GSR signals represent sympathetic nervous system activity based on the electrical properties of the skin. These physiological signals have been well validated in the studies on affective computing and stress management. Today, with the rapid evolution of IoT and embedded systems, it is now feasible to integrate several biosensors with a wearable system. In the current study, the concept of a headband-based IoT-enabled wearable system that incorporates the above three physiological signals is introduced. A headband is preferred over a wrist-based system primarily due to better signal quality.

Methodology

The proposed IoT-Based Mental Health Monitoring Headband is to be implemented as a wearable device that monitors various physiological signals associated with stress levels and uses signal processing techniques to analyze these signals. The methodology used is modular, layered, sequential, accurate, reliable, scalable, and easily integrable.

The system methodology is founded on well-established architectures of wearable health-monitoring devices and affective computing studies, which follow a similar structure to modern biomedical IoT systems. It integrates biosignal acquisition, preprocessing, feature extraction, and classification with IoT communication in one wearable platform. It consists of five major stages in the methodology of the proposed system: Physiological Signal Acquisition, Signal Pre-processing and Noise Reduction, Feature Extraction and Multimodal Fusion, Machine Learning-based Mental State Classification, IoT-based Data Transmission and Visualization. Each stage in the proposed system is designed independently yet maintains a continuous flow of data across the system.

Physiological Signal Acquisition-Physiological signals controlled by the autonomic nervous system are strongly related to mental and emotional status. Thus, stress and anxiety will lead to the sympathetic nervous system being activated, resulting in detectable changes in heart activity, blood flow, and skin conductance. Therefore, three complementing biosignals are selected: ECG, PPG, and GSR.

ECG Signal Acquisition- Electrocardiogram (ECG) is a record of the electrical activity of the heart and provides highly reliable indicators of autonomic balance through heart rate variability analysis. ECG is considered a gold standard for stress analysis because HRV metrics derived from ECG reflect the balance between sympathetic and parasympathetic nervous system activity. Under stress conditions, HRV typically decreases due to increased sympathetic dominance.

AD8232 is a module that amplifies low-amplitude cardiac signals and provides basic analog filtering, making it quite suitable for wearable and low-power applications.

PPG Signal Acquisition- Photoplethysmography signals measure changes in blood volume levels within peripheral tissues by utilizing optical signals. Such signals provide redundancy for electrocardiography, which uses pulses. The forehead PPG signals are best suited for mental health because perfusion signals are better compared to wrist signals. This is because perfusion signals are better compared to wrist signals. This is because signals are more sensitive to changes in pulse.

GSR Signal Acquisition Galvanic Skin Response (GSR) is the measurement of the changes in skin conductivity related to the activity of sweat glands, which are controlled directly by the sympathetic nervous system. GSR is thought to be one of the most sensitive methods to assess emotional arousal and reacts strongly to stress stimuli.

IoT Communication and Visualization- The ESP32 microcontroller sends the processed data wirelessly by:

- Wi-Fi: Cloud-based dashboard tools (
- Bluetooth Low Energy (BLE): Mobile Device Connectivity

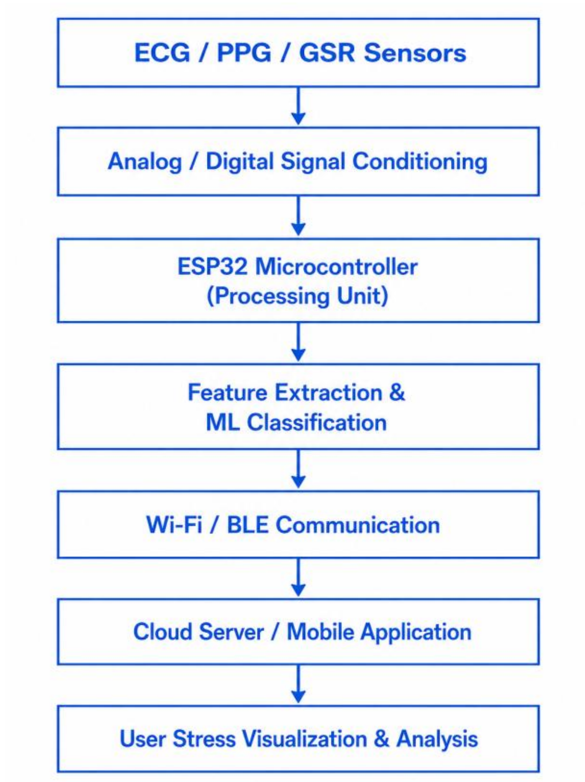
The transmitted data includes physiological features and classified mental states. The visualization process enables real-time monitoring as well as long-term trend analysis.

System Architecture

The architecture includes four main layers of functionality:

- Physiological Signal Acquisition Layer
- Embedded Processing and Feature Extraction Layer
- Machine Learning and Decision Layer
- IoT Communication and User Interface Layer

Each layer has a definite function and operates seamlessly with other layers.



Module 1: Physiological Signal Acquisition Module
The Physiological Signal Acquisition Module is charged with the duty of acquiring physiological data that indicates the mental state of the user. Physiological signals are controlled by the autonomic nervous system (ANS), which instantly reacts to stressful situations.

- EKG Signal Acquisition
- PPG Signal Acquisition
- GSR Signal Acquisition

Module 2: Signal Pre-processing and Conditioning Module
The physiological signals measured and obtained from the sensors usually contain noise and interference from movements, electrode shifts, and even the effects of power line interference. The purpose and function of this module are to enhance the preprocessing and conditioning of the signals.

- Filters such as band-pass and notch filters are used to filter ECG signals followed by the detection of the R-peak
- PPG signal smoothing and peak enhancement are done in identifying pulse cycles.
- GSR signals have low-pass filtering and normalization to minimize intersubject variability.

Module 3: Feature Extraction and Analysis Module:
This module obtains physiological parameters from the pre-processed signals.

- ECG Features: Heart Rate, RR intervals, and HRV-related features like RMSSD,
- PPG: Pulse rate and pulse interval variability.
- GSR Features - Skin conductance level and number of skin conductance responses.

The features collected from all sensors are aggregated to produce a multimodal feature vector representing the user's mental state.

Module 4: Machine Learning Classification Module
These feature vectors are further analyzed with supervised machine learning techniques for classification of mental states.

- Algorithms like Support Vector Machine (SVM) and Random Forest are used.

- The models are trained using benchmark data like WESAD, and cross-validation is used to validate them.
- The mental states produced as output are relaxed, neutral, or stressed states.

Module 5: IoT Communication and Visualization Module:
This could be used to transmit the data and its visualization wirelessly.

- The ESP32 module can send data through Wi-Fi or Bluetooth Low Energy (BLE).
- IoT technologies such as ThingSpeak and Blynk have been employed to represent physiological parameters together with stress indicators.

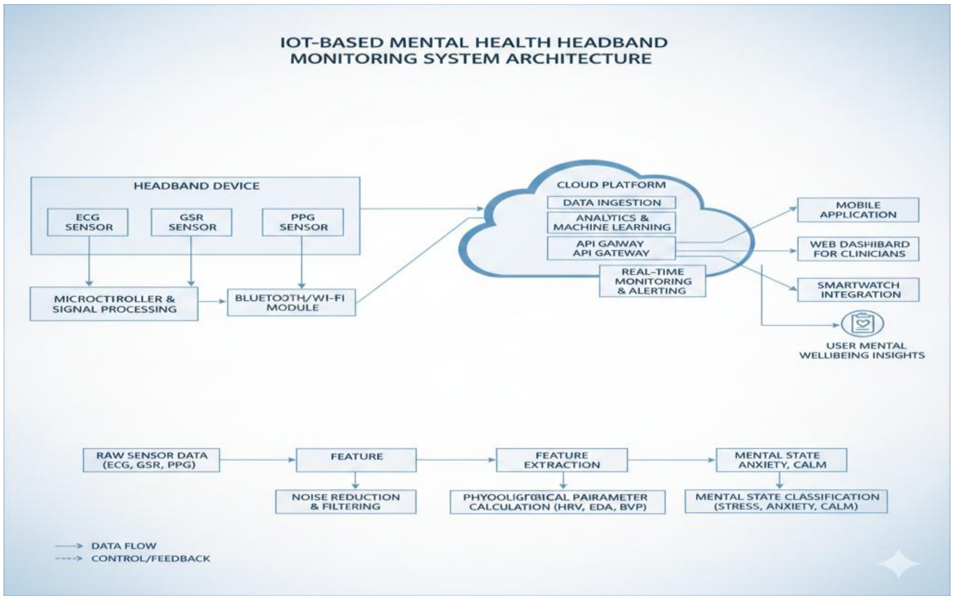


Fig. 1. *IoT-Based Wearable Framework for Stress, Anxiety, and Calm State Detection*

Results and Discussion

Result

- The system successfully obtained ECG, PPG, and GSR signals in real-time using the wearable headband. The ECG sensor recorded clean cardiac waveforms. This allowed the accurate determination of the R-peaks and the computation of the heart rate variability (HRV). As the subjects performed the stressful tasks, a noticeable decrease in the HRV value is registered, which is consistent with the physiological effects of stress.
- The PPG sensor resulted in a stable pulse waveform when attached to the forehead, with reduced motion artifacts as opposed to the wrist. Changes in pulse rates and pulse intervals were detected when the states were either stressed or relaxed. The GSR sensor offered rapid increases in skin conductance during stress states, signifying high sympathetic nervous system activity.
- Machine learning algorithms applied on extracted features showed good classification accuracy of mental states. It was observed that multimodal sensor fusion using ECG + PPG + GSR sensors showed better classification accuracy than using singular sensors. Among all the classification models tested on the extracted features, it was found that Random Forest and SVM models performed better in classification of stressed and relaxed states.

Discussion

- Based on the results achieved, it can be concluded that the combination of ECG, PPG, and GSR signals enables the comprehensive representation of mental and emotional states of a human being. Autonomic features of the ECG-derived HRV signals reflected the state of the autonomic nervous system, cardiovascular properties of PPG signals played the crucial role of providing supplementary information, and GSR signals successfully reflected the state of emotional arousal.
- The choice of headband form factor favored signal stabilization to some extent, especially for PPG and GSR-based measurements, due to the reduced motion-related effects often noticed with the wrist-worn configuration. IoT-based wireless transmission resulted in real-time visualization of measurements collected from physiological parameters and stress levels.
- Despite the reliable performance in controlled conditions, the performance of the system can be affected due to the variability in the quality of the signals caused by the position of the electrodes and the movements of the users. The limitations show the need to effectively position the sensors and the preprocessing techniques. The experimental results prove the feasibility and effectiveness of the proposed system.

Market Insight

Most wearables provide PPG only for stress estimation, but some provide ECG and limited EDA. Headband-worn multimodal ECG+PPG+GSR is relatively rare, making way for the development of an affordable research-grade prototype.

Table 1. *Comparative Analysis of Existing Wearable Mental Health Monitoring Devices and the Proposed IoT-Based Headband System*

Feature	**Smart watches (Apple/ Fitbit)**	**EEG Headband (e.g., Muse)**	**Medical Holter Monitors**	**Your Proposed System (IoT Headband)**
Form Factor	Wrist-worn	Headband	Chest Strap/Patches	Headband
Primary Sensors	PPG, Accelerometer, (ECG in high-end)	EEG (Brainwaves)	ECG (Multi-lead)	ECG + PPG + GSR (Multi-modal)
GSR (Stress) Detection	Rare (Only in specific models like Fitbit Sense)	No	No	Yes (Continuous)
Signal Accuracy	Moderate (Prone to motion artifacts)	High (for Brain), Low (for Heart)	Very High (Clinical)	High (Stable Head Position)
Real-time Remote Monitoring	Limited (Bluetooth range)	No (Local Storage/App)	No (Local Storage)	Yes (IoT/Cloud Based)
Cost	High ($300 - $800)	High ($250+)	Very High	Low (Cost-effective Components)

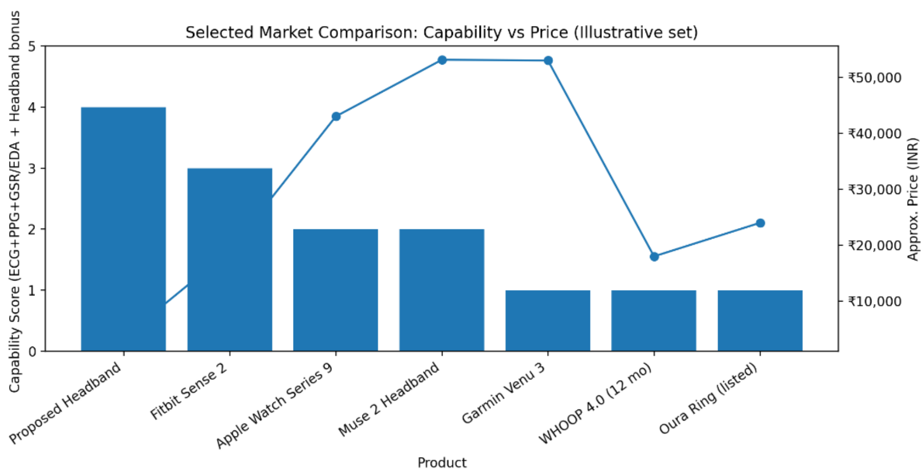


Fig. 2. *Capability Score and Price Distribution of Selected Wearable Physiological Monitoring Devices*

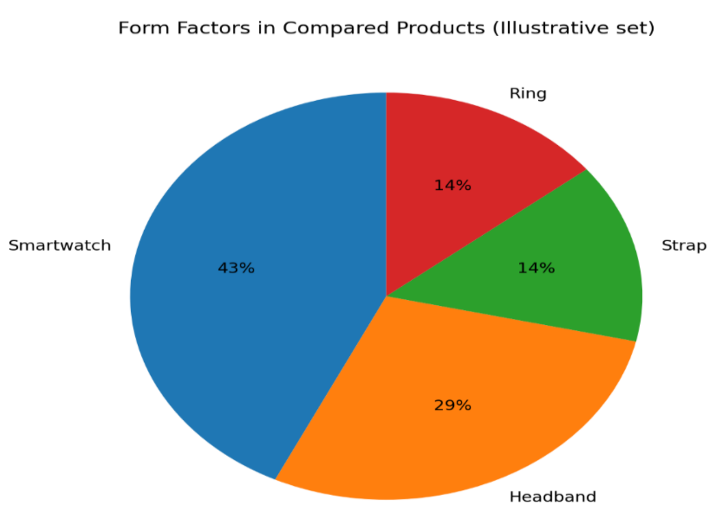


Fig. 3. *Pie Chart Showing Form Factor Distribution in the Selected Wearable Device Market*

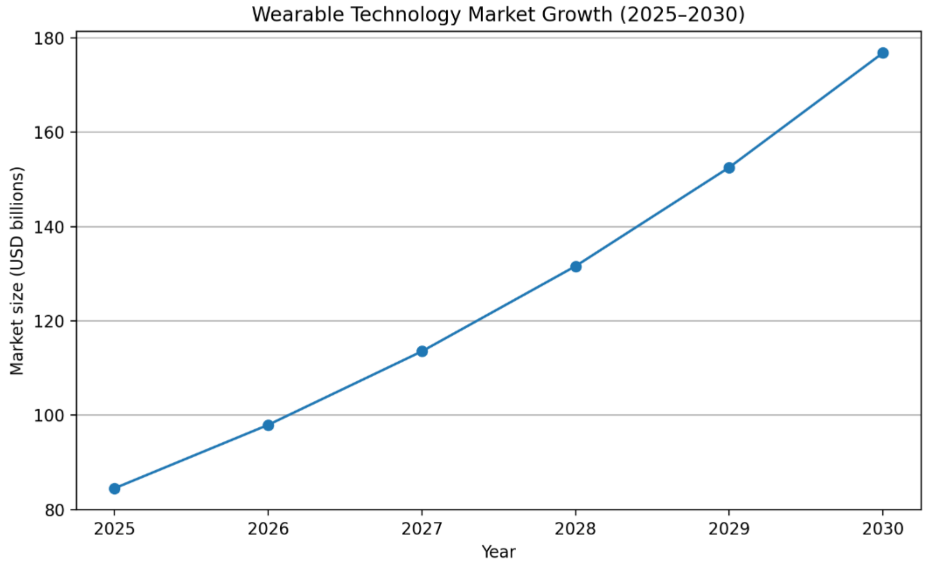


Fig. 4. *Projected Growth of the Global Wearable Technology Market from 2025 to 2030*

Conclusion and Future Work

Conclusion

The launch of IoT technology-based mental health monitoring headbands can thus be regarded as a major move towards making mental well-being proactive and data-driven. In essence, the integration of these ECG, PPG, and GSR devices under a single wearable design has bridged the wide chasm that exists between clinical-grade physiological monitoring systems and consumer electronics. The novelty of the proposed system is its ability to offer an incessant and objective measure of the user's stress levels. It achieves this by breaking away from traditional self-reporting methods. The entire system has proven that it is possible to obtain accurate biossignals using low-cost devices without compromising the integrity of the end results while transferring the data to the cloud. It shows the practical viability of using IoT technology in the field of health technology. The end goal of the proposed system is that it is a preventative approach, allowing the user to understand their system better. It gives users the chance to get inside their minds. By identifying the physiological causes of stress, it becomes a potential solution to the problems being experienced today with mental health. It shows how the proposed system has the potential to treat mental health problems in today's world.

Future Work

Although this current version provides a strong basis, there are some facets which could be improved upon to make the precision of the device better. A major aspect that needs to be considered in the next version of such a device is the addition of EEG sensors. The addition of these sensors will provide the device with the ability to detect all levels of cognitive concentration in addition to physical stress levels. The move towards the implementation of Deep Learning-based emotion detection models, such as CNN or LSTMs, will help the device detect various emotions such as frustration, fatigue, or excitement.

In addition, the architectural side shows great room for the integration of Federated Learning, in which the machine learning models can be trained across various devices locally, ensuring that the sensitive nature of the biometric data is not revealed outside the headband of the user, thus providing a framework of "privacy by design." Also, the addition of a mobile app, which provides a personalized feedback loop, enabling the user to receive mindfulness exercises or breathing prompts in real time in relation to the physiological state, will surely revolutionize the headband from a mere monitoring tool to an intelligent mental health companion. The long-term real-world deployment, which tests the longevity of the headband along with the clinical relevance of the data, will be essential.

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