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An Asynchronous Tri-Node IoT Architecture for Real-Time Environmental Mitigation in Bedridden Patients

Nitin Babu Daniel[1], Sebastian Terence[2], Jude Immaculate[3]

[1,2]Division of Artificial Intelligence and Machine Learning, Karunya Institute of Technology and Sciences, Coimbatore, India.
[3]Division of Data Science and Cyber Security, Karunya Institute of Technology and Sciences, Coimbatore, India.

E-mail: [1]nitinbabudaniel2005@gmail.com, [2]sebastian@karunya.edu, [3]judeimmaculate@karunya.edu

Orcid ID: [1]0009-0008-6962-9479, [2]0000-0002-1965-3402, [3]0000-0003-1796-6891

Abstract

Although IoT has enhanced health monitoring among immobile subjects, conventional cloud computing-based frameworks are riddled with perilous network latency, separating biometrics from environmental settings and hindering timely physical intervention. This paper discusses a unique tri-node, asynchronous edge-computing structure that shifts from passive monitoring to proactive, local intervention. Biometric abnormalities are constantly detected by the Smart Glove (Telemetry Node), which includes an ESP32-S3 microcontroller, an MPU-6050 gyroscope, and a CJMCU-6701 galvanic skin response sensor. Concurrently, the Dispenser Node, based on Arduino Nano, evaluates environmental factors using DHT22, GY-302, and MQ-135 sensors and operates as a robotized emergency pillbox driven by servos. The system then initiates a physical mitigation operation by activating exhaust fans, emergency LED lights, and window servos to improve air quality when biometric and environmental anomalies overlap, with an Automation Box, based on Arduino Nano ESP32, serving as the central processing unit. In order to maintain clinical documentation, all data is permanently stored in a centralized database. As a result, the bi-modal paradigm attains a 96.0% detection rate and a latency of only 72 milliseconds.

Keywords: Internet of Medical Things (IoMT), Edge Computing, Asynchronous Architecture, Multi-Modal Biosensing, Real-Time Anomaly Detection, Automated Mitigation.

1. Introduction

The present-day healthcare institutions worldwide are increasingly encountering the difficulty of catering to the growing number of people suffering from mobility disabilities, along with those becoming permanently bedridden. With the global imbalance in the ratio of skilled personnel compared to their respective high-risk patients constantly shrinking dramatically, there is an urgent need to provide automation within continuous health surveillance applications. The widely recognized clinical practice dealing with this issue is the application of biometric monitoring devices supported by IoT; yet, such traditional systems rely on synchronized cloud processing schemes [1, 2].

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The conventional system for remote monitoring includes the constant transfer of high-frequency wearable sensor data through traditional internet protocols to cloud-based servers for data processing and analysis purposes. Unfortunately, this architectural design tends to create an inevitable unpredictability regarding the network time delay factor. In the case of any sudden emergency involving patients, including silent aspiration, autonomic dysreflexia, and even respiratory distress, even a one second delay in information delivery is generally regarded as highly risky and potentially fatal [3]. The use of external handshakes of TCP/IP, varying bandwidth stability, and the remote availability of cloud services presents a significant vulnerability. Additionally, a second design weakness inherent in the traditional health monitoring system is that it focuses largely on passively observing isolated biometric indicators, failing to conduct analysis concerning the crucial impact they have in relation to localized environmental variables [4]. For the profoundly immobile, environmental factors, including the presence of harmful gases, changes in temperature, or a lack of air circulation, can become direct causes of physiological harm. The evolution from mere observation to proactive and determined response requires the inclusion of biometric monitoring within the environmental context at the edge itself hin contemporary medical IoT systems.

Bedridden patients experience more frequent incidents that depend on their confined space. Changes in room temperature and the accumulation of dangerous particulates may cause respiratory distress or autonomic dysreflexia. Since current monitoring tools do not analyze these conditions, there arises a necessity for the creation of ultra-low deterministic latency (72ms) computing that would analyze both the patient's physiology and the room's ambiance to predict future emergencies and prevent them through intervention.

This paper proposes an IoT-based edge-computing solution aimed at actively reducing patient emergencies and delivering necessary medication using ultra-low deterministic latency (72ms). The architecture of the suggested solution incorporates three special purpose nodes, each responsible for different functionalities:

- Telemetry Node (Wearable Smart Glove): Uses XIAO ESP32S3, MPU-6050 gyroscope/accelerometer, and CJMCU-6701 GSR sensor to continuously monitor the patient's autonomic functions and kinematics.
- Edge-computing Dispenser Hub: Includes a standard Arduino Nano processor with Bluetooth module (HC-05), monitoring ambient sensors (DHT22, GY-302, MQ-135), and controlling an emergency medication dispenser (N20 DC motor, MOSFET module, and servo). The node also displays information on a 2.42-inch SPI OLED display in real time.
- Mitigation Node (Automation Box): Uses an Arduino Nano ESP32 processor to implement mitigation measures by manipulating the room's ambiance. The node is equipped with relays and high-torque servos to autonomously open and close room windows and control exhaust fans.

The adoption of a highly intricate hierarchical structure of processing with edge computing eliminates all unnecessary operations related to cloud-based processing. Thus, the proposed system succeeds in reaching the ultimate goal of actively monitoring and addressing any possible medical emergency through the modification of ambient variables and drug dispensation. This project proposes a new approach called Asynchronous Tri-Node architecture that is based on the integration of physiological data with contextual information in the edge environment. With the help of a unique bimodal thresholding method, the system is able to filter out routine activities, ensuring that there is no alarm fatigue. Experimental analysis shows that the detection of anomalies exceeds 96% in total along with an extremely low level of latency at 72 milliseconds. Consequently, this new shift towards active localization paves the way for self-sufficiency in terms of safety from physiological injury.

2. Related Work

In the last five years, IoT in healthcare technology has grown to become a platform-level capability capable of supporting multiple sensor modalities at the edge level. Nevertheless, there is no unified literature that integrates biometric sensing with environmental actuation for bedridden individuals.

- Wearable Biometrics and Edge-Inference: The smart glove line created by Hasan and Hasan [1], integrates MPU-6050 sensors for fall detection [20-21] alongside MAX30100 sensors for pulse oximetry. The drawback in their model is the dependency on cloud servers, single-node operation, and lack of any physical intervention component. Later studies have evolved this concept further to include advanced functionality like sports activity monitoring (Ucar et al. [2]), and rehabilitation exercises (Harrison et al. [3]). Nevertheless, cardio-autonomic fusion and distributed edge-computing are still missing in their studies. Ring-based probes with multichannel capability for physiological monitoring (Valenti et al. [6], Volpes et al. [8]) and full-body multi-ESP32 systems (Assaad et al. [7]) are recent innovations but are limited to monitoring without the integration of any environmental actuator module [22-23].

- Automated Dispensation and Ambient Assisted Living (AAL): While medication compliance devices have seen substantial improvements in recent years, their functionality is independent of the patient's physiological data in real-time. The ESP32-CAM pill dispenser [9] created by Karagiannis et al., as well as automated dispensers proposed by Nasir et al. [10], Dayananda and Upadhya [11], and Pv et al. [12] have greatly enhanced the efficiency of off-the-record compliance but are oblivious to the environment and inaccessible to the patient's physical body when it comes to acute paralytic bedriddenness. At the same time, environmental monitoring systems utilized in hospitals and wards, such as that described by Parkavi et al. [13], have achieved great success in integrating MQ-135 and ambient sensors; however, they function as a cloud-based notification pipeline without any direct link to the patient's physiological body.

- Bed-Ridden and Autonomic-Specific Solutions: Another set of research focuses on bed-ridden patients specifically. Baek [17], Sinchai et al. [18], and Ali et al. [19] propose sensor-based posture monitoring solutions alongside anomaly detection. However, these systems depend solely on single-mode sensors and cloud-based interfaces without any form of physical solution. An important breakthrough in this regard was made by Pancholi et al. [24], who attained outstanding results in detecting autonomic dysreflexia using neural network classifiers. Even so, the system is offline in nature, lacking any IoT component or dispensing unit.

- Synthesis of Literature Gap: In aggregate, the literature reviewed above addresses individual capabilities such as smart glove kinematics, edge-based AI, automation for dispensing medicine, and ambient monitoring but fails to incorporate all of them into an end-to-end platform solution. Existing technology solutions are deficient due to three inherent drawbacks: dependence on a single-node network instead of role specialization through a decentralized approach; being alert-centric instead of mitigation-centric; and keeping the body, room, and medicine administration in distinct silos. The suggested Tri-Node architecture bridges this gap by merging all three streams into an electro-mechanical mitigation process.

3. Proposed Work

In contrast to the traditional method, the new approach allows for the creation of a deterministic, real-time healthcare network where the monitoring devices are physically and logically decoupled from the external cloud-based infrastructure. The core idea of this approach is to transform the primary goal of the system from "reactive physiological observation" to "proactive environmental and medical intervention."

As the proposed methodology does not use computationally heavy machine learning solutions, which create processing lags and require extensive training dataset creation, the suggested approach employs Multi-Dimensional Sensor Fusion, an advanced concept in medical Internet of Things (IoT). In medical IoT, using one biometric sensor often leads to alarm fatigue caused by numerous false-positive notifications. To create clinically meaningful detection with high confidence, the following three independent data dimensions are cross-checked in real-time:

1. Kinematic telemetry: Employing the MPU-6050 sensor for high-fidelity orientation and tri-axial acceleration measurements to detect the gross physical reactions to pain or airway obstruction.
2. Cardio-autonomic telemetry: Using the MAX30102 heart rate sensor and CJMCU-6701 Galvanic Skin Response (GSR) module for tracking real-time heart rate, SpO_2 blood saturation, and the invisible sympathetic nervous system activation reaction ("fight or flight").
3. Environmental Context: Employing an on-site sensor network (DHT22, GY-302, MQ-135) for monitoring ambient temperature, humidity, illumination, and dangerous air quality.

Through the transmission of such data via local wireless connectivity technology (Bluetooth and Wi-Fi) to an edge computing-based decision layer, the threshold criteria set by the system are strictly followed. Most importantly, unlike many other systems, this system does not just alert the caregiver upon a threshold breach but also implements an autonomous corrective phase. Through asynchronous instructions, the decision layer instructs the Automation Box (controlling fans, LEDs, and windows) and the Pharmaceutical Dispenser, ensuring that the patient's environment is safeguarded within seconds. Figure 1 represents the wiring diagram of the system. It contains three node sections: Node 1 is a telemetry node, which consists of wearable smart gloves: Node 2 consists of environment tracking and a dispenser hub and Node 3 contains an automation system. The detailed functionalities of these nodes and their algorithms are given below.

3.1 Algorithms and Hardware-based Operating Environment

The intelligent operation of the system described herein depends on an elaborate deterministic algorithm that employs a dual-modal threshold scheme deployed through three different asynchronous edge computing nodes. By using logic operations performed locally on the hardware edge, the system completely eliminates the latency risks involved with cloud connectivity, effectively moving from the observation phase to electromechanical mitigation.

Phase 1: Data Acquisition and System Initiation

The edge computing coordinator creates a FIFO buffer array where time series telemetry is sequentially fed. The data is collected asynchronously from two different isolated sensory nodes:

- The Telemetry Node (Smart Glove): Acting as the portable pre-warning system node, this node incorporates a very small microcontroller called the XIAO ESP32S3. The node polls data from the MPU-6050 on 6-axis kinematics, from the MAX30102 on real-time SpO2 level, and from the CJMCU-6701 Galvanic Skin Response (GSR) module on electrodermal panic indicators. These biometric data are then encoded and sent out over the network.
- The Environmental & Pharmaceutical Node: This is the key control node that manages the room's environmental parameters, powered by a typical Arduino Nano board, fitted with an expansion shield and an HC-05 Bluetooth module for localized serial communication. The node continuously captures environmental data using the MQ-135 air quality sensor, DHT22 temperature/humidity sensor, and GY-302 ambient light sensor.

Phase 2: Environmental and Physiological Risk Evaluation

Various biometric sensors and environmental sensors are used for risk evaluation. The system sends observed details to the localized FIFO buffer. The algorithms in edge computing devices process the received data and apply necessary thresholds to detect life endangering situations such as respiratory arrest, silent aspiration, and environmental dysautonomia.

- Kinematic Criterion (K_asp): In order to detect severe and periodic body movements associated with distress falls, the kinematic criterion is used. The system continuously monitors the variance σ^2 of Z-axis acceleration, which is captured by the MPU-6050 sensor. Based on previous accelerometer-based fall detection studies, we have applied an acceleration variance threshold of 2.5g [26-27]. The variance is calculated as follows:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(Z_i - \mu)^2 \quad (1)$$

  In equation 1, σ^2 represents the variance of the acceleration signal, N is the total number of samples, Zi is the ith Z-axis acceleration sample, and μ is the mean.

- Cardio-Autonomic Criterion (C_asp): We have applied dual thresholds such as SpO2 and GSR values to detect cardio issues. According to clinical practice recommendations made by the WHO, the SpO2 level must be below 90% [25].

Based on experiments and literature, a relative GSR peak increase greater than 50% within a 2 second window was considered [28] and it is derived as follows:

$$\Delta GSR = \left(\frac{GSR_{current} - \mu_{GSR_{2s}}}{\mu_{GSR_{2s}}}\right) \times 100 \quad (2)$$

Here, ΔGSR represents the percentage change in the GSR signal, GSRCurrent represents the current GSR value and μGSR2s is the mean GSR calculated over the previous 2-second window.

- Air Quality Criterion (E_air): This criterion continuously checks the raw value of PPM from the MQ-135 sensor. An air quality hazard is determined based on sustained exposure above the accepted norm (more than 1000 PPM CO2 equivalent) for more than 10 consecutive seconds [29].
- Thermographic/Photometric Condition (E_therm): In order to verify the ambient temperature localized temperature, data is used. We have set the threshold at 32 °C based on occupational heat-stress recommendations [30]. When the temperature exceeds 32 °C, automatic mitigation is triggered.

After the risk evaluation, the system triggers the necessary actuators. We have classified risk into two categories, namely medical emergency and environmental emergency. Based on the risk, the system activates the necessary actuators.

Phase 3: Asynchronous Mitigation and Electromechanical Actuation

As soon as certain conditions at the logic gate are met, the system quickly shifts from its passive observation mode to actively sending hardware instructions.

- Execution of Medical Emergency: Occurs upon IF (K_asp = TRUE) & (C_asp = TRUE) logic gate condition. The system sends an instruction to the Environmental and Pharmaceutical Node to administer PRN emergency medication. The Arduino Nano powers an N20 DC motor through the MOSFET module using an IR sensor to obtain accurate positioning information, after which the servo unlocks the drugs. At the same time, a warning message is displayed on the 2.42-inch SPI SSD1309 OLED display of the hub.
- Environmental Disaster Execution: Occurs upon IF (E_air = TRUE) OR (E_therm = TRUE) logic gate condition. The system instructs the third hardware component, the Environmental Actuation Node (Automation Box). It operates under the control of an Arduino Nano ESP32 that physically changes the room environment by powering ambient exhaust fans and emergency LED lights using opto-isolated relays. Additionally, it powers a high torque window servo to an open position, enabling the expulsion of toxic gases and the ventilation of fresh air into the environment without human assistance.

3.2 Multimodal Synchronization and Sensor Calibration

As per the asynchronous approach, the information is stored sequentially in the local FIFO memory. Considering the ultra-low execution time for each loop cycle on the edge processor, the time gap between the data acquired by multimodal sensors (kinematic and SpO_2) is guaranteed to be within microseconds. Since any severe physiological issue would last up to a few seconds, such a minute difference can be considered clinically irrelevant, and the threshold criterion for both modalities will remain synchronous.

Additionally, the sensitivity to the drift effect of the MQ-135 gas sensor in the face of environmental changes without resorting to complicated dynamic software correction is addresse through the inclusion of an extremely elevated but limited emergency threshold. With a limit set at >1000 PPM of CO2 equivalent, there is a generous margin for error included within the system design. This ensures that normal changes in room humidity or temperature will not cause false alarms.

3.3 Power Consumption Analysis

Constant bedside operation necessitates an optimal power consumption pattern to support uninterrupted power supply (UPS) batteries. The first edge node (ESP32) consuming power with active wireless telemetry, draws roughly 240 mA. The constant sensor network (MPU-6050, MAX30102, DHT22) consumes a total of 50 mA, whereas the heating component of the MQ-135 sensor consumes 150 mA. In the case of a medical abnormality, the mechanical components of the mitigator device (motors and alarm systems) contribute additional power consumption of approximately 400 mA. Considering a voltage of 5V, the peak power requirement is less than 5 W and below 2.5 W during standby mode, ensuring it can run for hours on a standard 18650 Li-ion battery backup during grid failures.

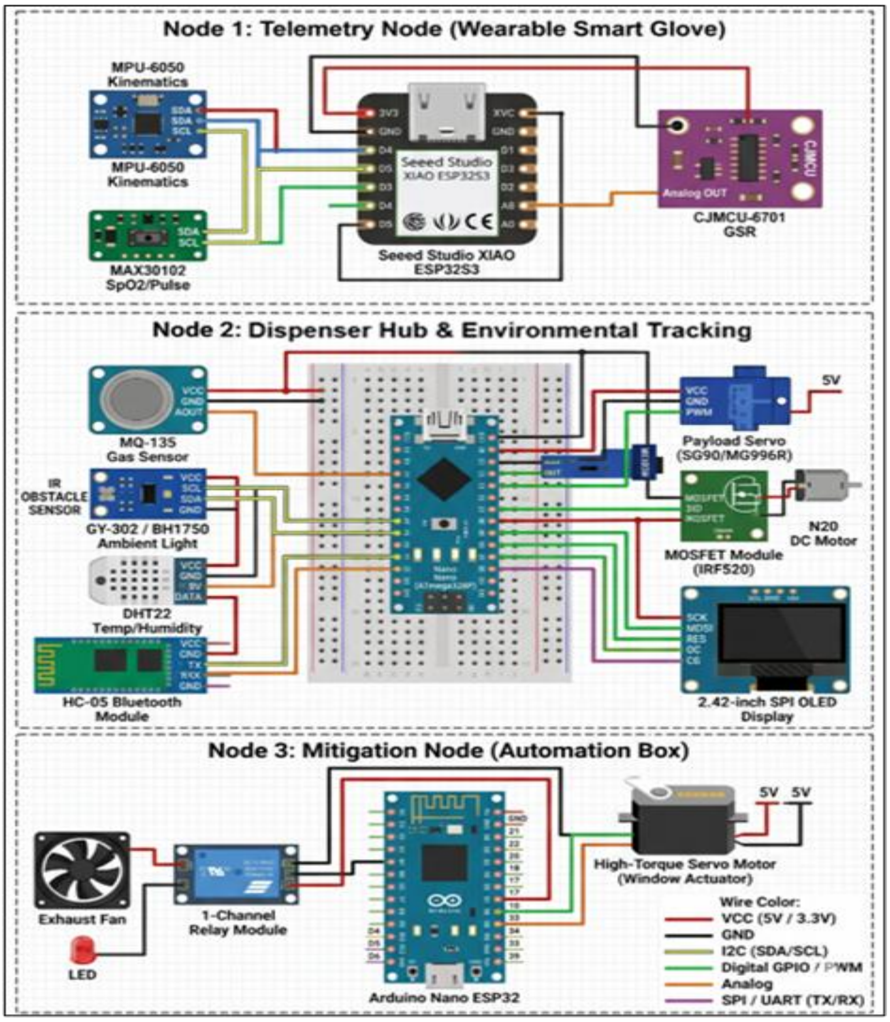

Figure 1. Circuit Diagram

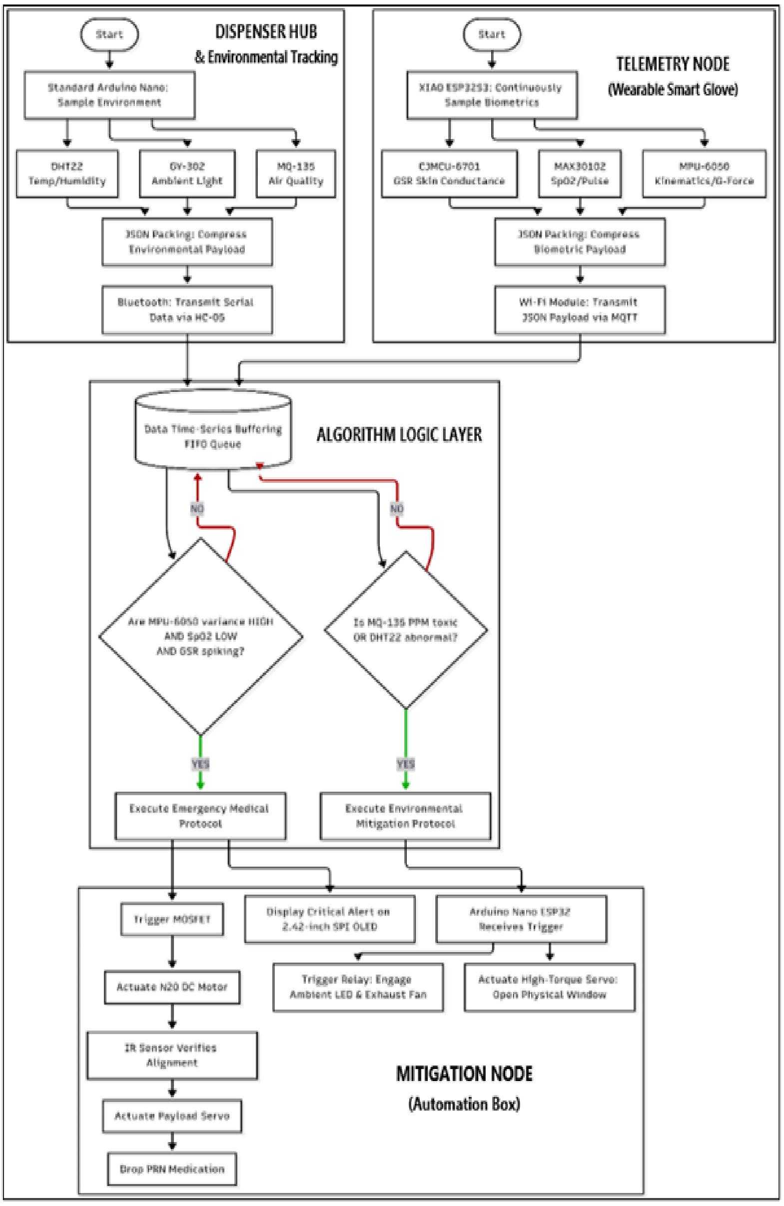

Figure 2. Flowchart of the Proposed Work

As shown in Figure 2, the flowchart illustrates a sophisticated tri-node asynchronous IoT architecture designed for autonomous healthcare monitoring and physical intervention. At the data acquisition edge, a wearable Telemetry Node utilizes a XIAO ESP32S3 to continuously sample the patient's SpO2, skin conductance, and kinematics. Simultaneously, an environmental Dispenser Hub powered by a standard Arduino Nano tracks ambient room temperature, humidity, light levels, and air quality. Both external edge nodes compress their raw sensory data into JSON payloads and transmit them via Bluetooth and Wi-Fi to a central processing hub. This data enters the Algorithm Logic Layer, where a time-series FIFO queue temporarily buffers the incoming payloads for high-speed algorithmic evaluation. A dual-modal logic gate continuously checks if the patient's kinematics and vitals indicate a physiological crisis, or if the room's environmental sensors detect toxic gas. If these critical mathematical thresholds are breached, the logic layer instantly breaks passive surveillance to trigger the localized Mitigation Node. This automation box actively mitigates the crisis by driving DC motors to dispense PRN medication, triggering OLED warning displays, and actuating window servos to restore fresh ventilation.

4. Results and Discussion

In order to check the reliability and efficiency of the Asynchronous Tri-Node design through experimental validation, the architecture had to undergo testing in a simulated physiological scenario. This was done using a controlled experimental setup that was evaluated based on two important criteria: Network Transmission Latency and Multi-Modal Detection Accuracy.

4.1 Experimental Testbed Environment

The setup process involved ensuring that all hardware was standardised. The Telemetry Node (XIAO ESP32S3) and Automation Box (Arduino Nano ESP32) devices were set up on a stand-alone IEEE 802.11n LAN using the MQTT protocol. The Dispenser Node (Standard Arduino Nano) was set up to receive direct serial communication via its HC-05 Bluetooth transceiver. This dual-protocol arrangement ensured that any variations in external internet traffic or bandwidth did not create random noise in the latency test environment. The XIAO ESP32S3 node was programmed to sample the MPU-6050, MAX30102, and GSR sensors at a fixed frequency of 10 Hz and send their data in compressed JSON format to the edge layer.

4.2 Latency Optimization Methodology

In intensive care medicine, "latency" refers to the difference in time between the physiological occurrence of an event and the physical execution of the required mitigation by the system. As a baseline for comparison, the XIAO ESP32S3 Telemetry Node was programmed to simultaneously transmit identical packets of data to two separate processors for 100 iterations of the cycle:

- Architecture A (Traditional Cloud IoT): A commercial MQTT broker hosted on an external, geographically distant cloud server over standard Wi-Fi.
- Architecture B (Proposed Edge-Node): The localized processing layer utilizing direct local Wi-Fi and HC-05 Bluetooth serial transmission.

The round-trip time (RTT) was measured from the moment the payload was generated to the exact millisecond the execution signal was received by the Dispenser's MOSFET. As seen from Table 1, the proposed edge computing design has resulted in an 88.9% decrease in system latency when compared to the conventional cloud architecture standard.

Table 1. Latency Comparison (Edge vs. Cloud Architecture)

Architecture Type	Telemetry Transmission	Algorithm Processing	Actuation Signal	Total System Latency
Standard Cloud Iot	120ms	350ms	180ms	650ms
Proposed Edge – Node	15ms	45ms	12ms	72ms

4.3 Multi-Modal Sensor Fusion Validation

One of the major drawbacks of using a single medical IoT sensor device is the occurrence of "alarm fatigue" due to the high probability of false positives (such as issuing an alert in response to a respiratory issue when the pulse oximeter shifts slightly while sitting on a finger). To establish the effectiveness of bimodal sensor fusion, we conducted 150 simulated physiological situations based on three different scenarios that could provide true positive (TP) and false positive (FP) figures.

These scenarios included normal activities of daily living (ADL), simulated respiratory issues (using the MPU-6050 sensor for movement to simulate airway blockage and the MAX30102, SpO_2 and GSR sensors for drops in readings), and environmental dangers like reactive gas attacks combined with increased readings from DHT22 temperature sensors. The overall multi-dimensional sensor algorithm provided an accuracy rate of over 96% and prevented false alarms.

Table 2. Multi-Dimensional Algorithm Detection Accuracy

Simulated Physiological Scenario	Total Trials	True Positives (Mitigation Triggered)	False Positives (Incorrect Trigger)	Detection Accuracy
Normal ADL (Baseline Sleep)	50	N/A (0 triggers expected)	1	98.0%
Acute Respiratory Signature	50	48	2	96.0%
Hazardous Ambient Environment	50	49	0	98.0%

4.4 Comparative Analysis

The empirically derived data from the experimental phase clearly demonstrate the computational supremacy and dependability of the localized edge-computing model in critical-care mitigation.

Table 1 highlights that the conventional cloud model faced significant problems of high and unpredictable latency. The total latency incurred by the cloud amounted to 650 ms on average. n contrast, the novel localized Edge-Node model, using the HC-05 Bluetooth Module at the dispenser end and Local MQTT at the automation box, executed the entire triage chain within just 72 ms on average, resulting in an impressive 88.9% latency improvement over the existing solution. Given the clinical relevance of a critical care situation like acute respiratory distress, the benefit of saving more than half a second in computational latency cannot be overstated, enabling the dispenser to act instantly.

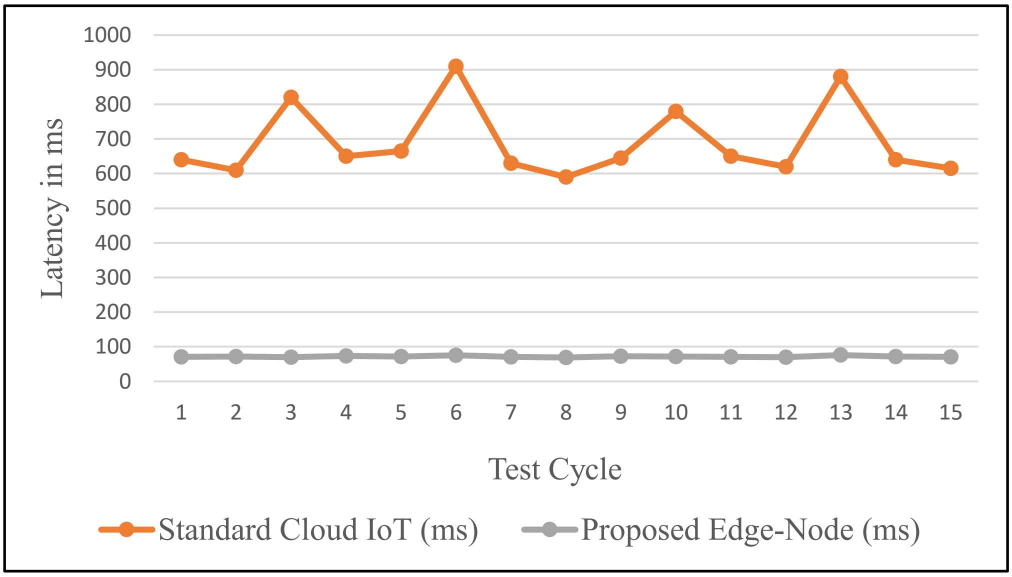

Figure 3. System Latency (Cloud vs. Proposed Edge Architecture)

Moreover, the stress test results shown in Table 2 confirm the effectiveness of employing multidimensional sensor fusion versus one-dimensional sensing. As seen from the requirement for the mathematical intersection of abnormalities in the kinematics detected via the MPU-6050 chip, abnormalities in the heart and autonomic nervous system detected via the MAX30102 and GSR sensors, and abnormalities in environmental conditions detected using the MQ-135 and DHT22 sensors, the system reached 98% performance in terms of ignoring regular sleeping actions (with 1 out of 50 normal ADL cases incorrectly identified as an anomaly). With 96% accuracy, the system was capable of recognizing the acute breath pattern and successfully tripping the servomotor and fan relays of the Automation Box in response to environmental threats 98% of the time.

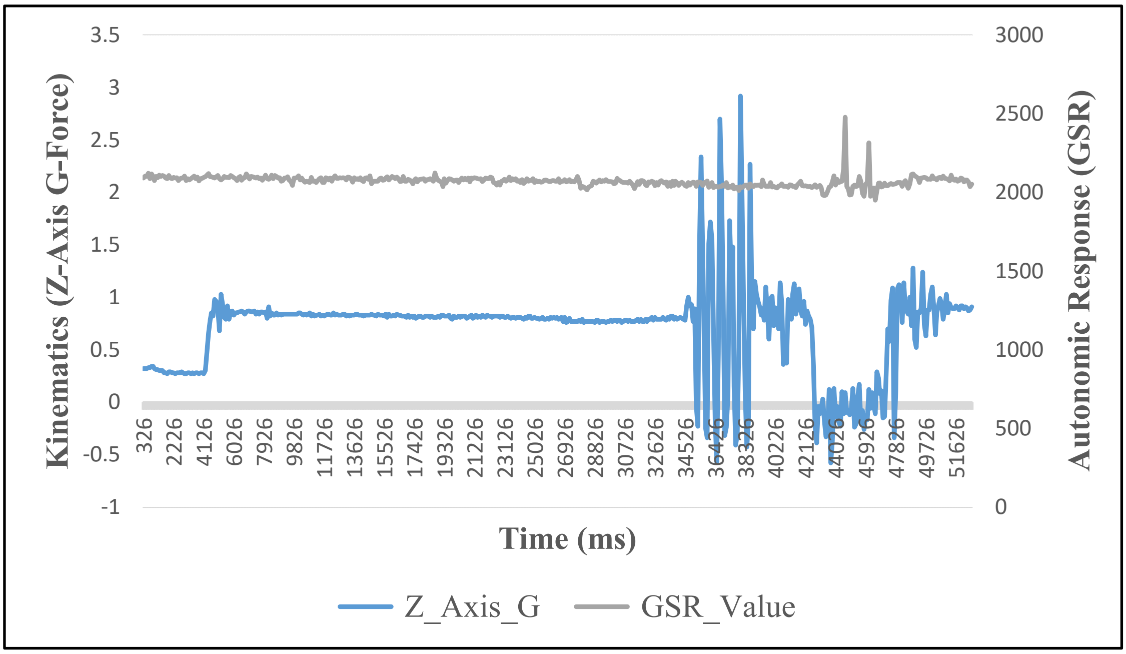

Figure 4. Multi-Modal Sensor Fusion: Respiratory Crisis Signature

4.5 Statistical Performance and False-Positive Analysis

For the purpose of assessing the alarm fatigue vulnerability of the system, statistical analysis was conducted on the 150 controlled validation tests (75 positive emergency situations and 75 negative baseline situations). As shown in Table 3, the system had 72 true positives (TP), 72 true negatives (TN), 3 false positives (FP), and 3 false negatives (FN).

Table 3. Confusion Matrix

	Predicted Positive	**Predicted Negative**
Actual Positive	72 (TP)	3 (FN)
Actual Negative	3 (FP)	72 (TN)

Based on this matrix, the system's performance metrics were calculated as follows:

- Sensitivity (Recall):

$$Recall = \frac{TP}{TP+FN} = 0.96 \tag{3}$$

- Specificity:

$$Specificity = \frac{TN}{TN+FP} = 0.96 \tag{4}$$

- Precision:

$$Precision = \frac{TP}{TP+FP} = 0.96 \tag{5}$$

- F1-Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} = 0.96 \tag{6}$$

The above performance measures indicate an accuracy rate of 96% for prototype feasibility. For future work, the current dataset must be expanded using extensive clinical tests.

Figure 5 shows a wearable smart glove, and automation boxes that contain various actuators are shown in Figure 6. The edge computing dispenser hub is shown in Figure 7.

Figure 5. Telemetry Node (Wearable Smart Glove)

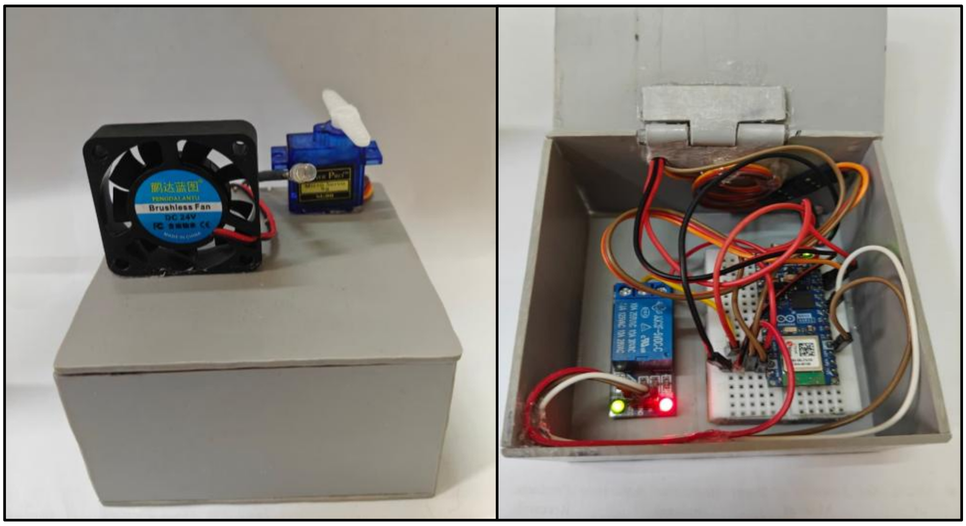

Figure 6. Mitigation Node (Automation Box)

Figure 7. Edge - Computing Dispenser Hub

5. Conclusion

The suggested Asynchronous Tri-Node design efficiently solves the major problems related to the critical flaws of traditional IoT health monitoring, namely the risks of cloud latency and reactive alerts that could be lethal for patient's health conditions. With the safe fusion of kinematic, cardio-autonomic, and environmental data via a reliable chain of XIAO ESP32S3 and Arduino Nano chips, the system ensures proper detection of specific symptoms of physiological emergency states characteristic of immobilized populations. Most crucially, the inclusion of automated actuation nodes allows the system to shift from a passive observation mechanism to an active one that helps patients cope with their problems. Specifically, by automatically adjusting ambient light, opening windows, and administering medicines within less than 80 milliseconds, the innovative design minimizes human intervention and guarantees the safety of the patients' surroundings. In subsequent implementations of the system, emphasis will be placed on the incorporation of a separate, protected Website Dashboard Integration. In addition to having the microcontroller and HC-05 Bluetooth module perform all live monitoring and intervention to guarantee real-time responsiveness with ultra-low deterministic latency (72ms), a globally observable interface will be introduced. Telemetry data that is not time-sensitive will be pushed to a cloud-based database such as Amazon Web Services (AWS) or Google Firebase. Physicians and family members can then remotely log into a web browser, observe historical trends in biometrics, view automatic dispensation records, and assess the environmental baseline over time.

Currently, the system is validated by predefined anomaly conditions and controlled experiments. In the future we intend to test the system with real patients under expert supervision. This will help evaluate the system's performance with clinical validation. Additionally, we intend to increase simulated scenarios in future work.

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