

IoT-Enabled Smart Cap for Real-Time Stress Monitoring

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Abstract—Stress is a physiological and psychological response that can affect the well-being and daily functioning of an individual. In this study, we propose an IoT-enabled smart cap for real-time stress monitoring using multiple physiological signals. The system uses electroencephalography (EEG), electrocardiography (ECG), galvanic skin response (GSR), and pulse measurements to monitor physiological changes associated with varying levels of stress. The sensor data is captured and communicated to the Blynk Cloud platform using a Raspberry Pi 3 Model B. The acquired data is processed by a Node.js backend and also allows real-time display using a web-based dashboard. The physiological measurements are combined with a rule-based stress classification method. Stress is classified as mild, moderate, and severe. Depending on the detected stress level, the system provides appropriate relaxation and intervention suggestions through the monitoring interface. The proposed architecture demonstrates the feasibility of integrating multimodal physiological sensing with IoT-based monitoring in a wearable form factor. The system is intended to provide continuous, accessible, and real-time stress monitoring while supporting personalized intervention. Further validation using larger datasets, diverse participants, and data-driven machine learning or deep learning models is required to establish the accuracy, generalizability, and clinical applicability of the proposed system.

Keywords—Stress monitoring; EEG; ECG; GSR; IoT; Blynk cloud platform; mental health management; real-time monitoring; personalized recommendations

I. INTRODUCTION

Stress has become an important concern because it can influence both psychological well-being and physical functioning. When stress persists for a long period, it may interfere with daily activities, concentration, and overall health. Stress is commonly assessed through questionnaires, psychological screening, and clinical evaluations [13], [14]. These methods can help determine how an individual experiences stress, but they are generally performed at particular points in time. As a result, changes in physiological responses between assessments may not be captured. Wearable monitoring provides an alternative approach by allowing physiological changes to be observed continuously and by making real-time measurements possible [14], [15].

Conventional approaches to stress assessment and management also have practical limitations when information about changing physiological conditions is required. Psychological assessments depend partly on an individual's responses, while clinical evaluations may not always be

immediately accessible. These limitations create a need for systems that can observe physiological changes and present the information without requiring repeated assessments [14]. IoT technology can support such systems by connecting sensors, computing hardware, cloud services, and monitoring interfaces. Through this type of arrangement, physiological measurements can be collected and transmitted for observation while the individual is being monitored [8].

Wearable physiological monitoring has received considerable attention in stress-related applications [14], [15]. Different sensors can capture different aspects of the body's response. EEG records electrical activity associated with brain function, whereas ECG records the electrical activity of the heart. GSR measures changes in skin conductance, and pulse sensing provides information related to cardiovascular activity. Using these measurements together can provide information from several physiological sources instead of relying on one signal alone [17]. For a practical wearable application, however, the collected signals also need to be handled efficiently and made available through a monitoring interface.

Wearable systems developed for stress monitoring still present several challenges. Some approaches concentrate on one physiological signal, while others depend on offline processing or separate devices for different measurements. Another consideration is that physiological responses are not identical across individuals. A measurement that represents a particular state for one person may not necessarily indicate the same state for another person. Factors such as physical activity, surroundings, and an individual's normal physiological condition can also affect the recorded signals [15], [19]. Therefore, classification based on generalized thresholds may have limited reliability when applied across different users [12], [15], [19].

The combination of wearable sensing and IoT connectivity offers a practical way of addressing these requirements. Sensor readings can be obtained continuously, handled by an embedded computing unit, transferred through a network, and made available through a cloud-based interface. Such an arrangement allows physiological information to be viewed while the system is operating rather than only after data collection has been completed. In this study, these components are brought together in a wearable smart-cap architecture using EEG, ECG, GSR, and pulse sensors. A Raspberry Pi is used for data acquisition and transmission, while the Blynk Cloud Platform is used for data visualization and monitoring.

The collected measurements also need to be interpreted so that the user can understand the current stress state. For this purpose, the proposed system uses a threshold-based approach to divide the detected stress state into three categories: mild, moderate, and severe. A corresponding suggestion is displayed through the user interface according to the classified level. The suggestions are intended to provide simple supportive information that may help the user respond to the detected state; they are not intended to constitute medical diagnosis or treatment. The system therefore serves as a monitoring and feedback platform, while medical or psychological assessment remains outside its scope.

The present work focuses on the development of an IoT-enabled smart cap that brings multimodal physiological sensing and real-time monitoring into a single wearable setup. The system connects EEG, ECG, GSR, and pulse sensors to a Raspberry Pi, which handles the acquired measurements and their transmission to the Blynk Cloud Platform. The cloud-connected interface allows the collected information and classification output to be observed during system operation. Rather than using an AI or deep-learning model for the current classification process, the prototype applies predefined threshold-based rules. More advanced machine learning approaches may be investigated in future work to improve the adaptability of the classification process [16], [19].

The main objective of this study is to examine the feasibility of using a wearable IoT architecture for continuous physiological monitoring and three-level stress classification. The work brings together multiple physiological sensors, Raspberry Pi-based data handling, cloud connectivity, real-time visualization, and threshold-based classification within a smart-cap prototype. System operation is examined through the acquisition and transmission of sensor measurements, visualization of the collected data, stress-level classification, and user feedback. The prototype provides a basis for further investigation, particularly through larger-scale data collection, more systematic validation, and the use of learning-based classification methods in future studies.

II. LITERATURE REVIEW

A. Stress Monitoring and Physiological Assessment

Stress has been examined from both psychological and physiological viewpoints because it can influence how people feel, behave, and function physically. Previous studies have looked at stress in different settings, including academic and occupational environments. Sattar et al. [1] studied the relationship between medical professionalism, coping, and the mental well-being of medical students, showing how demanding environments can influence psychological well-being. McDaid et al. [2] examined the economic and social effects of mental disorders in South Asia and discussed the broader consequences associated with limited mental-health support. Together, these studies show why stress and mental well-being require attention. However, their main focus is on psychological, social, and population-level aspects rather than continuous monitoring of physiological changes.

In most cases, stress is assessed through self-reported questionnaires, psychological assessments, clinical evaluations,

or a combination of these methods [13], [14]. These approaches can provide useful information about a person's condition, but the results generally describe the person's state at the time of assessment. Physiological monitoring can provide additional information by tracking changes as they occur over time. This has contributed to the use of wearable sensors for monitoring physiological signals outside conventional clinical environments [14], [15].

Wearable and pervasive-computing technologies have also been explored in healthcare because they can collect physiological information continuously. Dewi et al. [3] discussed the use of pervasive computing and wearable devices in sustainable healthcare applications and highlighted the role of connected wearable technologies in health monitoring. IoT-based healthcare systems have also been studied for collecting and transferring health-related information through connected devices [8]. However, a general healthcare monitoring system does not directly address all the requirements of stress monitoring. Stress-related applications also need to consider the selection of physiological signals, the combination of multiple signals, stress classification, and the delivery of timely feedback.

B. Wearable Physiological Sensing for Stress Monitoring

Wearable devices can measure physiological changes that occur when a person responds to psychological or environmental stress. Researchers have explored several types of signals for this purpose, including cardiac activity, electrodermal activity, brain activity, skin temperature, respiration, and physical activity. Bolpagni et al. [5] reviewed the use of bio signals from wearable devices for personalized stress detection and reported the use of different physiological measurements across stress-monitoring studies. Similarly, Vos et al. [12] examined machine-learning approaches for stress monitoring using wearable devices and discussed the importance of physiological data quality and generalizability. These studies indicate that the signals selected for stress monitoring depend on the type of wearable device, the conditions under which the data are collected, and the purpose of the monitoring system.

Cardiac measurements are commonly considered in stress-monitoring studies because changes in cardiac activity can occur during physiological arousal. ECG can be used to record the electrical activity of the heart and can also provide measures such as heart rate and heart-rate variability. Pulse or photoplethysmography-based measurements can provide related information about cardiovascular activity. Electrodermal activity, also known as galvanic skin response (GSR), measures changes in skin conductance and is another commonly used physiological signal in stress-related studies. The review by Bolpagni et al. [5] identified EDA and PPG among the commonly used signals in wearable stress-detection research, while Sosa et al. [17] examined multimodal approaches that combine different physiological indicators of sympathetic nervous system arousal. These findings support the use of multiple physiological signals when monitoring stress rather than relying on a single measurement.

EEG provides another sensing modality because it records electrical activity associated with brain function. It has been investigated for mental-stress assessment because changes in

brain activity may be related to cognitive and emotional states. Badr et al. [4] reviewed deep-learning methods for mental-stress assessment using EEG and discussed approaches based on convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and hybrid architectures. The use of EEG alongside other physiological measurements therefore provides another possible source of information for multimodal stress-monitoring systems [17].

Wearable sensing also brings some practical challenges. Sensor placement, movement artefacts, signal quality, environmental conditions, individual physiological differences, and user comfort can all affect the collected data. Bolpagni et al. [5] highlighted issues including signal quality, dataset representativeness, privacy, and real-world deployment in wearable stress detection. Abd Al-Alim et al. [15] also investigated wearable-sensor-based stress detection in free-living environments, where physiological measurements can be influenced by everyday conditions. In addition, Vos et al. [12] discussed the challenge of developing stress-monitoring models that generalize across wearable datasets and users. These findings suggest that the number of sensors alone does not determine the quality of stress classification; the quality of the collected signals and the way they are interpreted are also important.

Table I summarizes the physiological signals relevant to stress monitoring, the information they provide, and the main considerations associated with their use [5], [17].

TABLE I. PHYSIOLOGICAL SIGNALS RELEVANT TO STRESS MONITORING

Physiological Signal	Information Obtained	Relevance to Stress Monitoring	Considerations
EEG	Electrical activity of the brain	Provides information related to changes in brain activity and mental state	Can be affected by movement and electrical noise
ECG	Electrical activity of the heart	Provides cardiac information and can support heart-rate and HRV analysis	Electrode placement and movement can affect signal quality
GSR/EDA	Changes in skin conductance	Provides information associated with autonomic arousal	Can be influenced by temperature, movement, and skin condition
Pulse	Cardiovascular pulse activity	Provides information related to cardiovascular response	Can be affected by physical activity
Skin Temperature	Peripheral temperature changes	Can provide additional physiological information	Influenced by surrounding environmental conditions
Respiration	Breathing rate and pattern	May change during physiological arousal	Requires appropriate sensor placement

The smart cap uses EEG, ECG, GSR, and pulse measurements so that information can be obtained from several physiological sources. This multimodal configuration is

consistent with the broader direction of wearable stress-monitoring research, which has increasingly considered combinations of physiological signals and personalized monitoring approaches [5], [17]. The cap-based design therefore provides a wearable form factor for bringing several sensing modalities together within an IoT-enabled monitoring system.

C. Wearable Devices and Multimodal Stress Monitoring

Wearable devices have developed from systems that measure individual physiological signals into platforms capable of collecting several types of physiological measurements. The Empatica E4, for example, is a research-oriented wearable platform designed to collect multiple biosignals and has been used in studies involving wearable physiological monitoring [11]. Such systems illustrate how physiological measurements can be collected while the user is wearing the device rather than through a single assessment session. In stress-monitoring research, Bolpagni et al. [5] reviewed the use of biosignals from wearable devices and reported that different physiological measurements are used depending on the sensing configuration and monitoring objective. The review also discussed the increasing interest in personalized and multimodal stress-detection approaches.

The placement of a wearable device depends largely on the physiological signal being measured. Different wearable arrangements are used to accommodate the sensing requirements of cardiac, electrodermal, and brain-related measurements. EEG requires electrodes to be positioned on the scalp, making a head-worn arrangement suitable when brain activity is included. These differences in sensing requirements are important when designing a wearable system that combines several physiological signals. Bolpagni et al. [5] discussed practical factors such as signal quality, sensor configuration, and real-world deployment in wearable stress-detection systems. These considerations become particularly relevant when several sensors have to operate together in a single wearable form factor.

Riedl et al. [6] examined EEG and ECG responses in relation to videoconference fatigue. Rountree-Harrison et al. [18] reviewed EEG and ECG biomarkers in traumatic stress research and examined studies using both machine-learning and non-machine-learning approaches. Although fatigue and psychological stress are not the same condition, their study demonstrates the use of more than one physiological signal to examine changes associated with human cognitive and physiological states. Wang et al. [7] investigated wearable sensing technologies for monitoring construction workers, demonstrating the application of wearable sensing in an occupational environment. The studies show that the design and placement of wearable sensors can vary according to the application and the physiological information being collected.

The use of multiple physiological signals has received increasing attention in stress-detection research. Bolpagni et al. [5] identified EDA and PPG among the commonly used biosignals in wearable stress-monitoring studies and discussed multimodal approaches that combine different physiological measurements. Sosa et al. [17] specifically reviewed multimodal approaches for sympathetic nervous system arousal classification and examined how different physiological indicators can be considered together for stress-related

classification. This line of research is relevant to systems that do not rely on a single physiological measurement, since different signals can provide complementary information about physiological responses.

Another important issue is whether a wearable stress-monitoring system can maintain reliable performance across different users and real-world conditions. Vos et al. [12] reviewed machine-learning approaches for stress monitoring using wearable devices and discussed challenges related to generalizability. Abd Al-Alim et al. [15] investigated wearable-sensor-based stress detection in free-living environments, where physiological measurements are collected under less controlled conditions than laboratory settings. These studies suggest that signal collection and system design need to be considered together with the conditions in which the wearable system is used.

Table II compares representative wearable stress-monitoring approaches based on their typical physiological signals, main strengths, and limitations.

TABLE II. COMPARISON OF WEARABLE STRESS-MONITORING APPROACHES

Approach	Typical Signals	Main Strength	Main Limitation
Wrist-based wearable [5]	Pulse/PPG, EDA, motion	Portable and convenient for continuous monitoring	Does not normally provide EEG-based brain activity
Chest-based wearable [5]	ECG, respiration, motion	Suitable for cardiac and respiratory measurements	May be less convenient for everyday use
EEG-based wearable [4]	EEG	Provides information about brain electrical activity for mental-stress assessment	Sensitive to electrode placement and movement
Multimodal wearable [5], [17]	ECG/PPG, EDA, EEG and/or other signals	Combines information from different physiological sources	Requires additional hardware and signal processing
Proposed smart cap	EEG, ECG, GSR, pulse	Combines multiple physiological measurements with IoT monitoring	Current prototype uses threshold-based classification and requires wider validation

The proposed smart cap uses EEG, ECG, GSR, and pulse measurements within a single head-worn arrangement. The inclusion of EEG provides access to brain-related physiological activity, while ECG, GSR, and pulse provide additional physiological measurements. Unlike the commercial and conventional wearable examples discussed above, the proposed system combines these sensing modalities in a cap-based prototype and connects the acquired measurements to an IoT monitoring platform. The purpose is to examine the feasibility of integrating multimodal physiological sensing, IoT connectivity, and real-time monitoring within a single wearable

setup rather than to claim superiority over existing wearable devices.

D. IoT Integration and Cloud-Based Monitoring

The Internet of Things (IoT) allows sensing devices to exchange information with computing systems and cloud platforms. In healthcare applications, this can involve several connected components, including sensors, embedded processors, communication networks, cloud services, and user interfaces. Pradhan et al. [8] discussed the use of IoT technologies in healthcare and their role in collecting and transferring health-related information.

For a wearable stress-monitoring system, IoT connectivity makes it possible to move beyond simply collecting data on the device. Sensor readings can first be received by an embedded computing unit and then sent over a network to a cloud-based platform. The information can be displayed through a dashboard, allowing the measurements to be observed while the system is operating.

The Blynk platform used in this study provides the cloud-connected environment for displaying and monitoring the collected measurements [9]. The platform itself, however, does not determine whether a particular physiological response represents stress. The sensor measurements still need to be interpreted using an appropriate classification or decision-making method.

In the developed prototype, EEG, ECG, GSR, and pulse sensors collect the physiological measurements. A Raspberry Pi receives the sensor data and handles its processing and transmission. The processed information is then sent through the IoT connection to the Blynk Cloud Platform, where it can be viewed through the monitoring interface. This allows both the physiological readings and the resulting stress level to be observed while the system is running.

Table III summarizes the functional components of the proposed IoT architecture and describes the role of each layer in the collection, processing, transmission, visualization, and feedback of physiological data.

TABLE III. FUNCTIONAL COMPONENTS OF THE IoT ARCHITECTURE

Layer	Component	Function
Sensing Layer	EEG, ECG, GSR, Pulse	Collects physiological measurements
Processing Layer	Raspberry Pi	Receives and processes sensor data
Communication Layer	IoT/Wi-Fi connectivity	Transfers measurements to the cloud platform
Cloud Layer	Blynk Cloud Platform	Supports data transmission and visualization
Application Layer	Monitoring interface	Displays physiological information and stress level
Feedback Layer	Supportive content	Provides suggestions corresponding to the detected stress level

The architecture brings sensing, processing, communication, visualization, and feedback together within the same monitoring framework rather than treating them as separate components.

E. Machine Learning and Deep Learning for Stress

Stress classification can be approached using predefined rules as well as conventional machine-learning and deep-learning methods. Castro-García et al. [10] reviewed human stress and activity recognition using low-cost wearable technologies and discussed the use of physiological measurements for automated recognition. Their work illustrates how wearable sensing can be combined with computational methods for recognizing stress-related states. More recent research has examined machine-learning pipelines in greater detail. Vos et al. [12] reviewed wearable stress-monitoring studies using machine learning and considered issues such as data labelling, biomarker validity, and the ability of models to generalize to previously unseen data.

The development of a learning-based stress classifier depends not only on the choice of algorithm but also on the data used for training and evaluation. Vos et al. [12] emphasized that generalization and reproducibility remain important challenges in wearable stress-monitoring research. In practical use, physiological signals can differ across individuals and can also be affected by factors such as physical activity and the conditions in which the measurements are collected. Abd Al-Alim et al. [15] addressed this issue by investigating stress detection using wearable sensors in free-living environments rather than relying only on controlled laboratory conditions. Their study demonstrates the importance of evaluating stress-detection approaches under conditions that more closely resemble everyday use.

Deep-learning methods have received particular attention for EEG-based stress assessment. Badr et al. [4] reviewed deep-learning approaches for mental-stress assessment using EEG and discussed CNN, LSTM, and hybrid architectures. The review also examined how different forms of EEG representation are used as inputs to these models. These approaches show the potential of learning complex patterns from physiological signals, but their effectiveness depends on suitable datasets, reliable stress labels, and appropriate evaluation.

The current smart-cap prototype does not use a machine-learning or deep-learning model as its main classification method. Instead, it uses predefined threshold-based rules to divide the monitored state into three levels: mild, moderate, and severe. This approach allows the prototype to demonstrate the complete sensing, processing, IoT connectivity, and real-time classification pipeline without requiring a large labelled dataset for model training. However, fixed thresholds may not account for differences between users. The literature on wearable stress monitoring therefore provides a basis for considering machine-learning and deep-learning methods as future extensions once a sufficiently large and reliably labelled dataset is available.

F. Critical Analysis and Research Gap

The studies reviewed above show a gradual shift from conventional stress assessment toward continuous physiological monitoring using wearable technologies. Bolpagni et al. [5] examined the use of biosignals from wearable devices for stress detection and discussed the growing interest in multimodal and personalized approaches. IoT-based healthcare research has also demonstrated how connected devices can support the collection

and transfer of physiological information between sensing units and monitoring platforms [8].

The use of multiple physiological signals can provide information from different aspects of the body's response to stress. Sosa et al. [17] reviewed multimodal approaches for stress-related physiological arousal and examined the use of different physiological indicators together. The availability of wearable platforms such as the Empatica E4 also demonstrates the practical use of multi-sensor physiological monitoring in wearable form factors [11].

Machine-learning and deep-learning methods provide further possibilities for identifying patterns in physiological data. Badr et al. [4] reviewed deep-learning approaches for EEG-based mental-stress assessment, including CNN, LSTM, and hybrid models. However, Vos et al. [12] highlighted generalization as an important challenge in wearable stress-monitoring research. Abd Al-Alim et al. [15] also investigated stress detection in free-living environments, where physiological measurements are collected under less controlled conditions.

These findings indicate that reliable stress monitoring involves more than selecting sensors or classification algorithms. Individual physiological differences, signal quality, environmental conditions, and the availability of suitable labelled data can all affect system performance. A model developed from a limited participant group may therefore not necessarily produce the same results when applied to new users [12].

Another challenge is integrating the different functions required in a practical wearable stress-monitoring system. The system needs to acquire physiological signals, process the measurements, transfer the information, present the results, and provide feedback. The proposed smart cap addresses this integration by combining EEG, ECG, GSR, and pulse sensing with a Raspberry Pi and the Blynk Cloud Platform.

The current implementation uses a threshold-based mechanism to classify the monitored state into mild, moderate, and severe levels. This allows the prototype to demonstrate multimodal sensing, IoT connectivity, real-time visualization, and stress-level classification without requiring a large labelled dataset for model training. However, fixed thresholds may not account for differences between users.

The main research gap addressed by this work is therefore the integration of multiple physiological sensing modalities, IoT-based monitoring, and real-time stress-level feedback within a single cap-based wearable prototype. The system is not intended to claim better performance than existing machine-learning or deep-learning methods. Instead, it provides a prototype that can be further investigated through larger datasets, systematic stress labelling, personalized calibration, and learning-based classification.

III. METHODOLOGY

The smart cap was developed by combining physiological sensors with a Raspberry Pi, IoT connectivity, and a monitoring dashboard. The work was carried out in four phases. First, the required physiological signals were collected through the

sensors. The second phase focused on arranging the hardware and software components and defining their data flow. The third phase involved implementing the prototype, followed by functional and usability testing in the fourth phase.

A. Phase 1 - Data Collection and Sensor Integration

Fig. 1 shows the proposed arrangement of the smart cap. EEG, ECG, GSR, and pulse sensors were selected to obtain different types of physiological measurements. The sensors were fitted into the cap-based setup and connected to the Raspberry Pi for data acquisition.

The measurements obtained from the sensors were monitored through the IoT connection. Based on the predefined conditions used in the prototype, the monitored state was grouped into three levels: Level 1 (mild), Level 2 (moderate), and Level 3 (severe).

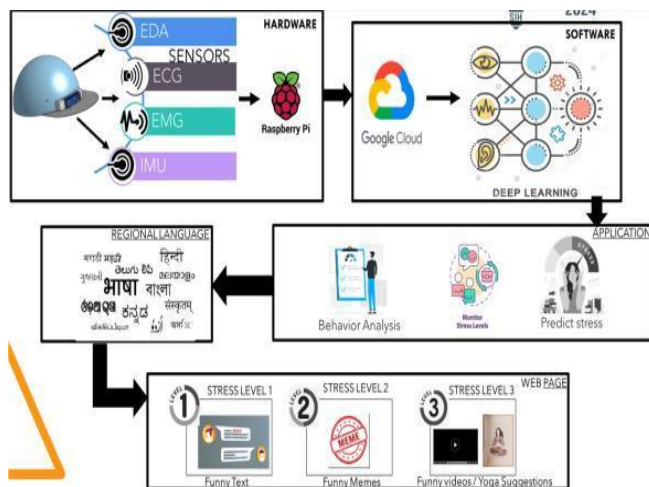


Fig. 1. Full level design of the smart cap.

B. Phase 2 – System Design

Fig. 2 illustrates the top, side, bottom, and isometric views of the proposed IoT-enabled smart cap, providing an overview of its physical structure and component arrangement. The design was divided into four parts: hardware, cloud connectivity, backend processing, and the dashboard.

1) *Hardware*: The EEG, ECG, GSR, and pulse sensors were connected to a Raspberry Pi 3 Model B. It receives the measurements generated by the sensors and prepares them for further processing and transmission.

2) *Cloud connectivity*: The sensor information from the Raspberry Pi is sent wirelessly to the Blynk Cloud Platform. Blynk is used in the prototype to monitor and display the incoming measurements.

3) *Backend*: The Node.js backend receives the relevant sensor information and applies the threshold conditions defined for the prototype. The output of this process is the corresponding stress level.

4) *Frontend*: The dashboard was developed using HTML, CSS, and JavaScript. It displays the physiological readings together with the detected stress level. The dashboard also provides supportive material, such as relaxation videos,

breathing exercises, and yoga suggestions, depending on the displayed stress level.

The main data path used in the prototype is: Sensor → Raspberry Pi → Blynk Cloud → Node.js → Dashboard. Keeping these components separate also makes it easier to modify individual parts of the prototype during further development.

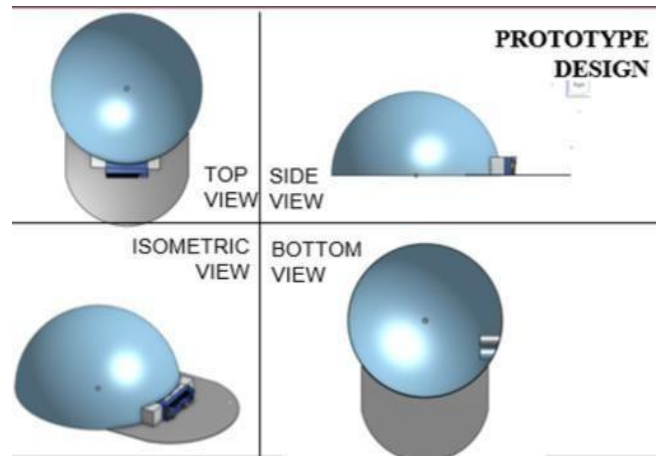


Fig. 2. Top, side, bottom, and isometric views of the proposed IoT-enabled smart cap.

C. Phase 3 – Implementation

During implementation, the sensor connections and software components described in the system design were integrated into the working prototype. The EEG, ECG, GSR, and pulse sensors were connected to the Raspberry Pi and checked for proper data acquisition and communication. The Raspberry Pi program was configured to receive the sensor readings and forward the collected information to the Blynk Cloud Platform at regular intervals. The Node.js backend was used to apply the predefined threshold-based rules and generate the corresponding stress-level output. The dashboard then displayed the sensor information and stress classification.

D. Threshold-Based Stress Classification

The stress level was determined using predefined threshold-based rules applied to the physiological measurements. The classification process can be represented conceptually as

$$S=f(HR,ECG,GSR,P)$$

where, *HR*, *ECG*, *GSR*, and *P* represent the physiological measurements obtained from the sensors, and *S* represents the resulting stress level. Based on the predefined conditions implemented in the Node.js backend, the output was grouped into three categories: Level 1 (mild), Level 2 (moderate), and Level 3 (severe).

Depending on the detected level, the interface presented the relevant supportive content, including relaxation material, breathing exercises, and yoga-related suggestions. The complete processing path was therefore:

Sensor Signal → Raspberry Pi → Blynk Cloud → Node.js Backend → Frontend Display

E. Phase 4 – Testing

The prototype was tested to check whether the major components operated as intended. The testing covered sensor data acquisition, system response, and interaction with the dashboard.

1) *Test case 1: sensor data verification:* The sensor readings were observed under the test conditions to check whether measurements could be acquired and transmitted without interruption.

2) *Test case 2: system response:* Different input conditions were provided to the threshold-based classification component. The resulting stress level was checked against the expected output, and the dashboard response was observed for each case.

3) *Test case 3: user interface evaluation:* The dashboard was checked for basic usability aspects such as readability, ease of navigation, and response to changes in the displayed stress level. Feedback was also collected regarding the presentation of the physiological information and the supportive content.

Fig. 3 presents the developed prototype of the smart cap, showing the integration and placement of the sensing and processing components within the wearable structure.



Fig. 3. Prototype of the cap.

IV. RESULTS AND DISCUSSION

A. Prototype Outcome and Functionality

The developed Stress Monitoring Cap combines EEG, ECG, GSR, and pulse sensors in a cap-based wearable setup. The sensors are connected to a Raspberry Pi 3 Model B, which acts as the main unit for receiving the physiological readings and passing the required information to the connected IoT platform. Fig. 3 shows the developed smart-cap prototype with the integrated EEG, ECG, GSR, and pulse sensing components.

During operation, the sensor readings can be viewed through the monitoring dashboard. The system also produces a stress-level output using the threshold conditions implemented in the Node.js backend. Based on these conditions, the monitored state is displayed as Level 1 (mild), Level 2 (moderate), or Level 3 (severe).

The prototype brings sensor acquisition, data transmission, stress-level classification, and user feedback together in one system. The stress level shown by the prototype represents the

result of the implemented classification rules and is not intended to be used as a clinical diagnosis.

B. Software Design and System Performance

Fig. 4 shows the overall architecture of the Stress Monitoring Cap. The system is arranged into different functional stages, beginning with physiological signal acquisition and ending with the presentation of the results through the dashboard.

The EEG, ECG, GSR, and pulse sensors are the starting point of the data flow. Their readings are picked up by the Raspberry Pi, which prepares the acquired information for transmission. The readings are subsequently sent over the wireless connection to the Blynk Cloud Platform. This allows the physiological information to be monitored while the system is operating.

The Node.js backend receives the relevant sensor information and applies the threshold conditions defined for the prototype. The resulting stress category is then passed to the frontend. The dashboard, developed using HTML, CSS, and JavaScript, displays the physiological readings and the corresponding stress level.

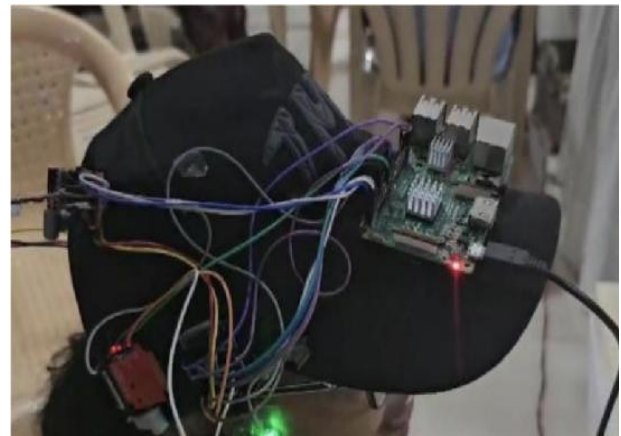


Fig. 4. Overview of the cap.

The interface also provides supportive content based on the detected level. This includes short textual suggestions, relaxation videos, breathing exercises, and yoga-related recommendations. The intention is to provide the user with simple actions that may help them respond to the displayed stress level.

C. Prototype Testing and Observations

The prototype was tested to check the operation of the sensor connections, data transmission, stress-level classification, and dashboard response. The testing focused mainly on whether the individual components could work together through the complete data path.

For sensor-data verification, the EEG, ECG, GSR, and pulse readings were observed during system operation. The Raspberry Pi was checked for its ability to receive the sensor outputs and forward the collected information to the connected platform.

The threshold-based classification was also tested with different input conditions. The resulting output was compared with the expected category defined by the implemented rules.

The dashboard was then checked to ensure that the corresponding stress level and supportive content were displayed.

The dashboard was checked during system operation to see whether the displayed information remained readable and whether the interface responded when the stress-level output changed. Navigation between the available dashboard elements was also checked. These observations were used to confirm that the interface could be used for viewing the sensor readings and the corresponding system output.

D. Discussion

The prototype demonstrates the feasibility of combining multiple physiological sensors with IoT connectivity in a wearable cap. The system receives the sensor measurements and forwards the required information through the wireless connection. Blynk provides the cloud-based monitoring component, while the Node.js backend handles the threshold-based stress classification. Fig. 5 shows the smart-cap monitoring dashboard, where the physiological readings, stress-level output, and supportive content are presented to the user. The web dashboard then presents the measurements and classification result to the user.

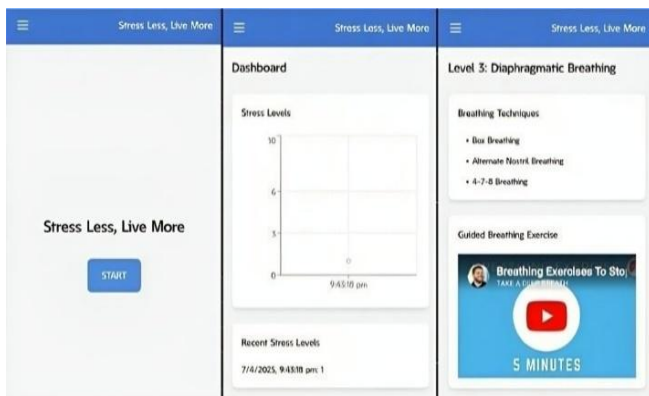


Fig. 5. Smart cap monitoring dashboard.

One practical advantage of the threshold-based approach is that it can be implemented without requiring a large labelled dataset for model training. This is useful for an initial prototype because the complete sensing, communication, classification, and feedback pipeline can be demonstrated without depending on a trained machine-learning model.

However, fixed thresholds also introduce limitations. Physiological measurements can vary from one person to another, and a value that represents an increased physiological response for one user may not have the same meaning for another user. Sensor placement, movement, environmental conditions, and signal noise can also affect the measurements.

Therefore, the current prototype should be considered a feasibility demonstration rather than a clinically validated stress-detection system. The testing carried out in this work mainly examines whether the hardware, communication, classification, and dashboard components operate together as intended. It does not provide sufficient evidence to claim clinical accuracy or generalizable performance across a wider population.

Another limitation is the current use of predefined rules instead of a data-driven classification model. Machine-learning and deep-learning methods could be explored in future versions of the system. With a sufficiently large dataset containing reliable stress labels, models could be trained using the combined physiological signals and evaluated using appropriate training and testing procedures.

The IoT component also provides scope for further development. Continuous cloud-based monitoring could allow the system to maintain longer-term records of physiological measurements and stress-level changes. Such information could be useful for studying individual patterns and developing personalized thresholds or learning-based models.

Overall, the developed prototype demonstrates the integration of multimodal physiological sensing, Raspberry Pi-based data handling, IoT communication, real-time visualization, threshold-based classification, and supportive feedback within a wearable cap. Further validation with a larger and more diverse participant group would be required before assessing its effectiveness for real-world or clinical applications.

V. CONCLUSION AND FUTURE ENHANCEMENT

The Stress Monitoring Cap was developed as a wearable prototype for monitoring physiological signals related to stress. EEG, ECG, GSR, and pulse sensors were integrated with a Raspberry Pi 3 Model B for data collection and processing. The measurements were transmitted through the Blynk Cloud Platform and presented on a web-based dashboard. Based on the predefined threshold conditions, the system displays the detected state as mild, moderate, or severe. The dashboard also provides relaxation videos, breathing exercises, and yoga-related suggestions according to the displayed level.

The prototype shows that multiple physiological signals and IoT connectivity can be combined in a single cap-based monitoring system. The present implementation is mainly intended to demonstrate the working of the proposed system. It does not establish clinical accuracy or provide a medical diagnosis. The threshold-based method is also limited because physiological responses can differ between individuals, and factors such as sensor placement, movement, and signal quality may affect the readings.

Future work can focus on improving the stress-classification method using machine-learning and deep-learning techniques. Such methods would require a larger dataset with reliable stress labels for proper training and evaluation. Personalized calibration can also be introduced so that the system considers the normal physiological range of individual users instead of applying the same thresholds to everyone.

Longer-term data collection could further help in studying changes in an individual's physiological patterns over time. Improvements to sensor placement, motion-noise handling, and the physical design of the cap may also make the system more suitable for extended use. The IoT interface could additionally be extended to include historical readings, trend visualization, and user-specific monitoring.

Overall, the proposed system demonstrates the feasibility of combining multimodal physiological sensing with IoT-based monitoring in a wearable cap. Larger-scale testing with reliable stress labels and different users will be required to evaluate the classification performance and determine how well the system works under real-world conditions.

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