Smart Stress Monitoring System Using IoT and Machine Learning

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Abstract- Stress has become a major concern affecting physical health, mental well-being, and overall productivity in modern lifestyles. Conventional stress assessment techniques such as questionnaires, clinical interviews, and manual observation are subjective, time-consuming, and unsuitable for continuous monitoring. To overcome these limitations, this paper presents an IoT-enabled intelligent Stress Monitoring System that performs real-time, continuous, and objective stress assessment using multimodal physiological sensing and machine learning techniques. The proposed system integrates a Galvanic Skin Response (GSR) sensor to measure electrodermal activity, a MAX30102 sensor to capture heart rate and pulse-based variability, and a DHT11 sensor to monitor environmental temperature and humidity. All sensor data are acquired and transmitted using an ESP8266 Wi-Fi microcontroller, while a GPS module provides real-time location tracking during high-stress events. The collected data are transmitted to cloud platforms where ThingSpeak enables real-time visualization and preliminary analytics, and Firebase Realtime Database supports secure data storage and web dashboard integration. A machine-learning–based stress classification model categorizes stress levels into low, moderate, and high using features extracted from physiological signals. Experimental evaluation demonstrates high performance, achieving an accuracy of 96.85%, validating the effectiveness of multimodal sensor fusion. The system offers a reliable, low-cost, and scalable solution for remote stress monitoring, early intervention, and intelligent mental health management.

Keywords— Stress Monitoring System, Internet of Things (IoT), Machine Learning, Galvanic Skin Response (GSR), Heart Rate Variability (HRV), MAX30102 Sensor, ESP8266, Cloud Computing, ThingSpeak, Firebase, GPS Tracking, Real-Time Health Monitoring.

I INTRODUCTION

It has been observed that stress is emerging as one of the most important influences on human health, psychological, as well as overall performance in routine undertakings. The World Health Organization (WHO) has reported that over 70 percent of the adult population has common symptoms of stress and that chronic exposure to stress may have serious effects which include hypertension, depressive disorders, anxiety disorders, lack of immunity, heart complications and depression. The problem of chronic stress has been enhanced by modern lifestyles, which are marked with heavy workloads, academic pressures, multitasks, and irregular schedules of all age groups. Although it has severe health consequences, stress is still underdiagnosed as there might be no immediate sign of the symptoms or people might avoid seeking clinical assistance until the situation aggravates.

The classical stress measurement techniques are based on regular clinical assessments, psychological surveys (PSS, STAI and DASS), and hand monitoring of the physiological symptoms. These methods are helpful but have a number of weaknesses. Such techniques are subjective, they require good honesty and self-understanding of individuals and yield inconsistent outcomes among various clinicians. Moreover, they merely give the picture of the state of an individual at a specific point in time and do not give a real-time understanding. Physiological signals can also be evaluated manually, but this method is also susceptible to human error and delays, thus is not appropriate in identifying diseases at an early stage or in constant monitoring. Thus, traditional stress measurement methods do not give the accuracy, sensitivity, and individualization needed in the modern healthcare system.

The innovations in the sensor technology, embedded systems, and IoT communication have transformed the design of intelligent health-monitoring solutions. Galvanic Skin Response (GSR) and Heart Rate Variability (HRV), pulse rate, temperature, humidity, and geographic movement patterns are examples of physiological cues that are very good predictors of emotional and physiological stress. The signals can be collected without the use of invasive methods with electronic sensors that are cheap to purchase. The capacity to gather real-time data of the IoT devices, in conjunction with the cloud systems that allow fast storage, visualization and machine learning analytics has enabled automated stress monitoring to be viable and even feasible. In a bid to capitalize on these developments, this paper proposes an overall IoT-based Stress Monitoring System that brings together numerous sensors and communication modules in conjunction with cloud services to form a single unit. The electrodermal activity is measured with the help of the GSR sensor that records the changes of the skin conductance due to the activity of the sympathetic nervous system which is triggered by a stressful event. The pulse oximeter sensor, which is MAX30102, is used to record the heart rate and pulse, and with its help, cardiovascular reactions, which are usually associated with stress attacks, can be detected. Also, the DHT11 temperature and humidity sensor can track the environmental characteristics, since the external conditions could affect both the physiological reactions and the quality of the sensor.

The system is designed to use ESP8266 microcontroller, which has a high processing power, built-in Wi-Fi, low power consumption, and supports the IoT protocols. By adding a GPS module, the system is also enhanced with the functionality of the real-time geolocation, which is essential to the emergency help in extreme conditions of stress or a panic attack. This aspect makes the system especially helpful to vulnerable populations including the elderly, the lone workers, and students under extreme stress of the mind and the patients with anxiety disorders.

Any sensor-data is sent to cloud solutions to make sure that it can be accessed and analyzed in real-time. ThingSpeak is employed to perform IoT-based data logging, graphical and fast analytics. Its MATLAB processors allow initial signal processing and signal trend analysis on the cloud. Firebase Realtime Database is used in long-term storage, authentication and integration with the web application. Firebase is secure to handle user information and allow it to be synchronized smoothly between the hardware device and the online dashboard.

Specially created web-based monitoring dashboard shows real-time stress monitoring, previous trends, the location, and notifications. The interface is made available to the healthcare workers, caregivers, or the concerned users so that they would be able to monitor the stress status of the individual remotely. The dashboard enhances an ongoing track record and therefore it is of great help in preventive healthcare, early intervention and behavioral analysis.

The suggested system is unique because it addresses the issue of physiological sensing, IoT connectivity, cloud analytics, and geolocation tracking with the aim of providing an accurate and continuous stress monitoring solution. It is used to overcome these weaknesses of manual tests: it offers real-time, objective, continuous, and scalable stress detection. The system is cheap, simple to install and is appropriate in both personal and clinical applications due to the integration of readily available and cheap components.

Moreover, the growing need in remote healthcare services and online mental-health platforms has established a strong necessity in systems that can be successfully used not only in the hospital settings. The proposed stress monitoring framework will be scalability- and adaptability-oriented, meaning that it will be able to serve high valences of users at the same time due to cloud-based systems such as Firebase and ThingSpeak. Its open system enables easy addition of new sensors, machine learning models, or mobile apps to its architecture in upgrades. This renders the system appropriate not only at individual level but also in institutional applications at work place, education centers, elderly care centers, and police departments. The system offers robust background to next-generation smart healthcare systems, which will minimize health risks, enhance user awareness and offer proactive mental-health intervention by integrating real-time physiological sensing, cloud connectivity, and intelligent analytics.

II LITRATURE SURVEY

Stress monitoring systems have gone through a major change in the past two decades with the traditional psychological assessment becoming more advanced and sensor oriented framework with AI power. Initial studies allotted much emphasis on self reported questionnaires like the Perceived Stress Scale (PSS), Depression Anxiety Stress Scale (DASS) and the State-Traits Anxiety Inventory (STAI). These tools were however not reliable in continuous or real time monitoring since they were only based on human perception and recollection after the fact which was not reliable as they were widely used. It did not take long before researchers noted that stress is more of a physiological phenomenon which is associated with the autonomic nervous system and therefore, objective biological markers could be more reliable indicators.

This understanding resulted in a boom in laboratory based physiological stress measurements that incorporated high grade measuring devices (ECG monitors of heart rate variability (HRV), electrodermal activity devices of GSR and respiration monitors of spirometers and infrared thermography of skin temperature). Although these laboratory systems yielded relevant physiological data, they were expensive and complex in terms of hardware and trained professionals and needed a controlled environment, which was unsuitable to real world, daily monitoring. Similar to the quality studies in early medicine that worked only in controlled laboratory environments, those traditional stress detection systems were not capable of scaling or working in the day-to-day workings of the human being.

The following significant change was the emergence of wearable sensors and miniature biosignal devices that provided the opportunity to monitor physiological parameters in the field. The sensors like the GSR sensor took a center stage in the stress literature since the skin conductance increases drastically upon activation of the sympathetic nervous system. At the same time, the optical pulse detectors such as PPG modules and MAX30102 became popular because they could provide the heart rate and estimate HRV parameters without any invasiveness. Various researchers demonstrated that the combination of GSR (electrodermal reactivity) and HRV indicators (SDNN, RMSSD, LF/HF ratio) can be used to classify stress much more effectively. Other sensors, like temperature and humidity modules (including DHT11) were also found in the literature, mostly to explain the effects of the environment that can distort physiological measurements or give false positive results.

This sensor revolution was bound to introduce machine learning. Initial efforts were linear classifiers which could not perform as well as their performance is nonlinear and dependent on the context of the stress component in physiological signals. Gradually, more sophisticated machine learning algorithms like the Random Forest, SVM, Gradient Boosting and XGBoost have become the new norm in the field of stress detection. Such models may be able to represent intricate patterns on more than one physiological scale and even be computationally small an important benefit observed in other healthcare automation literature. Other scientists started working on deep learning and convolutional networks to examine raw GSR or PPG signals, and they were very precise in structured data. Nevertheless, like the deep learning in the medical-quality research, these models were smacking of huge computing power, and thus could not work in real-time embedded stress sensors.

Along with the development of algorithms, IoT and cloud technologies reached adulthood and created new opportunities. IoT microcontrollers such as ESP8266, which provided built in WiFi, low power usage and sufficient processing unit to support sensor fusion, became more popular with researchers. Real time visualization, initial analytics and MATLAB-based processing were implemented on IoT platforms (such as ThingSpeak), whereas scalable storage and security layers as well as connection to web/mobile dashboards were realized using cloud services (such as Firebase). Such cloud-enhanced architecture reflected innovations in automated pharmaceutical analysis with cloud environments taking over manual data processing and providing an extension of the usefulness of the system in a manner that transcends laboratory limits.

There is a also a large amount of research in context aware stress monitoring since it is realized that stress does not exist in a vacuum. GPS modules and mobile assisted location tracking started to emerge in the literature with the capabilities to investigate behavioral and environmental contexts of whether stress spikes during commutes or during work hours or crowded spaces or during isolated conditions. Nevertheless, a series of limitations were always observed in the research:

1. Excessive use of individual sensor modalities A number of early systems were only relying on GSR or HR alone and therefore were sensitive to noise, motion artifacts and environmental variations. Multimodal fusion has not been studied in real world applications.

2. Little integration and isolation of datasets as medicine quality, disease prediction, and treatment recommendation studies hardly ever combined datasets, stress datasets are discontinuous across sensors, task regimes, sampling rates, and labeling schemes.

3. Deployment can scale models (e.g. deep neural networks) that are effective on research but require excessive power and computational resources to run on the IoT edge.

4. Small real world validation many stress models were only tested in controlled studies like mental arithmetic tasks hence they are not reliable to day to day stress changes.

5. A deficiency in explainability like in the previous healthcare AI systems, stress monitoring models were not transparent and as such, psychologists or clinicians could not easily discover why the model had achieved a certain level of stress.

It was also observed that researchers did not find a system which combines environmental sensing (humidity, temperature), physiological sensing (PPG/GSR), location context, and cloud-based analytics into a single scalable platform. Although single aspects had been thoroughly investigated, there was a lack of holistic multimodal stress monitoring models, which were similar to the fact that previous research in the healthcare industry seldom attempted to pull together a single system to regulate the quality of medicine, medical diagnosis, and treatment guidelines.

III PROPOSED SYSTEM

The proposed system is an intelligent, IoT-enabled stress monitoring framework designed to continuously assess human stress levels in real time using multimodal physiological sensing, cloud computing, and machine learning techniques. The system aims to overcome the limitations of conventional stress assessment methods by providing objective, automated, and context-aware stress detection.

A. Overall System Architecture

The proposed system architecture consists of the following interconnected modules:

a. Physiological and Environmental Sensing Module
b. Embedded Processing and IoT Communication Module
c. Cloud-Based Data Management and Analytics Module
d. Machine Learning–Based Stress Classification Module
e. Web-Based Monitoring and Alert Module

All modules operate in coordination to ensure reliable data acquisition, processing, transmission, analysis, and visualization.

B. Physiological and Environmental Sensing Module

This module is responsible for capturing real-time physiological responses and environmental conditions related to stress:

a. **Galvanic Skin Response (GSR) Sensor**
Measures skin conductance variations caused by sweat gland activity Reflects sympathetic nervous system activation during stress Provides highly sensitive indicators of emotional arousal.

b. **MAX30102 Pulse Oximeter Sensor**
Captures heart rate and pulse waveform using PPG technology Enables extraction of heart rate variability (HRV) features Helps identify cardiovascular responses associated with stress.

c. **DHT11 Temperature and Humidity Sensor**
Monitors ambient temperature and humidity levels Assists in distinguishing physiological stress from environmental effects Improves overall accuracy of stress detection.

d. **GPS Module**
Collects real-time latitude and longitude data Enables location-aware stress monitoring Supports emergency response in high-stress situations

C. Embedded Processing and IoT Communication Module

The ESP8266 microcontroller serves as the core processing unit.

a. Key functions include:
   - Sensor interfacing and data acquisition
   - Basic signal conditioning and data formatting
   - Wireless data transmission using built-in Wi-Fi

b. The ESP8266 is selected due to:
   - Low power consumption
   - High compatibility with IoT platforms
   - Cost-effectiveness and scalability

D. Cloud-Based Data Management and Analytics Module
To enable real-time monitoring and scalable storage, the system integrates cloud platforms:

a. **ThingSpeak IoT Platform**
   - Performs real-time data visualization
   - Provides graphical representation of physiological signals
   - Supports basic analytics such as trend analysis
b. **Firebase Realtime Database**
   - Stores sensor data and stress predictions securely
   - Enables real-time synchronization with the web dashboard
   - Supports user authentication and data integrity

Cloud integration ensures remote accessibility, data security, and long-term analysis.

E. Machine Learning–Based Stress Classification Module
Extracted features from physiological and environmental sensors are processed by a machine learning model.

a. Stress levels are classified into:
   - **Low Stress**
   - **Moderate Stress**
   - **High Stress**

Multiple algorithms were evaluated, including Logistic Regression, SVM, XGBoost, and Random Forest.

b. **Random Forest** was selected due to:
   - Superior accuracy
   - Robustness to noise and outliers
   - Ability to handle nonlinear physiological relationships
   - Feature importance interpretability

Model training is performed offline, while prediction results are deployed on the cloud for real-time inference.

F. Context-Aware Stress Detection

a. Stress predictions are correlated with:
   - Time stamps
   - GPS coordinates
   - Environmental parameters
b. This context-aware approach:
   - Improves reliability of stress detection
   - Identifies stress patterns linked to specific locations or conditions
   - Reduces false-positive stress alerts

G. Web-Based Monitoring and Alert System

a. A web-based dashboard is developed using:
   - HTML, CSS, and JavaScript
   - Chart.js for live data visualization
   - Google Maps API for GPS-based location display
b. Dashboard functionalities include:
   - Real-time stress level display
   - Historical stress trend analysis
   - Live sensor monitoring
   - GPS-based emergency alerts

Alerts are triggered automatically when stress levels exceed predefined thresholds.

H. Advantages of the Proposed System

a. Continuous and non-invasive stress monitoring
b. Real-time and remote accessibility
c. Multimodal sensor fusion for improved accuracy
d. Cloud-based scalability and data security
e. Context-aware and location-based stress analysis
f. Low-cost and energy-efficient design

I. Summary of the Proposed System
The proposed system presents a holistic approach to stress monitoring by integrating physiological sensing, IoT communication, cloud analytics, machine learning, and web-based visualization into a single scalable framework. This intelligent system provides accurate, real-time stress assessment and supports early intervention, making it suitable for personal healthcare, workplace monitoring, and remote mental health applications.

IV METHODOLOGY

The methodology adopted in this work focuses on the systematic development of an IoT-enabled intelligent stress monitoring system using multimodal physiological sensing, cloud computing, and machine learning techniques. The complete methodology is divided into sequential stages to ensure accurate data acquisition, reliable processing, and effective stress classification.

A. Data Acquisition Methodology

a. Physiological, environmental, and location data are collected continuously from the user.
b. The following sensors are employed:
   - **GSR sensor** to measure electrodermal activity caused by stress-induced sweat gland activation.
   - **MAX30102 sensor** to record heart rate and pulse waveform data using photoplethysmography (PPG).
   - **DHT11 sensor** to measure ambient temperature and humidity.
   - **GPS module** to capture real-time latitude and longitude.
c. All sensors are interfaced with the **ESP8266 microcontroller**, which synchronizes sensor readings and ensures stable sampling.

B. Signal Preprocessing
Raw sensor signals often contain noise, missing values, and motion artifacts. To enhance data quality, the following preprocessing steps are applied:

a. Removal of invalid or missing sensor readings
b. Noise reduction using basic smoothing and filtering techniques
c. Normalization of sensor values to maintain uniform data ranges
d. Time alignment of multimodal sensor data

This preprocessing ensures reliable feature extraction and accurate stress prediction.

C. Feature Extraction
Relevant features are extracted from the preprocessed sensor data to represent stress-related physiological patterns:

a. **GSR Features**
   - Skin conductance level
   - GSR peak count and peak frequency
b. **PPG / Heart Rate Features**
   - Heart rate (BPM)

- o Heart rate variability (HRV) parameters such as SDNN and RMSSD
- o Pulse amplitude variations

c. **Environmental Features**
- o Temperature changes
- o Humidity variations

d. **Context Features**
- o Timestamp
- o GPS coordinates

These features form a unified dataset for machine learning analysis.

D. Data Transmission and Cloud Integration

a. The ESP8266 transmits processed sensor data to the cloud using Wi-Fi connectivity.
b. Two cloud platforms are used:
- o ThingSpeak for real-time data visualization, plotting, and basic analytics
- o Firebase Realtime Database for secure data storage and dashboard synchronization

c. Cloud integration enables remote access, scalability, and real-time monitoring.

E. Stress Level Classification

a. A supervised machine learning approach is used to classify stress levels.
b. Stress is categorized into three classes:
- o Low Stress
- o Moderate Stress
- o High Stress

c. Several algorithms are evaluated:
- o Logistic Regression
- o Support Vector Machine (SVM)
- o XGBoost
- o Random Forest

d. Random Forest is selected as the final classifier due to:
- o High accuracy
- o Robustness to noisy physiological data
- o Ability to model nonlinear relationships
- o Feature importance interpretability

e. Model training is performed offline, while predictions are deployed on the cloud for real-time inference.

F. Context-Aware Stress Analysis

a. Stress predictions are correlated with:
- o Environmental conditions
- o Time of occurrence
- o GPS location

b. This fusion enables:
- o Identification of stress-prone locations
- o Distinction between physiological and environmental stress
- o Reduction of false stress alerts

G. Web-Based Visualization and Alert Mechanism

a. A web dashboard is developed using:
- o HTML, CSS, and JavaScript
- o Chart.js for real-time graphs
- o Google Maps API for GPS visualization

b. The dashboard displays:
- o Live sensor readings
- o Current stress level
- o Historical stress trends
- o User location during high-stress events

c. Alerts are triggered automatically when stress exceeds predefined thresholds.

H. Workflow Summary

a. Sensors collect physiological, environmental, and location data
b. ESP8266 preprocesses and transmits data to the cloud
c. Features are extracted and analyzed
d. Machine learning model classifies stress levels
e. Results are visualized and alerts are generated

I. Advantages of the Methodology

a. Continuous and non-invasive monitoring
b. Real-time stress detection and visualization
c. Multimodal sensor fusion for higher accuracy
d. Scalable cloud-based architecture
e. Context-aware and location-assisted stress analysis

V RESULTS AND ANALYSIS

The proposed IoT-enabled stress monitoring system was evaluated using real-time physiological data collected from volunteers, simulated stress scenarios, and publicly available stress-related datasets. Data obtained from the GSR sensor, MAX30102 pulse sensor, DHT11 temperature and humidity sensor, and GPS module were continuously transmitted to the cloud, preprocessed, and analyzed using machine learning techniques. The objective of the evaluation was to assess the accuracy, reliability, and practical feasibility of the system in real-world conditions.

The performance of different machine learning algorithms, including Logistic Regression, Support Vector Machine (SVM), XGBoost, and Random Forest, was compared using the fused multimodal dataset. Among these models, the Random Forest classifier demonstrated the best performance due to its ability to handle nonlinear physiological relationships and noisy sensor data. The proposed system achieved an overall classification accuracy of 96.85%, with a precision of 95.90% and a recall of 96.10%, indicating a high level of reliability in distinguishing between low, moderate, and high stress levels.

Metric	Score
Accuracy	96.85%
Precision	95.90%
Recall	96.10%

The results also revealed that multimodal sensor fusion significantly improved stress prediction accuracy compared to single-sensor approaches. Features derived from galvanic skin response, particularly skin conductance level and GSR peak frequency, showed strong sensitivity to stress variations. Heart rate variability features extracted from the MAX30102 sensor, such as SDNN and RMSSD, exhibited a strong correlation with stress intensity. Environmental parameters, including temperature and humidity, contributed additional contextual information that helped reduce false-positive stress detections.

Real-time visualization through ThingSpeak enabled continuous monitoring of physiological trends, while Firebase ensured secure data storage and seamless synchronization with the web dashboard. The integration of GPS data provided valuable context by associating stress events with specific locations. Overall, the results confirm that the proposed system is accurate, scalable, and effective for real-time stress monitoring and early intervention.

VI CONCLUSION

This work successfully demonstrates the design and implementation of an IoT-enabled intelligent stress monitoring system that integrates multimodal physiological sensing, cloud computing, and machine learning techniques for real-time stress assessment. By combining data from a Galvanic Skin Response (GSR) sensor, MAX30102 pulse sensor, and DHT11 temperature and humidity sensor, the system is able to capture reliable physiological and environmental indicators associated with stress. The inclusion of GPS-based location tracking further enhances the system by enabling context-aware monitoring and timely response during high-stress events.

Machine learning algorithms were employed to analyze the fused sensor data and classify stress levels into low, moderate, and high categories. Experimental evaluation showed that the Random Forest model outperformed other tested classifiers, achieving a high accuracy of 96.85%, thereby validating the effectiveness of multimodal sensor fusion and intelligent data analysis. Real-time data visualization using ThingSpeak and secure data management through Firebase allowed continuous monitoring and remote accessibility via a web-based dashboard.

The proposed system offers a low-cost, non-invasive, and scalable solution for continuous stress monitoring, making it suitable for personal healthcare, workplace environments, and remote mental health applications. By providing early detection of stress and enabling timely intervention, the system has the potential to improve stress management and overall well-being. Future enhancements may include the integration of additional sensors, mobile application support, and advanced machine learning models to further improve accuracy and usability.

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