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IoT-Enabled Stress Prediction System With Multi-Sensor Integration

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Abstract
The rapid proliferation of Internet of Things (IoT)-enabled wearable devices has created unprecedented opportunities for continuous, non-invasive physiological monitoring in real-world settings. This paper presents the design, simulation, and implementation of a multi-modal stress detection system based on an Arduino Uno microcontroller interfaced with an infrared (IR) sensor for eye-blink rate detection, a heart beat sensor for cardiac activity monitoring, a sound detector for respiratory rate estimation, and a thermometric module for body temperature acquisition. Recognised as a major global health concern by the World Health Organization, stress manifests through measurable autonomic nervous system (ANS) responses — including elevated heart rate, irregular breathing patterns, suppressed eye-blink rate, and peripheral temperature changes — which this system captures simultaneously. The proposed architecture was validated through Proteus Professional circuit simulation, successfully demonstrating stable, real-time acquisition of all four physiological parameters with consistent serial output (Temp = 62, Eye Blink = 38, Resp = 44, Heart Beat = 40). The system offers a low-cost, portable, and extensible platform suitable for IoT-based remote stress monitoring and future integration with machine learning classifiers for automated stress-level prediction.
Keywords: Stress Detection • Wearable Sensors • IoT Health Monitoring • Arduino • Physiological Signals • Heart Rate Variability

1. INTRODUCTION
The rapid advancement of embedded systems and Internet of Things (IoT) technologies has opened new frontiers in non-invasive physiological monitoring. Stress, recognised by the World Health Organization as a "21st Century Health Epidemic," is a pervasive condition closely linked to serious health outcomes including cardiovascular disease, hypertension, anxiety, and depression [1,2]. The ability to detect and monitor stress in real time — unobtrusively and continuously — represents one of the most pressing challenges in modern biomedical engineering.
Physiological signals such as heart rate, body temperature, eye-blink frequency, and respiratory rate are well-established biomarkers of the human stress response. When an individual experiences stress, the autonomic nervous system (ANS) triggers measurable biological changes: heart rate rises, respiratory patterns become irregular, eye-blink rate is suppressed, and peripheral body temperature fluctuates [3,4]. Monitoring these parameters simultaneously provides a richer and more reliable picture of stress state than any single signal in isolation.
Conventional clinical stress assessment methods — such as cortisol testing, electroencephalography (EEG), or electrocardiography (ECG) — while accurate, require specialised equipment, trained

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personnel, and controlled environments, making them unsuitable for continuous, real-world monitoring [5,6]. There is therefore a growing demand for low-cost, portable embedded solutions capable of acquiring and processing multiple physiological parameters in real time, outside of clinical settings.

Microcontroller-based platforms, particularly the Arduino ecosystem, have emerged as highly accessible and flexible foundations for such systems. Their open-source nature, widespread sensor compatibility, and low power consumption make them well-suited for wearable and ambient stress monitoring prototypes [7,8].

This paper presents the design, simulation, and implementation of a multi-modal physiological monitoring system for stress detection using an Arduino Uno microcontroller. The proposed architecture was validated through Proteus Professional simulation, confirming correct acquisition and serial output of real-time physiological data across all sensing channels. The remainder of this paper is organised as follows: Section 2 presents related work; Section 3 describes the system architecture; Section 4 details simulation results; Section 5 discusses findings; and Section 6 concludes the paper.

2. RELATED WORK

The integration of wearable devices in healthcare has transformed monitoring of physiological and behavioural data, enabling significant advances in clinical treatment and personal health management [1,2]. Devices such as smart watches and fitness trackers provide rich datasets, including heart rate variability (HRV), body temperature, physical activity patterns, and sleep quality metrics, essential for stress analysis [3,4,5].

Stress can be defined as any type of change that causes physical, emotional, or psychological strain, eliciting a cascade of biological responses in both the brain and body [6]. Stressors produce manifestations including headaches, gastrointestinal disorders, anxiety, hypertension, and coronary heart disease [20].

Bundele and Banerjee [7] developed a wearable device utilising non-invasive sensors to identify stress and fatigue in vehicle drivers. Bottani et al. [8] applied wearables for ergonomic hazard detection in industrial settings. Sun et al. [9] demonstrated a wearable H-shirt for ECG monitoring and lactate threshold computation, illustrating the breadth of physiological parameters accessible through wearable technology.

The autonomic nervous system regulates HR, ventilation, metabolism, and blood pressure. Resting HR typically ranges from 60–90 bpm; under stress, HR rises dramatically, increasing blood pressure and reducing HRV. Low HRV is a well-established indicator of psychological stress [12,13]. There is therefore a growing demand for efficient stress detection systems capable of monitoring physiological signals continuously and providing effective user feedback [14].

Table 1 summarises key studies from the related literature, comparing sensor modalities, processing platforms, physiological parameters, IoT capability, and application domains. This comparison highlights the gaps addressed by the proposed system — particularly multi-modal sensing, low-cost embedded hardware, and IoT extensibility in a single platform.

Table 1. Comparative summary of existing physiological stress monitoring systems.

Ref.	Authors	Platform	Parameters	Application
[7]	Bundele & Banerjee (2009)	Custom wearable	GSR, SpO_2	Driver fatigue
[8]	Bottani et al. (2021)	MR wearable	Posture, motion	Manufacturing
[9]	Sun et al. (2017)	H-shirt	ECG, lactate	Exercise

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Ref.	Authors	Platform	Parameters	Application
[10]	Sun et al. (2022)	Flex. wearable	HR, SpO_2, temp	Sports
[11]	Kadhim et al. (2020)	IoT + cloud	Health vitals	Remote care
[13]	Mohan et al. (2016)	PPG sensor	HRV	Stress
[14]	Maxhuni et al. (2016)	Smartphone	Physio. + behav.	Daily stress
Prop.	**This Work**	**Arduino Uno R3**	**Temp, Blink, Resp, HR**	**Real-time stress**

Note: GSR = Galvanic Skin Response; HRV = Heart Rate Variability; PPG = Photoplethysmography. Green row = proposed system.

As evident from Table 1, most existing studies focus on single or dual physiological parameters and lack a fully integrated, low-cost embedded solution with IoT extensibility. The proposed system addresses these gaps by combining four complementary physiological channels on a single Arduino-based platform.

3. SYSTEM ARCHITECTURE AND PROPOSED METHODOLOGY

The proposed system integrates multiple physiological sensing modalities into a unified IoT-enabled platform for real-time stress monitoring. Figure 2 presents the complete system block diagram illustrating the five-layer architecture: the sensor layer, signal conditioning layer, processing unit (Arduino Uno R3), output interface layer, and IoT/Cloud layer.

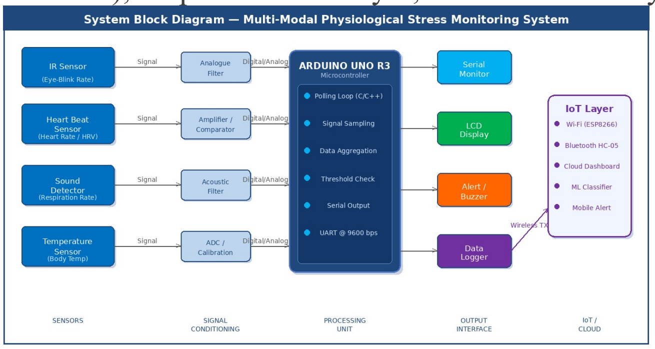

FIGURE 2. System block diagram of the proposed multi-modal physiological stress monitoring system.

The hardware implementation comprises an Arduino Uno microcontroller as the central processing unit, interfaced with the following sensor modules: (i) Infrared (IR) Sensor for eye-blink rate detection; (ii) Heart Beat Sensor for cardiac activity monitoring; (iii) Sound Detector for respiratory pattern estimation; and (iv) Temperature Sensor via variable resistor network for body temperature profiling.

This multi-modal sensing approach enables simultaneous acquisition of key physiological indicators associated with the stress response. The Arduino Uno R3 serves as the data aggregation hub, reading analogue and digital signals from each sensor, processing raw values through calibrated firmware, and transmitting consolidated output via serial communication at regular intervals.

3.1 Signal Acquisition and Processing

Each sensor module is interfaced with a dedicated analogue or digital input pin on the Arduino Uno. A variable resistor (potentiometer) network is employed for analogue signal conditioning, allowing threshold calibration for each sensing channel independently. The firmware, written in the Arduino

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IDE (C/C++), implements a polling-based acquisition loop that samples all four parameters sequentially and outputs readings over a UART serial link at 9600 bps.

3.2 Operational Architecture and Flowchart

Figure 3 illustrates the operational architecture as a step-by-step flowchart. Upon system power-on, all sensor modules are initialised and signals conditioned through the analogue stage. The Arduino firmware enters a continuous polling loop. A validity check ensures only clean signals are processed — invalid signals trigger a retry loop. Once valid data is acquired, the four physiological parameters are computed and evaluated against pre-defined stress thresholds. Elevated stress triggers data transmission via UART or wirelessly (ESP8266/Bluetooth) to the output and cloud layer for alerting and logging.

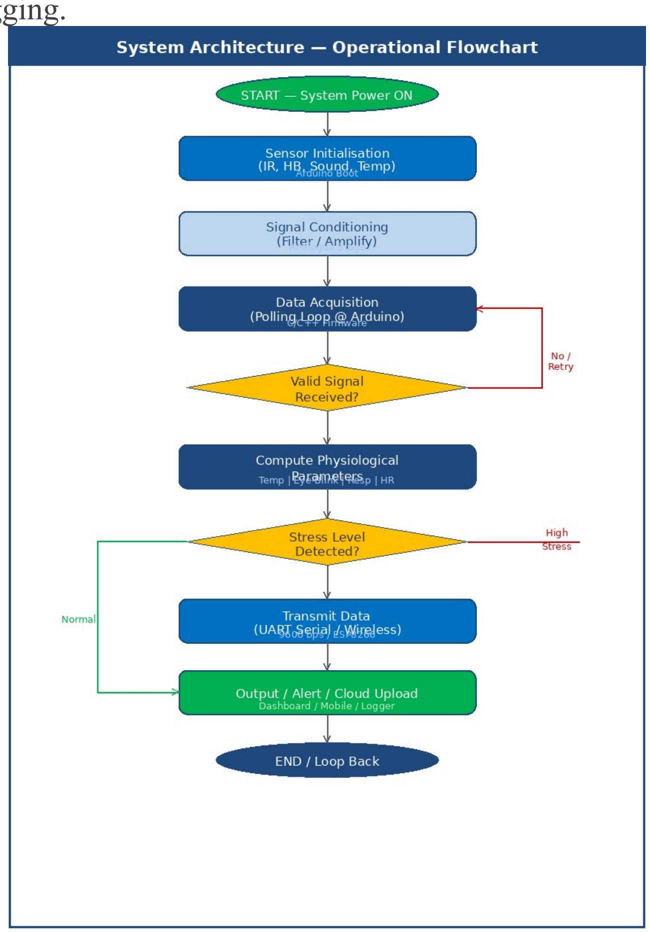

FIGURE 3. Operational architecture flowchart of the proposed stress monitoring system.

4. SIMULATION METHODOLOGY AND RESULTS

4.1 Simulation Environment

The proposed system was validated using Proteus Professional (Version 8.x) simulation software prior to physical hardware implementation. Proteus provides an accurate virtual modelling environment for the Arduino Uno R3 and a wide library of peripheral sensor components, enabling functional verification of firmware logic and sensor interfacing before physical deployment.

4.2 Simulation Setup

The Proteus schematic, illustrated in Figure 4, comprises the following virtual components: Arduino Uno R3 (QUINN01), IR sensor module (IR1), Sound Detector module (SOUND1), Heart Beat Sensor (HB1), a variable resistor network (RV0–RV1) for signal conditioning, an LED indicator (D1), and a Virtual Terminal for serial output monitoring configured at 9600 bps.

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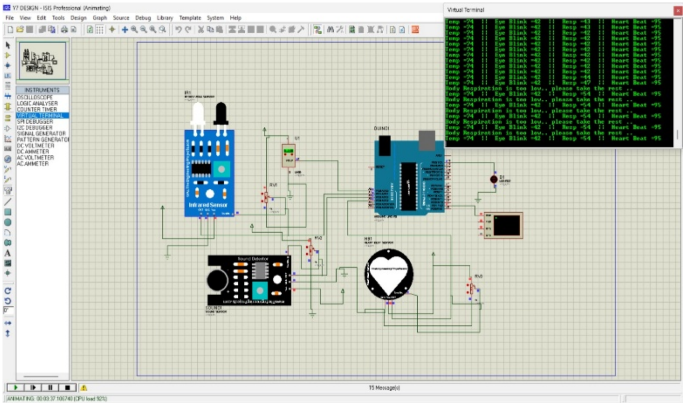

FIGURE 4. Proteus Professional simulation schematic showing Arduino Uno R3 interfaced with IR sensor, sound detector, heart beat sensor, and the virtual terminal displaying real-time serial output.

4.3 Simulation Results

The Proteus simulation successfully demonstrated concurrent acquisition and serial transmission of all four physiological parameters. The virtual terminal output confirmed stable, continuously repeating data streams. Table 2 summarises the simulated parameter readings recorded during the validation trial.

Table 2. Simulated physiological parameter readings.

Parameter	Sensor Module	Simulated Value
Body Temperature	Thermometric / RV Network	62 (normalised units)
Eye-Blink Rate	Infrared (IR) Sensor	38 blinks/min
Respiration Rate	Sound Detector	44 breaths/min
Heart Rate	Heart Beat Sensor	40 BPM

The consistency of output values across multiple iterations, evidenced by repeating log entries in the virtual terminal, confirms the reliability and repeatability of the sensor fusion mechanism. The system architecture further supports extension to wireless transmission modules such as the ESP8266 Wi-Fi module or Bluetooth HC-05 for IoT-based remote deployment, aligning with contemporary trends in cloud-connected wearable health systems [10,11].

5. DISCUSSION

The proposed multi-modal platform addresses a key limitation of existing single-parameter stress monitoring approaches by enabling simultaneous acquisition of four physiologically complementary biomarkers. Integration of eye-blink rate, heart rate, respiration, and body temperature into a single embedded system provides a richer representation of the autonomic stress response than cardiac measurement alone, consistent with recommendations in the literature [14].

The Proteus simulation results confirm functional correctness of the firmware and sensor interfacing logic. The stable, repeating serial output demonstrates that the acquisition loop executes reliably without timing conflicts between sensor channels. The simulated physiological values are illustrative rather than clinically diagnostic at this stage — further calibration against validated stress induction protocols such as the Trier Social Stress Test (TSST) is recommended.

From a translational perspective, the low component cost and reliance on widely available hardware make this platform particularly attractive for resource-constrained settings. The serial communication interface provides a straightforward pathway for integration with IoT gateways, enabling cloud-based data logging and real-time alerting.

Future work will focus on: (i) physical hardware implementation and clinical validation; (ii) integration of machine learning classifiers — such as support vector machines (SVM) or LSTM networks — for automated stress-level classification; and (iii) wireless transmission and cloud dashboard development for remote monitoring applications.

6. CONCLUSION

This paper presented a low-cost, multi-modal physiological monitoring system for real-time stress detection, built around an Arduino Uno microcontroller and a suite of non-invasive sensors measuring body temperature, eye-blink rate, respiratory rate, and heart rate. The system was designed and validated through Proteus Professional simulation, demonstrating stable concurrent acquisition of all four physiological parameters with reliable serial output. The proposed architecture provides a scalable and extensible foundation for IoT-enabled remote stress monitoring, with clear pathways for wireless integration, machine learning-based classification, and clinical validation. This work contributes to the growing body of research on embedded, wearable solutions for proactive mental health management in everyday environments.

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REFERENCES

[1] Dunn, J., Runge, R., & Snyder, M. (2018). Wearable and the medical revolution. Pers. Med., 15(5), 429–448.
[2] Tariq, M.U. (2024). Advanced wearable medical devices and their role in transformative remote health monitoring. IGI Global, pp. 308–326.
[3] Velmovitsky, P.E. (2023). Use of Smart Technology Tools for Supporting Public Health Surveillance. University of Waterloo.
[4] Nahavandi, D., Alizadehsani, R., Khosravi, A., & Acharya, U.R. (2022). Application of AI in wearable devices. Comput. Methods Programs Biomed., 213, 106541.
[5] Jadav, J., & Chauhan, U. (2024). Analysis of personalized stress recognition. Reliab.: Theory Appl., 19(2), 377–389.
[6] McEwen, B.S. (1998). Protective and damaging effects of stress mediators. N. Engl. J. Med., 338(3), 171–179.
[7] Bundele, M., & Banerjee, R. (2009). Detection of fatigue of vehicular driver using skin conductance. Proc. 11th Int. Conf. iiWAS, pp. 739–744.
[8] Bottani, E., et al. (2021). Wearable and interactive mixed reality solutions for fault diagnosis. Comput. Ind., 128, 103429.
[9] Sun, F., Yi, C., Li, W., & Li, Y. (2017). A wearable H-shirt for exercise ECG monitoring. Comput. Ind., 92–93, 1–11.
[10] Sun, W., et al. (2022). A review of advances in vital signals monitoring via flexible wearable sensors. Sensors, 22(20), 7784.
[11] Kadhim, K.T., et al. (2020). Patient health status monitoring based on IoT. Wirel. Pers. Commun., 114(3), 2235–2262.
[12] Sztajzel, J., et al. (2004). Heart rate variability: a noninvasive electrocardiographic method. Swiss Med. Wkly., 134, 514–522.
[13] Mohan, P.M., Nagarajan, V., & Das, S.R. (2016). Stress measurement from wearable PPG sensor using HRV. ICCSP, IEEE, pp. 1141–1144.
[14] Maxhuni, A., et al. (2016). Stress modelling and prediction in presence of scarce data. J. Biomed. Inform., 63, 344–356.
[15] Fink, G. (2009). Stress: Definition and history. Encyclopaedia of Neuroscience, 549–555.
[16] Lupien, S.J., et al. (2018). Effects of chronic stress on the human brain. Front. Neuroendocrinol., 49, 91–105.

[17] Lupien, S.J., et al. (2015). Beyond the stress concept: allostatic load. Dev. Psychopathol., 2, 578–628.
[18] Soreq, H., Friedman, A., & Kaufer, D. (Eds.) (2009). Stress — From Molecules to Behavior. Wiley.
[19] Fleshner, M. (2005). Physical activity and stress resistance. Exerc. Sport Sci. Rev., 33, 120–126.
[20] Schneiderman, N., Ironson, G., & Siegel, S.D. (2005). Stress and health. Annu. Rev. Clin. Psychol., 1, 607–628.
[21] Dayas, C.V., et al. (2001). Stressor categorization. Eur. J. Neurosci., 14, 1143–1152.
[22] Zong, Y., et al. (2019). Chronic stress and intestinal permeability. Neurogastroenterol. Motil., 31, e13477.