

IOT – Based Overthinking and Stress Monitoring System for Students

Nafia A W¹, Harini H P², Chris Vashni V³, Varsikha T R⁴

Department of Information Technology, Arunachala College of Engineering for Women

Abstract

Student stress has become a major concern due to increasing academic pressure and lifestyle challenges. This paper proposes an IoT-based wearable system to monitor stress levels in students in real time. The system uses physiological sensors such as heart rate, GSR, and temperature sensors to collect body signals. These signals are processed using a microcontroller and transmitted to a cloud platform for analysis. A multi-parameter analysis approach is used to improve the accuracy of stress detection by evaluating combined variations in physiological signals. The analyzed data is displayed through a mobile application for real-time monitoring. Additionally, the system provides alerts and simple suggestions to help students manage stress effectively.

Key Words: IoT, Stress Monitoring, Wearable Device, GSR Sensor, Heart Rate, Temperature Sensor, Multi-Parameter Analysis, Student Mental Health, ESP32, Mobile Application.

1. Introduction

In recent years, stress among students has become a major concern due to increasing academic pressure, competition, and lifestyle changes. Students often experience stress and overthinking as a result of examinations, assignments, peer comparison, and personal challenges. If not managed properly, continuous stress can lead to serious issues such as anxiety, reduced concentration, and poor academic performance. Therefore, early monitoring and management of stress is essential for maintaining both mental and physical well-being. The advancement of technology, particularly the Internet of Things (IoT), has enabled the development of smart systems capable of monitoring real-time data. IoT refers to a network of interconnected devices that can collect, transmit, and analyze data over the internet without human intervention. These devices use sensors and communication technologies to provide continuous monitoring and intelligent decision-making in various applications such as healthcare, smart homes, and wearable systems.

In the healthcare domain, IoT-based wearable devices have gained significant attention due to their ability to monitor physiological parameters in real time. These systems allow continuous tracking of body conditions in a non-invasive and efficient manner. However, most existing systems rely on single parameters such as heart rate, which may not always provide accurate results, as these signals can be affected by external factors like physical activity or environmental conditions. To overcome these limitations, that proposes an IoT-based wearable system for stress monitoring in students using a multi-parameter approach. The proposed system integrates physiological sensors such as heart rate, Galvanic

Skin Response (GSR), and temperature sensors to collect real-time body data. These sensors are connected to a microcontroller, which processes the data and transmits it to a cloud platform through IoT connectivity. In the system, IoT plays a key role by enabling communication between the wearable device, cloud platform, and mobile application. The collected data is transmitted over the internet to the cloud, where it is analyzed using a multi-parameter decision-making logic. Based on the analysis, stress levels are identified and the results are sent to a mobile application for real-time monitoring. Additionally, the system provides alerts and stress management suggestions when high stress levels are detected. This implementation of IoT ensures continuous monitoring, remote accessibility, and timely intervention. The proposed system is specifically designed for students, aiming to provide a practical, user-friendly, and effective solution for managing stress and improving overall academic performance.

2. Proposed Method

The proposed method uses an IoT-based wearable system to monitor stress levels in students in real time. The system collects physiological data using sensors such as heart rate, GSR, and temperature sensors. These sensors continuously capture body signals and send them to a microcontroller (ESP32) for processing. The microcontroller preprocesses the data and transmits it to a cloud platform through internet connectivity. In the cloud, the data is stored and analyzed using a multi-parameter approach. Instead of relying on a single signal, the system evaluates combined variations in all parameters. This helps to improve accuracy and reduce false detection caused by external factors. A decision-making logic is applied to identify stress patterns from the collected data. Based on the analysis, stress levels are determined and updated in real time. The results are displayed in a mobile application for easy monitoring. Additionally, alerts and suggestions are provided when high stress levels are detected. An IoT-based overthinking and stress monitoring system for students relies on wearable biometric sensors that stream real-time physiological data to a cloud dashboard for machine learning classification. A Facial and Vocal Expression Based Comprehensive Student Stress Monitoring Framework

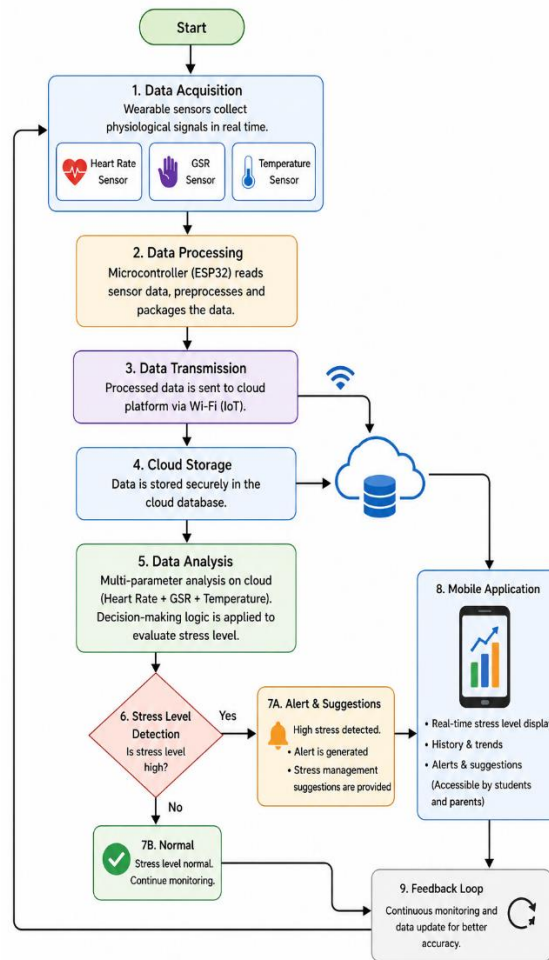


Fig 1. Flow chart

The system begins with the data acquisition stage, where wearable sensors such as heart rate, GSR, and temperature sensors continuously collect physiological signals from the student in real time. These sensors measure body parameters like heart rate, skin conductivity, and temperature. The collected data is then sent to the microcontroller (ESP32), which performs data processing. In this stage, the microcontroller reads the sensor values, filters noise if necessary, and prepares the data for transmission. Next, in the data transmission stage, the processed data is sent to a cloud platform using wireless communication (Wi-Fi), enabling IoT connectivity. In the cloud storage stage, the incoming data is securely stored in a database for further analysis and future reference. The system then moves to the data analysis stage, where a multi-parameter analysis approach is applied. Here, the system evaluates the combined variations of heart rate, GSR, and temperature instead of relying on a single parameter. A decision-making logic is used to identify patterns that indicate stress.

After analysis, the system checks whether the detected stress level is high. This is represented by a decision block in the flow chart. If high stress is detected, the system generates alerts and provides suggestions such as relaxation techniques or short breaks to help the student manage stress. These alerts are sent to the mobile application. If the stress level is normal, the system continues monitoring without triggering any alerts. The analyzed results, including real-time stress levels and historical trends, are displayed in the mobile application, which can be accessed by both students and parents. Finally, the

system operates in a continuous feedback loop, where data is continuously collected, analyzed, and updated to ensure accurate and real-time stress monitoring.

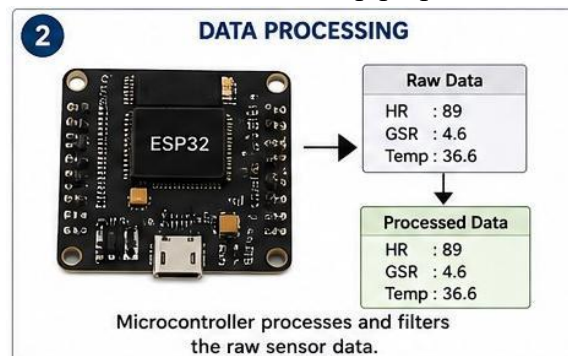
Data Acquisition

In this stage, wearable sensors are used to collect physiological data from the student. The system uses heart rate, GSR, and temperature sensors to measure body signals. These sensors continuously monitor the user in real time. The collected data reflects the physical condition of the student. This stage acts as the input layer of the system.



Data Processing

The collected sensor data is sent to the microcontroller (ESP32) for processing. The microcontroller reads the raw data from all sensors. It performs basic filtering to remove noise or unwanted variations. The data is then organized into a suitable format. This step prepares the data for transmission.



Data Transmission

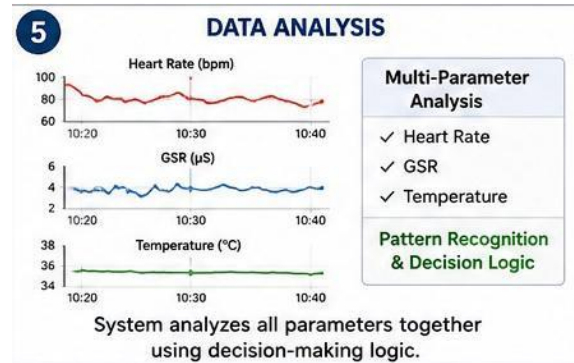
After processing, the data is transmitted to the cloud platform. The ESP32 uses Wi-Fi or internet connectivity for communication. This enables real-time data transfer without delay. The transmission ensures continuous monitoring. It forms the connection between the device and the cloud.

Cloud Storage

Once the data reaches the cloud, it is stored in a database. The cloud platform securely saves the incoming data. It allows access to both current and past data. This helps in tracking stress patterns over time. It also supports further analysis.

Data Analysis

In this stage, the stored data is analyzed using a multi-parameter approach. The system evaluates heart rate, GSR, and temperature together. It avoids relying on a single parameter. A decision-making logic is applied to identify patterns. This improves accuracy in stress detection.



Stress Level Detection

The analyzed data is used to determine the stress level of the student. The system checks for abnormal variations in the parameters. It compares the values with predefined conditions. Based on the analysis, stress is classified as high or normal. This step acts as a decision point in the system.

Alert & Suggestions (If Stress is High)

If high stress is detected, the system generates alerts. Notifications are sent to the mobile application. The user is informed immediately about the stress condition. The system also provides simple suggestions like relaxation or breaks. This helps in reducing stress effectively.

Normal Condition (If No Stress)

If no stress is detected, the system continues monitoring. No alerts are generated in this case. The system maintains normal tracking of data. This avoids unnecessary notifications. It ensures smooth and continuous operation.

Mobile Application

The analyzed results are displayed through a mobile application. The app shows real-time stress levels clearly. It also provides historical data for reference. Notifications and alerts are received through the app. Both students and parents can monitor the data easily.

Feedback Loop

The system operates in a continuous loop for real-time monitoring. Data is collected and analyzed repeatedly. Each cycle updates the stress level information. This ensures accuracy over time. The feedback loop enables continuous improvement and tracking.

Reference

1. J. Liu, J. Hlávka, R. J. Hillestad, and S. Mattke, Assessing the Preparedness of the U.S. Health Care System Infrastructure for an Alzheimer's Treatment. Santa Monica, CA, USA: RAND, 2017.

2. X. Zhu, H.-G. Lee, G. Perry, and M. A. Smith, "Alzheimer disease, the twohit hypothesis: An update," *Biochimica Biophys. Acta (BBA)-Mol. Basis Disease*, vol. 1772, no. 4, pp. 494–502, Apr. 2007.
3. G. Atlanta, "American cancer society. Cancer facts and figures 2013," *Amer. Cancer Soc.*, vol. 7, 2013. [Online]. Available: <http://www.cancer.org/research/cancerfactsstatistics/cancerfactsfigures2013>
4. C. P. Ferri, M. Prince, C. Brayne, H. Brodaty, L. Fratiglioni, M. Ganguli, K. Hall, K. Hasegawa, H. Hendrie, Y. Huang, A. Jorm, C. Mathers, P. R. Menezes, E. Rimmer, and M. Scazufca, "Global prevalence of dementia: A delphi consensus study," *Lancet*, vol. 366, no. 9503, pp. 2112–2117, Dec. 2005.
5. C. G. Lyketsos, O. Lopez, B. Jones, A. L. Fitzpatrick, J. Breitner, and S. DeKosky, "Prevalence of neuropsychiatric symptoms in dementia and mild cognitive impairment: Results from the cardiovascular health study," *Jama*, vol. 288, pp. 1475–1483, 2002.
6. Global Action Plan on the Public Health Response to Dementia 2017– 2025, World Health Organization, Geneva, Switzerland, 2017.
7. I. O. Kang, S.-Y. Lee, S. Y. Kim, and C. Y. Park, "Economic cost of dementia patients according to the limitation of the activities of daily living in Korea," *Int. J. Geriatric Psychiatry*, vol. 22, no. 7, pp. 675–681, 2007.
8. O. L. Lopez, "Cholinesterase inhibitor treatment alters the natural history of Alzheimer's disease," *J. Neurol., Neurosurg. Psychiatry*, vol. 72, no. 3, pp. 310–314, Mar. 2002.
9. H. Jang, B. S. Ye, S. Woo, S. W. Kim, J. Chin, S. H. Choi, J. H. Jeong, S. J. Yoon, B. Yoon, K. W. Park, Y. J. Hong, H. J. Kim, S. N. Lockhart, D. L. Na, and S. W. Seo, "Prediction model of conversion to dementia risk in subjects with amnesic mild cognitive impairment: A longitudinal, multi-center clinic-based study," *J. Alzheimer's Disease*, vol. 60, no. 4, pp. 1579–1587, Nov. 2017.
10. S. H. Kim and S.-H. Han, "Prevalence of dementia in the elderly population of Seoul, Korea," *Int. J. Geriatric Psychiatry*, vol. 22, no. 7, pp. 675–681, 2007.