Stress Level Detection System Based on Internet of Things

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Abstract

Stress is a critical contemporary health issue, causing significant mental and physical damage. Regular monitoring of a person's stress level is vital for early diagnosis of abnormalities that can lead to chronic diseases in the future. While various stress detection methods exist, this research introduces a novel and accessible IoT-based system that integrates a unique combination of physiological parameters: heart rate, body temperature, and, distinctively, exhaled CO_2 concentration. This approach utilizes low-cost, readily available components, including an Arduino Mega microcontroller, an ESP8266 Wi-Fi module, a Pulse Heart Rate sensor, a DS18B20 temperature sensor, and an MQ-2 sensor to measure respiratory CO_2. The significance of this work is demonstrated through its successful implementation and testing on five young adult subjects. The results establish a clear correlation between the measured biometrics and four distinct stress classifications (severe, moderate, mild, and normal). All data is displayed in real-time on a local LCD and transmitted to the Thingspeak IoT platform for continuous analysis. This study confirms the feasibility of using this novel sensor combination to create an affordable, real-time stress monitoring tool, offering a significant contribution to preventive healthcare through early detection and intervention.

Keywords— Arduino Mega, Stress Level Detection, DS18B20, MQ-2, Pulse Heart Sensor

1. INTRODUCTION

The escalating prevalence of psychological stress in contemporary society represents a significant and pervasive public health challenge. Beyond its immediate impact on mental well-being, chronic stress is a well-established precursor to a host of severe physiological conditions, including cardiovascular disease, metabolic disorders, and compromised immune function [1] [2] [3]. The societal and economic burdens are substantial, leading to increased healthcare costs and reduced productivity [4]. This underscores the urgent need for accessible and reliable methods for the early detection and continuous monitoring of stress levels, enabling timely interventions before acute stress transitions into chronic illness [5]. Depression can be caused by a history of severe depression during adolescence and continuing into early adult life [6].

Preventive action can be taken by detecting stress early, which is done to prevent it, and it can be treated immediately by visiting a professional in the field. In recent years, the field of biomedical engineering has made significant strides in developing technologies for physiological monitoring. The primary approaches for objective stress detection have centered on measuring autonomic nervous system responses through various biosignals. High-fidelity systems employing electroencephalography (EEG) or electrocardiography (ECG) provide detailed neural and cardiac data but are often intrusive, expensive, and require clinical settings, making them unsuitable for daily, real-world monitoring [7] [8]. Wearable technologies have emerged as a more practical alternative, with many commercial devices relying on photoplethysmography

(PPG) for heart rate monitoring and Galvanic Skin Response (GSR) to measure electrodermal activity. While valuable, these solutions often face two key limitations: the high cost of sophisticated multi-sensor devices and, in more affordable models, a reliance on a limited set of parameters that may not provide a complete picture of the stress response [9].

The stress level is calculated based on sensor values, and the information is transmitted using IoT. The results of the sensor readings are compared with the stress level limit table, so that a decision on the condition of human stress levels is obtained. IoT (Internet of Things) based wireless networks offer various opportunities to regularly monitor stress levels and transmit information so that affected people can take immediate action [10] [11].

This research uses variables that cause human stress levels based on a table of physical limits on stress levels in young adults. Young adulthood begins around 18 to 22 years of age and ends at 35 to 40 years of age [12]. These variables consist of heart rate, temperature, and CO_2 gas concentration. Much research has been carried out on detecting stress levels before, such as research conducted by [13], which only took the variables heart rate and body temperature. Research conducted by [14] only took the CO_2 gas concentration variable.

This points to a distinct and critical research gap in the literature: the need for a stress detection system that is not only low-cost and non-invasive but also integrates a more holistic and insightful combination of physiological markers. While much research has focused on heart rate and body temperature, a crucial, yet often overlooked, indicator of the acute stress response is respiration. Psychological stress is known to directly influence respiratory rate and depth, which in turn alters the concentration of carbon dioxide (CO_2) in exhaled breath. Some studies have explored this link in isolation; however, the synergistic potential of combining this respiratory marker with other established indicators like heart rate and body temperature in a single, accessible IoT device remains largely unexplored. The integration of exhaled CO_2 offers a novel dimension for analysis, potentially providing a more sensitive and comprehensive assessment of a user's physiological state.

This paper directly addresses this gap by designing, implementing, and validating a novel Stress Level Detection System based on the IoT. Our primary contribution lies in the unique and strategic integration of three specific physiological parameters: heart rate, body temperature, and exhaled CO_2 concentration. We hypothesize that this multi-modal approach yields a more robust and accurate classification of stress levels than systems reliant on a more limited set of inputs. To ensure broad accessibility, our system is intentionally architected using affordable, commercially available components: a Pulse Heart Rate sensor for cardiac monitoring, a DS18B20 sensor for accurate temperature measurement, and, critically, an MQ-2 gas sensor repurposed for the novel application of detecting exhaled CO_2. These sensors are controlled by an Arduino Mega microcontroller, with data transmitted via an ESP8266 Wi-Fi module to both a local LCD for immediate feedback and the Thingspeak IoT platform for continuous, remote monitoring and data logging. The system is designed to automatically classify a user's state into one of four distinct levels—severe stress, moderate stress, mild stress, and normal—thereby providing actionable insights for personal health management. Ultimately, this research aims to demonstrate the feasibility and efficacy of this novel sensor fusion, presenting a significant and practical contribution to the field of preventive health technology. The four threshold parameters used in this project to determine the range of variable values in both normal and abnormal conditions for heart rate, temperature, and CO_2 gas concentration are shown in Table 1. The threshold parameters refer to the journal [15].

Table 1. Stress Level Parameter Variable

Condition	**Parameter**		
	Heart Rate (BPM)	***Temperature (ºC)***	***CO2 concentration (PPM)***
Severe Stress	*> 100*	*<33 and >40*	*>50*
Moderate Stress	90-100	33-35	>45
Mild Stress	70-90	35-36	>40
Normal	60-70	36-37	<40

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2. RESEARCH METHODS

Designing a stress level detection system based on the Internet of Things can be used to detect stress early to take preventive action for mental problems [16]. The hardware components used in designing this tool are the pulse heart rate sensor, MQ-2 sensor, Arduino Mega, LCD, and ESP8266 Wifi Module. The software used in making this tool is Arduino IDE. This tool works with the Pulse heart rate sensor, which is used to detect heartbeats, the DS18B20 sensor to detect temperature, and the MQ-2 to detect the concentration of CO_2 gas, which is displayed on the LCD and Thingspeak. Arduino Mega is used as a controller that is programmed using Arduino IDE software. The experimental protocol involved human subjects to test the system's efficacy.

- Participants: A total of five individuals were recruited as research subjects for this study.
- Inclusion Criteria: All participants were within the young adulthood age range, specifically between 18 and 23 years old. A key condition for participation was that subjects had not engaged in any strenuous physical activities before the testing session, ensuring that the physiological readings were representative of a baseline or mentally induced state rather than physical exertion.

The sensors can take accurate detections in about 1 minute, with the output stress levels appearing namely severe stress, moderate stress, mild stress, and normal.

2.1. *Block Diagrams and device design*

Figure 1 shows that the block diagram consists of a pulse heart rate sensor as a heart rate and oxygen saturation detector, the MQ-2 sensor is used to detect CO_2 gas concentration [17], and the DS18B20 is used as a temperature detector [18]. Arduino Mega and ESP8266 Wifi module are used as processing blocks. LCD is used as a display of stress level results, and Thingspeak is an IoT display for results from sensors, used as a data receiver or output block.

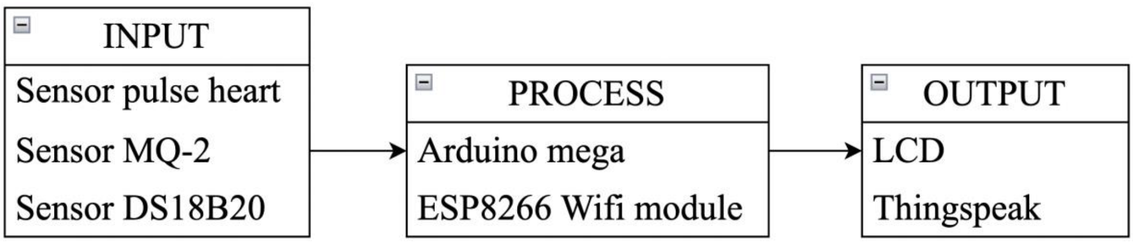

Figure 1. Block Diagram

2.2. *Flowchart*

The WiFi module used in this system is the ESP8266, which is paired with an Arduino Mega to enable internet connectivity [19]. This combination allows for seamless data transmission to various online platforms. Figure 2 presents a detailed system flowchart illustrating the initialization process of the sensors. The first sensor to be initialized is the Pulse heart rate sensor, responsible for measuring the heart rate of the user. Upon successful initialization, the sensors can display their respective results on an LCD screen. These results include critical health metrics such as Beats Per Minute (BPM) for heart rate, temperature readings, parts per million (PPM) measurements for air quality, and stress level conditions.

In addition to local display, the sensor readings are also transmitted to an IoT platform, specifically Thingspeak. This online platform allows for real-time monitoring and analysis of the data, providing a convenient and efficient way to track health and environmental conditions [20]. The integration of the ESP8266 WiFi module with the Arduino Mega and the sensors facilitates a robust system. This robust system is capable of both local and remote monitoring, ensuring that users have access to accurate and up-to-date information at all times [21].

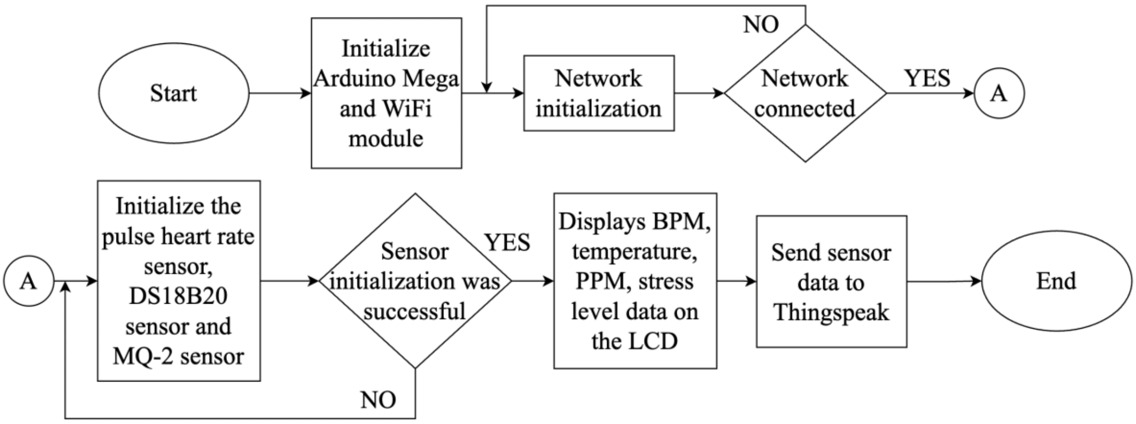

Figure 2. System Flowchart

A systematic procedure was followed for data collection from each subject to ensure consistency and accuracy.

1. Preparation: Each subject was seated and instructed to remain in a state of rest.
2. Sensor Placement: The three sensors were carefully attached to the subject's body in their designated locations to optimize signal acquisition. The Pulse Heart Rate sensor was placed on the subject's fingertip. The DS18B20 temperature sensor was positioned within a fold of the body, such as the armpit, to obtain a stable temperature reading. The MQ-2 sensor was fitted inside an oxygen mask, which was then placed over the subject's nose and mouth to specifically capture the concentration of CO_2 in their exhaled breath.
3. Data Acquisition: Once the sensors were in place, the system was initiated. The device was programmed to perform data acquisition for approximately one minute to ensure a stable and accurate detection of all three physiological parameters.
4. Data Processing and Output: During the acquisition period, the Arduino Mega continuously read the incoming sensor data. It then compared these values (BPM, °C, PPM) against the predefined thresholds from Table 1 to classify the subject's current stress level.
5. Real-Time Display: The results were displayed in real-time. Both the raw sensor values and the final stress classification ("Severe stress," "Mild stress," etc.) were shown on the integrated LCD screen. Simultaneously, the ESP8266 module transmitted the sensor data to a dedicated channel on the Thingspeak IoT platform, allowing for remote monitoring and logging of the results.

Figure 3 illustrates a closed-loop flowchart designed to monitor and evaluate sensor data conditions. This flowchart outlines specific conditions that the system uses to detect various states based on the data read by the sensors.

- Severe Stress: If the Pulse heart rate sensor detects a heart rate of over 100 BPM, the DS18B20 temperature sensor reads a temperature below 33°C or above 40°C, and the MQ-2 sensor detects a CO_2 gas concentration above 50 PPM, the system will categorize this as a severe stress condition. This information will be displayed on the LCD screen, alerting the user to the high stress level.
- Moderate Stress: If the Pulse heart rate sensor measures a heart rate between 90 BPM and 100 BPM, the DS18B20 sensor reads a temperature above 40°C, and the MQ-2 sensor shows a CO_2 concentration above 45 PPM, the system will classify this state as Moderate stress. This stress level will be displayed on the LCD, informing the user of a moderate stress condition.

- Mild Stress: If the Pulse heart rate sensor records a heart rate between 70 BPM and 90 BPM, the DS18B20 sensor detects a temperature between 36°C and 38°C, and the MQ-2 sensor measures a CO_2 concentration of 45 PPM or lower, the system will identify this as mild stress. The LCD screen will display this information, indicating a lower level of stress.
- Normal Stress Levels: If the Pulse heart rate sensor reads a heart rate between 60 BPM and 70 BPM, the DS18B20 sensor records a temperature between 36°C and 38°C, and the MQ-2 sensor detects a CO_2 concentration below 40 PPM, the system will determine that the stress level is normal. This normal stress level will be displayed on the LCD, indicating that the user's physiological parameters are within a healthy range.

These conditions enable the system to provide real-time feedback on the user's stress levels by analyzing the combined data from the heart rate sensor, temperature sensor, and CO_2 gas sensor. The closed-loop flowchart ensures continuous monitoring and immediate display of stress levels, thereby facilitating timely awareness and management of the user's health status.

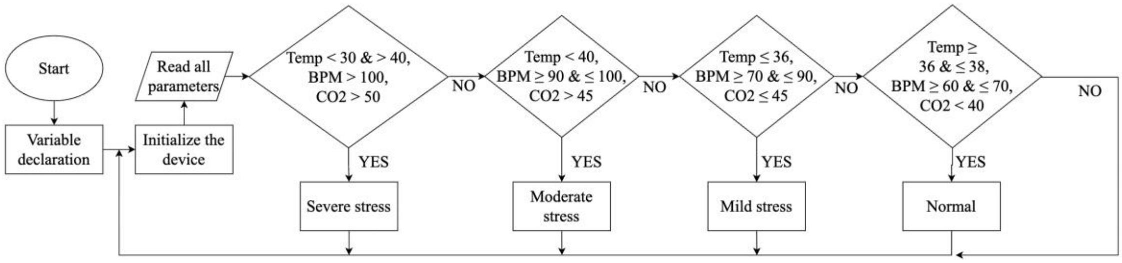

Figure 3. Condition Flowchart

3. RESULT AND DISCUSSION

The research results consist of comprehensive testing and evaluation of three distinct sensors: the DS18B20 temperature sensor, which measures precise temperature changes; the pulse heart rate sensor, designed to detect and monitor heart rate data; and the MQ-2 gas sensor, which is used to detect combustible gases such as methane and propane.

3.1. Pulse Heart Rate Sensor Testing and Analysis

Figure 4 is a finger that is placed on the Pulse heart Rate sensor. The finger placed on the sensor aims to detect the pulse, which is processed by the microcontroller. Table 2 is a comparison table for testing pulse heart rate sensors with fingertips. In tests carried out by comparing pulse heart rate sensors with fingertips, the average error was found to be 2,952%. An error margin below 3% is considered highly acceptable for a non-clinical screening device using photoplethysmography (PPG) [22]. This result confirms the sensor's viability for this application. The scientific basis for this measurement is the detection of blood volume changes in the microvascular bed of the fingertip. While this method is effective, minor errors can arise from motion artifacts or variations in sensor placement. A significant contribution of this finding is demonstrating that an affordable, market-available Pulse Heart Rate sensor can achieve sufficient accuracy for stress screening. This stands in contrast to previous studies that relied on more expensive Galvanic Skin Response (GSR) sensors to assess autonomic arousal, thereby supporting our objective of creating an accessible system.

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Figure 4. The finger is placed on the sensor

Table 2. Comparison of the pulse heart rate sensor with the fingertip

Fingertip (BPM)	Pulse Heart Rate (BPM)	Error (%)
69	65	5,79
66	68	3,03
67	65	2,98
65	66	1,53
70	69	1,43
Mean error (%)		2,952

3.2. *DS18B20 sensor testing*

Figure 5 is an image of the DS18B20 sensor placed in the folds of the body, which aims to detect body temperature. Table 3 shows a comparison table between the DS18B20 sensor and a digital thermometer, and produces an average error of 0,9. This low error margin signifies a high degree of accuracy and reliability. Accurate temperature measurement is physiologically relevant as the stress response can induce peripheral vasoconstriction, leading to a drop in skin temperature at the extremities. In a direct comparison with previous research by Deza [15], which used an LM35dz sensor with an error rate of 1.455% shown in Table 4, our choice of the DS18B20 sensor represents a measurable improvement in measurement rigor. This enhanced accuracy strengthens the validity of the temperature data as a reliable input for our stress classification algorithm.

Figure 5. The sensor is placed in the folds of the body

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Table 3. Testing the sensor with a thermometer

Thermometer (ºC)	DS18B20 (ºC)	Error (%)
34,2	34,5	0,87
34,6	34,9	0,87
34,2	34,4	0,58
34,4	34,0	1,16
32,7	32,4	0,91
Mean error (%)		0,9

Table 4. Comparison of research on temperature sensors used

Research	Sensor used	Sensor accuracy level
Deza [15]	LM35dz	1,455%
Current research	DS18B20	0,9%

3.3. *MQ-2 sensor testing*

Placing the sensor near the mouth and nose shown in Figure 6, is important for several reasons. First, this area is the place where the concentration of CO_2 gas exhaled by a person is highest [23], so the sensor can capture more accurate and relevant measurements. Second, the level of exhaled CO_2 can change based on a person's physiological conditions, such as an increase in respiratory rate when experiencing stress [24], which can increase the concentration of exhaled CO_2. Third, placing the sensor near the mouth and nose allows detection of changes in the respiratory process directly, which is very important for stress level testing. Lastly, this placement reduces interference from other gas sources in the surrounding environment, ensuring that the data collected truly originates from the breath of the individual being tested.

The scientific rationale for this approach is the well-documented link between psychological stress and the respiratory system. The "fight-or-flight" response, triggered by stress, increases the activity of the sympathetic nervous system, which typically elevates the respiratory rate. This altered breathing pattern changes the composition of exhaled air, often increasing the concentration of CO_2. While many past studies did not utilize the MQ-2 sensor for stress detection, our work demonstrates its potential as a low-cost proxy for monitoring stress-induced respiratory changes. This provides a novel and accessible method for adding a respiratory dimension to physiological stress assessment. Research using the MQ-2 to measure stress levels was conducted by Anusha [14]. Sensor results are shown in Table 4.

Figure 6. Use of the MQ-2 Sensor in oxygen masks

3.4. *Overall testing*

Overall testing of the tool was carried out using experimental subjects aged 18-23, young adults. Testing is carried out with subjects who are not in a condition where they have carried out strenuous activities. The use of these sensors can be seen in Figure 7.

Figure 7. Overall testing of the device

The values from the sensors used will later be sent to the LCD and also to Thingspeak. The LCD will display the value output from each sensor and the stress condition, while Thingspeak is used to display the value output from each IoT-based sensor. Figure 8 is the output from the LCD, and Figure 9 is the output image from Thingspeak. Table 5 is a table of results from system testing that has been carried out.

Based on Table 5, a clear correlation between the measured biometric readings and the classified stress levels can be concluded. The findings are summarized as follows:

- Severe Stress: Subjects in this category (aged 22 and 23) were characterized by high heart rates (109 and 112 BPM) and high exhaled CO_2 concentrations (53.3 and 52 PPM), combined with body temperatures below the normal range (29.4°C and 32.1°C).
- Moderate Stress: A participant aged 21 exhibited moderate stress with a heart rate approaching the severe threshold (97 BPM), a slightly low temperature (33.6°C), and an elevated CO_2 level (47.2 PPM).
- Mild Stress: The subject with mild stress (aged 23) showed a heart rate within the 70-90 BPM range (72 BPM), a temperature of 35.1°C, and a CO_2 concentration of 42.3 PPM.
- Normal: The subject with normal stress levels (aged 18) displayed biometric data within typical resting ranges, including a heart rate of 67 BPM, a temperature of 36.2°C, and a CO_2 level of 38.2 PPM.

These findings collectively illustrate that higher BPM and PPM values are strongly associated with increased stress levels, while normal physiological states correspond to lower BPM and PPM values and temperatures within the typical human range.

Table 5. Device testing

Age	BPM	°C	PPM	Condition
23	112	32,1	52	Severe stress
22	109	29,4	53,3	Severe stress
23	72	35,1	42,3	Mild stress
21	92	33,6	47,2	Moderate stress
18	67	36,2	38,2	Normal

Figure 8. LCD Output

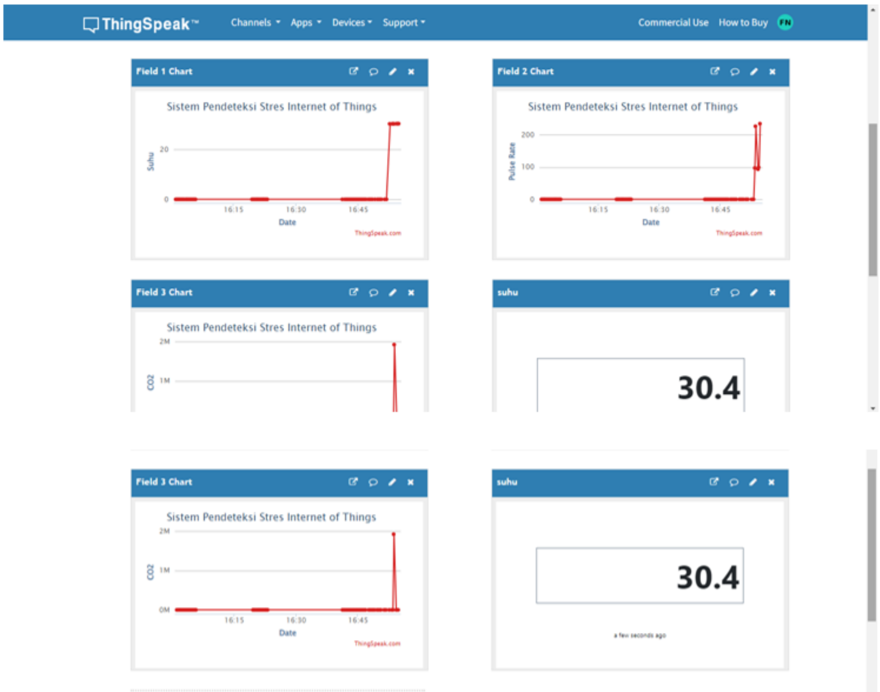

Figure 9. Thingspeak output

The key finding is that higher BPM and PPM values are directly associated with increased stress levels. Table 6 compares our system with prior research. While work by Deza [15] used more parameters, including complex ones like blood pressure and GSR, our system demonstrates that a streamlined approach using a novel combination of heart rate, temperature, and exhaled CO_2 can effectively differentiate between stress states. Our contribution lies in validating a simpler, more accessible system that incorporates a novel respiratory marker (CO_2) to achieve a robust, multi-faceted assessment of stress. This addresses the need for practical, low-cost tools for continuous, real-world stress monitoring.

Table 6. Overall research parameter comparison

Research	Parameters used	Sensor used
Deza [15]	Skin resistance and heart rate, blood pressure, body temperature	GSR, MPX5050dp, LM3dz
Anusha [14]	Blood pressure, heart rate, temperature, and respiration CO_2 gas concentration	Blood pressure sensor, LM35, dan MQ-2
Current research	Heart rate, temperature, and CO_2 gas concentration	Pulse heart rate sensor, DS18B20, dan MQ-2

4. CONCLUSION

This research successfully designed, built, and validated a low-cost, IoT-based system for real-time stress detection. The system demonstrated a clear and physiologically consistent correlation between the measured biometric data, heart rate, body temperature, and exhaled CO_2 concentration and the classified stress levels in a cohort of young adults. The scientific contributions of this work are threefold. First, we have introduced and validated a novel, multi-modal sensing approach that uniquely integrates exhaled CO_2concentration with heart rate and temperature as a combined indicator of stress. This presents a more holistic yet streamlined method compared to previous studies that either used fewer parameters or relied on more complex and expensive sensors. Second, by utilizing the DS18B20 sensor, our system achieved a higher degree of accuracy in temperature measurement (0.9% error) than that reported in related prior research, thereby enhancing the rigor of the data. Third, this study confirms the feasibility of creating an affordable and accessible tool for continuous stress monitoring, lowering the barrier to entry for personal health management.

While this study establishes a strong proof-of-concept, we recommend several avenues for future development. The primary limitation of the current work is the small sample size of five individuals; therefore, future research should focus on validating the system with a larger, more diverse demographic cohort to improve the generalizability of the findings. Furthermore, the current rule-based classification system, while effective, could be significantly enhanced by incorporating machine learning. Future iterations should involve collecting a larger dataset to train and deploy algorithms capable of providing more personalized and adaptive stress detection. Finally, testing the system's dynamic response using standardized stress-induction protocols would provide deeper insights into its real-world efficacy.

In summary, this research contributes a novel and practical approach to non-invasive stress monitoring, paving the way for accessible technologies that can empower individuals to proactively manage their well-being and prevent the onset of chronic, stress-related diseases.

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REFERENCES

[1] M. R. Hidayatullah dan W. Maharani, “Depression Detection on Twitter Social Media Using Decision Tree,” RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 6, no. 4, pp. 677 - 683, 2022.

[2] d. V. V. Handayani, “Kesehatan Mental Bisa Memengaruhi Kesehatan Fisik,” 08 Oktober 2021.

[3] S. Adepua, K. P. Samudralab, S. Kamsani dan S. Aruvanti, “Smart Technology for Real-time Evaluation of Stress Levels,” dalam International Conference on Environmental Development Using Computer Science (ICECS’24), Tamil Nadu, India, 2024.

[4] P. Chyan dan Y. Kasmara, “Sistem Monitoring dan Deteksi Stres Pada Anak Berbasis Wearable Device,” RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 5, no. 5, pp. 943 - 949, 2021.

[5] Y. Huang dan N. Zhao, "Generalized anxiety disorder, depressive symptoms and sleep quality during COVID-19 outbreak in China: a web-based cross-sectional survey.," Psychiatry Research, vol. 228, no. 1, 2020.

[6] D. J. Smith dan D. H. R. Blackwood, "Depression in young adults. Advances in Psychiatric Treatment," BJPsych Advances, vol. 10, no. 1, pp. 4-12, 2004.

[7] T. Waili, Y. S. Alshebly, K. A. Sidek dan M. G. M. Johar, "Stress recognition using Electroencephalogram (EEG) signal," dalam Indonesian Clinical Training and Education Center, Cipto Mangunkusumo Hospital, Jakarta, Indonesia., 2020.

[8] L. R, "ECG signatures of psychological stress," Journal of electrocardiology, vol. 48, no. 6, pp. 1000-1005, 2015.

[9] C. Wall, V. Hetherington dan A. Godfrey, "Beyond the clinic: the rise of wearables and smartphones in decentralising healthcare," npj Digital Medicine, vol. 6, no. 213, 2023.

[10] F. Antonius dan A. Saepudin, "The Impact of IoT on The Storing Process of Leather Raw Material," RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 7, no. 4, pp. 782 - 790, 2023.

[11] I. R. Nugraha, W. H. N. Putra dan E. Setiawan, "A Comparative Study of HTTP and MQTT for IoT Applications in Hydroponics," RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 8, no. 1, pp. 119 - 126, 2024.

[12] J. J. Arnett, Emerging Adulthood: The Winding Road from the Late Teens Through the Twenties (3rd edn), Oxford: Oxford University Press, 2023.

[13] E. Suwarto, "Alat Pendeteksi Tingkat Stress Manusia Berbasis Atmega16," ORBITH, vol. 8, no. 1, pp. 1-9, 2012.

[14] A. Anusha, N. Padmaja, D. Manaswi dan B. S. Kumar, "IOT Based Stress Detection and Health Monitoring System," Helix, pp. 161-167, 2020.

[15] F. Deza, P. Madona dan N. Rahmardy, "Alat Pendeteksi Tingkat Stress Manusia Berdasarkan Suhu Tubuh, Kelembaban Kulit, Tekanan Darah dan Detak Jantung.," Jurnal Politeknik Caltex Riau, pp. 31-42, 2017.

[16] Y. Yuhefizar, A. Nasution, R. Putra, E. Asri dan D. Satria, "Alat Monitoring Detak Jantung Untuk Pasien Beresiko Berbasis IoT Memanfaatkan Aplikasi OpenSID berbasis Web," Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 3, no. 2, pp. 265 - 270, 2019.

[17] R. Kumar, S. Singla dan J. Bansal, "IOT Based Air Pollution Monitoring System," International Scientific Journal of Engineering and Management, vol. 2, no. 4, pp. 1-6, 2023.

[18] Izhangghani, I. Hikmah dan S. Indriyanto, "Prototype of Body Temperature and Oxygen Saturation Monitoring System Using DS18B20 and MAX30100 Sensors based on IOT," Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 6, no. 5, pp. 810 - 817, 2022.

[19] J. Waworundeng, "Design Prototype Detector of Temperature, Humidity, and Air Quality using Sensors, Microcontrollers, Solar Cells, and IoT," CogITo Smart Journal, vol. 10, no. 1, p. 271–284, 2023.

[20] S. Ali, A. Atef, E.-B. Nirmeen, E. B. Ghada dan A. E.-S. Fathi, "Smart Health Monitoring System based on IoT and Cloud Computing," Menoufia Journal of Electronic Engineering Research, vol. 28, no. 1, pp. 37-42, 2024.

[21] E. P. Tenda, A. V. Lengkong dan K. F. Pinontoan, "Sistem Peringatan Dini Banjir Berbasis IoT dan Twitter," CogITo Smart Journal, vol. 7, no. 1, p. 26–39, 2021.

[22] A. N. L. Hermans, J. L. Isaksen*, M. Gawalko, N. A. H. A. Pluymaekers, R. M. J. v. d. Velden, H. Snippe, S. Evens, G. D. Witte, J. G. L. M. Luermans, M. Manninger, J. Lumens, J. K. Kanters dan D. Linz, "Accuracy of continuous photoplethysmography-based 1 min mean heart rate assessment during atrial fibrillation," EP Europace – EHJ Arrhythmias and Electrophysiology (EP Europace), vol. 25, no. 3, p. 835–844, 2023.

[23] halodoc, "Mengenal Struktur dan Fungsi dalam Rongga Hidung," Halodoc, 04 01 2023. [Online]. Available: https://www.halodoc.com/artikel/mengenal-struktur-dan-fungsi-dalam-rongga-hidung. [Diakses 11 07 2024].

[24] Alodokter, "Seperti Ini Cara Kerja Sistem Pernapasan pada Manusia," Alodokter, 08 06 2022. [Online]. Available: https://www.alodokter.com/seperti-ini-cara-kerja-sistem-pernapasan-pada-manusia. [Diakses 11 07 2024].

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