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A Multi-Parameter IoT Framework for Continuous Physiological Monitoring of Comatose Patients

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Abstract

Comatose patients are unable to report discomfort or signal physiological deterioration, so their safety depends entirely on the frequency and reliability of external observation. Conventional practice relies either on manual bedside checks, which are labour-intensive and prone to omission, or on critical-care instrumentation that is expensive and largely unavailable in rural hospitals and home-care settings. This paper presents a low-cost, multi-parameter monitoring framework built on an Arduino Uno acquisition unit and an ESP8266 Wi-Fi module, which together acquire, threshold and publish five physiological indicators: heart rate, body temperature, electromyography (EMG) muscle activity, eye-blink occurrence and urine-bag fill level. The combination of eye-blink detection and urine-output measurement with conventional vital signs distinguishes the design from prior single-purpose monitors, since both parameters are clinically relevant to long-term unconscious patients yet are rarely instrumented together. Threshold logic executes locally on the microcontroller so that buzzer and LED alerts remain available during network loss, while the ESP8266 forwards compact status flags to an IoT dashboard for remote supervision. Bench validation against reference instruments gave heart-rate agreement within ±1 bpm across four comparison points, temperature agreement within ±0.5 °C of a calibrated thermometer, and correct alert actuation at the 80 % urine-bag threshold. The prototype sustained continuous operation over a multi-hour test without loss of data integrity. Two limitations are reported openly: the EMG channel remains susceptible to mains and motion-induced noise, and eye-blink detection is sensitive to sensor alignment relative to the patient's face. The system is positioned as a complementary early-warning aid rather than a substitute for hospital-grade monitoring.

Introduction

Advances in embedded systems and the Internet of Things (IoT) have made continuous, low-cost health monitoring practical outside the intensive-care unit. The benefit is greatest for patients who cannot describe their own condition, and among these the comatose patient represents the limiting case. A coma is a prolonged state of unconsciousness in which the patient neither responds to external stimuli nor retains awareness of the surroundings, leaving every aspect of care to medical staff or family attendants [1], [3].

Continuous observation of vital signs is therefore essential to detect irregularities before they become life-threatening. In practice this observation is performed manually or through medical-grade instrumentation. Manual observation is time-consuming and prone to human error; instrumentation is effective but is designed for critical-care wards and is seldom available in rural hospitals or home-based care. Elevated body temperature, abnormal heart rate, muscle spasm or a full urine bag may consequently pass unnoticed, leading to infection, pressure sores or more serious complications.

This work addresses that gap with a monitoring system assembled from widely available components: an Arduino microcontroller, an ESP8266 Wi-Fi module and a set of low-cost biomedical sensors. Five parameters are acquired — heart rate, body temperature, muscle activity via EMG, urine output level and eye-blink occurrence — and transmitted to a cloud dashboard for remote review, with local alerting retained on the bedside unit.

1. Problem Statement

Patients in a comatose condition cannot respond to pain, discomfort or a developing emergency. Where nurse-to-patient ratios are low, or in home care where professional attention is intermittent, the absence of continuous monitoring directly compromises patient safety. What is required is a system that observes the relevant physiological parameters automatically, alerts an attendant when any of them leaves its accepted range, and does so at a cost and complexity compatible with non-hospital deployment.

2. Objectives

The specific objectives of the work are as follows:

- To monitor heart rate, body temperature, EMG muscle activity, urine output and eye-blink activity continuously.
- To generate alerts through an IoT platform whenever a monitored parameter deviates from its defined limits.
- To provide remote visibility for caregivers and clinical staff, reducing the need for constant bedside presence.
- To retain data logs suitable for medical review and longer-term trend analysis.
- To achieve the above in a low-cost, energy-efficient and easily installed form suitable for both hospital and home-care environments.

3. Scope and Delimitation

The study covers sensor selection and interfacing, microcontroller firmware, wireless transmission via ESP8266, cloud-side visualisation and threshold-based alerting. It explicitly excludes advanced diagnostic modalities such as electroencephalographic brain-activity analysis and any invasive monitoring technique. The system is not offered as a replacement for hospital-grade devices; it is a complementary tool for early alerting and basic supervision.

4. Contributions

1. A five-parameter bedside acquisition unit that combines conventional vital signs with eye-blink and urine-output sensing, two parameters rarely instrumented together in low-cost monitors.
2. A local-first alert architecture in which threshold evaluation and actuation execute on the microcontroller, so that alerting survives loss of network connectivity.
3. Bench validation of each sensing channel against reference instruments, with the measured deviations reported rather than summarised qualitatively.
4. An explicit statement of the two failure modes observed during testing — EMG noise susceptibility and eye-blink alignment sensitivity — together with the mitigations applied.

The remainder of the paper is organised as follows. Section II reviews related work. Section III presents the system architecture and contrasts it with existing practice. Section IV details the hardware, firmware and methodology. Section V reports the measured results, Section VI discusses them, and Section VII states the limitations. Sections VIII and IX give the conclusion and future scope.

Related Work

IoT-based patient monitoring has developed rapidly, but the reviewed literature concentrates on a recurring core of parameters and leaves others largely unaddressed. Table 1 summarises the studies surveyed during this work, together with the principal advantage and the principal limitation identified for each.

Table 1. Surveyed Work on IoT-Based Patient Monitoring

Study / Year	Focus	Reported strength	Reported limitation
Kumar, Pal and Mohapatra (2021)	Heart rate, temperature and SpO_2 via NodeMCU ESP8266 to a cloud server	Real-time tracking; reduces hospital visits in underserved areas	Depends on stable connectivity; limited parameter set
Imran, Hossain and Alam (2020)	Arduino with Firebase cloud storage and push alerts	Secure storage and long-term trends for diagnosis	No sophisticated interface for real-time analysis
Gopi, Vignesh and Arun (2019)	Bedridden patients; vitals plus bed moisture sensing	Adds hygiene monitoring to vital signs	Moisture sensors degrade; false positives from sweat
Swathi and Sanjay (2022)	Eye-blink communication for patients with limited motor ability	Communication route for otherwise non-expressive patients	Cannot separate involuntary from intentional blinks without calibration
Wang, Liu and Rahman (2021)	EMG monitoring of muscle activity in neurological recovery	High sensitivity; applicable to involuntary activity detection	EMG prone to electrical noise; needs precise electrode placement
Natarajan and Harish (2020)	Load-cell urine volume measurement for catheterised patients	Non-invasive fluid-output measurement without contact	Accuracy affected by vibration and bag movement
Patel and Shah (2018)	Wireless ICU vital-sign relay over Zigbee	Improves staff response time in ICU	Short transmission range; scalability limited
Rashid and Bibi (2021)	Home monitoring with Arduino Uno and Blynk	Simple to deploy; suited to rural use	No predictive or analytic capability
Vishnu and Maheshwari (2019)	Infrared detection of eye movement and blinking	Non-invasive channel for semi-conscious patients	Requires controlled lighting and stable alignment
Chatterjee and Mitra (2022)	Multi-parameter critical care with machine-learning anomaly detection	Comprehensive monitoring with predictive alerts	Higher cost and system complexity

Three observations follow from Table I. Heart rate and temperature appear in almost every system, because both are clinically fundamental and simple to measure. Eye-blink and muscle-activity sensing appear only in specialised studies, despite their particular relevance to non-verbal patients. Urine-output detection is the least explored of the five parameters considered here, even though fluid balance is a routine concern in long-term care. The present work combines all five in a single low-cost unit, which is the specific gap it addresses.

System Architecture

1. Limitations of Existing Practice

Comatose patients in hospital are monitored with heart-rate monitors, electrocardiographs, temperature probes and urine drainage systems.

These are effective but are provisioned for critical-care units, and their availability is limited in rural or resource-constrained settings. In home care, real-time intelligent monitoring is generally absent altogether, and attendants must rely on periodic manual inspection. The resulting observation gaps are the practical motivation for the proposed design.

2. Proposed System

The proposed system is a multi-parameter IoT monitor built around Arduino and ESP8266. Low-cost sensors and a wireless link acquire, process and transmit the following quantities:

- Heart rate, using a pulse sensor.
- Body temperature, using a DS18B20 digital sensor.
- Muscle activity, using an EMG sensor.
- Urine output, using a level sensor on the collection bag.
- Eye-blink occurrence, using an infrared reflective sensor.

Readings are forwarded over Wi-Fi by the ESP8266 to an IoT platform that provides real-time visualisation and notification, while a mobile or web dashboard gives caregivers remote access. Local alerting through a buzzer and LED indicators is retained on the bedside unit and is triggered directly by the microcontroller, so that a full urine bag or an out-of-range heart rate still raises an alarm when the network is unavailable. The overall arrangement is shown in Fig. 1.

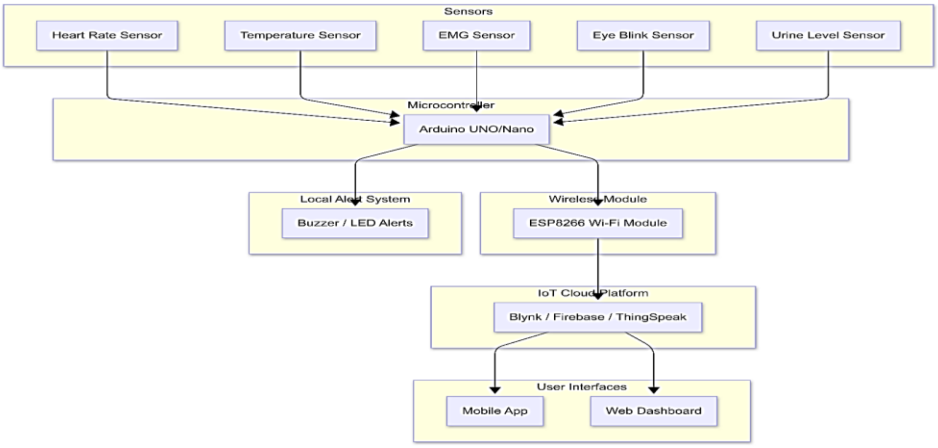

Figure 1: Block diagram of the proposed monitoring system, showing the sensor group, the Arduino acquisition unit, the local alert path and the ESP8266 cloud path.

Materials and Methods

1. Hardware Components

Table 2 lists the components used and the function of each within the system.

Table 2. Hardware Components and Their Function

Component	Model / type	Function
Microcontroller	Arduino Uno / Nano	Central processing unit
Wi-Fi module	ESP8266	Wireless data transmission
Pulse sensor	MAX30100	Heart rate and SpO_2
Temperature sensor	DS18B20	Body temperature
EMG sensor	MyoWare	Muscle activity detection
Eye-blink sensor	IR-based or EOG	Eyelid movement detection
Urine level sensor	Load cell / ultrasonic	Urine bag volume
Buzzer	Passive buzzer	Audible alerting
Power supply	5 V battery pack	Portable power source

Each sensor is connected to a designated analogue or digital pin on the Arduino. The EMG and infrared blink channels require calibration before use, since both are susceptible to false readings if left at default thresholds.

2. Sensing Subsystems

The Arduino Uno acts as the acquisition unit, sampling the analogue channels and evaluating the threshold logic. The ESP8266 provides the network interface and communicates with the Arduino over a serial link. Figs. 2 and 3 show the two processing elements.

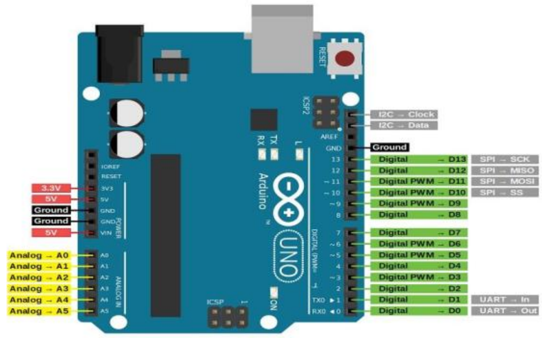

Figure 2: Arduino Uno microcontroller board used as the acquisition and threshold-evaluation unit.

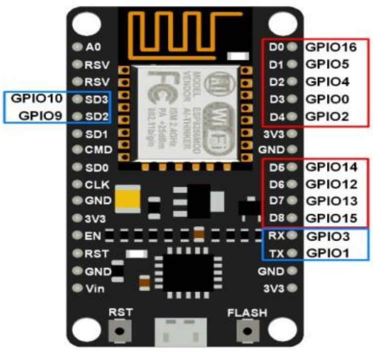

Figure 3: ESP8266 Wi-Fi module providing the cloud uplink.

The heart-rate sensor (Fig. 4) provides pulse and oxygen-saturation measurement. Body temperature is acquired by the DS18B20 digital sensor (Fig. 5), which communicates over a one-wire bus and requires no analogue conditioning. The EMG channel (Fig. 6) uses surface electrodes to detect involuntary muscle activity, which in an unconscious patient may indicate discomfort or a neurological response.

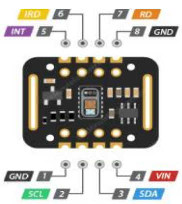

Figure 4: Heart rate sensor module.

Figure 5: DS18B20 digital temperature sensor.

Figure 6: EMG sensor with surface electrodes for muscle-activity detection.

Eye-blink detection (Fig. 7) uses an infrared reflective arrangement positioned near the eye. In patients with partial consciousness the blink channel can serve as an elementary communication or distress route. Urine output is measured by a level sensor mounted on the collection bag (Fig. 8), which allows fluid output to be tracked without contact with the fluid itself.

Figure 7: Eye-blink detection arrangement using an infrared reflective sensor.

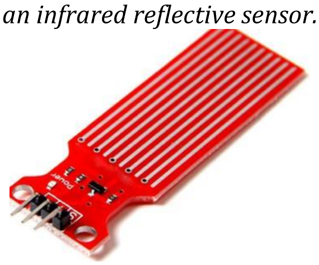

Figure 8: Urine level sensor mounted on the collection bag.

Alert actuation-Alerts are produced by a passive buzzer for audible warning and by RGB LED indicators for visual state, green denoting normal operation and red denoting an alert condition. The mapping between parameter condition and alert type is given in Table 3.

Table 3. Alert Signal Mapping

Parameter	Condition	Alert type
Heart rate	< 60 or > 100 bpm	Buzzer + red LED
Temperature	< 36 °C or > 38 °C	Buzzer
Urine level	> 80 % full	Buzzer

EMG	Spikes detected	LED
Eye blink	Excessive blinking	LED

3. Circuit Integration

The complete circuit (Fig. 9) integrates all sensors with the Arduino and ESP8266 and shows the power distribution and signal routing. The system is powered from a 5 V battery pack or a regulated USB supply; a regulator provides the 3.3 V rail required by the ESP8266.

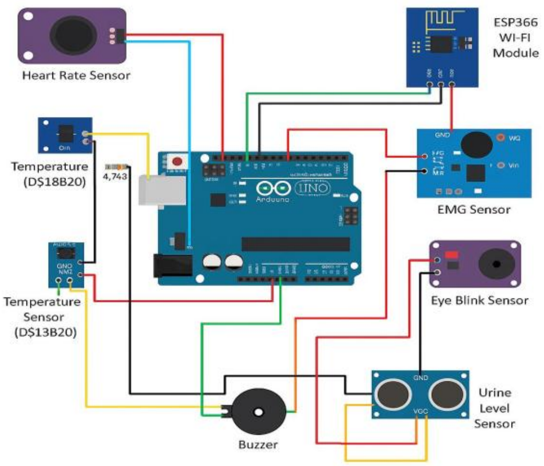

Figure 9: Complete circuit diagram of the proposed system, showing sensor interfacing, the local alert path and the ESP8266 uplink.

4. Firmware and Software

The Arduino is programmed in the Arduino IDE (Fig. 10) using a simplified C/C++ dialect. The following libraries are used: OneWire and DallasTemperature for the DS18B20; Wire and the MAX30100 pulse-oximeter library for heart rate; and SoftwareSerial for the link to the ESP8266. Firmware tasks comprise reading the analogue and digital channels, applying conditional logic to detect abnormality, transmitting values to the cloud at fixed intervals, and triggering alerts when thresholds are breached.

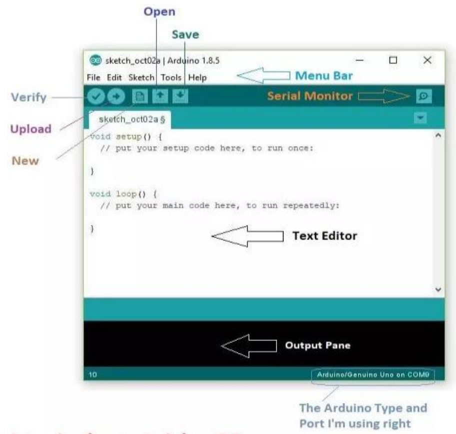

Figure 10: Arduino IDE development environment used for firmware compilation and upload.

The ESP8266 may be driven either through AT commands or programmed directly as a NodeMCU device. It handles Wi-Fi association, packages readings as JSON and issues HTTP or MQTT requests to the cloud endpoint. The IoT platform provides real-time display of sensor values, storage of historical data and push notification on alert. Dashboard elements include heart-rate and temperature graphs, an EMG status bar, a urine-level gauge, a blink-detection indicator and an alert notification widget.

Data flow-The end-to-end logic is summarised in Fig. 11 and proceeds as follows: the sensors acquire physiological data; the Arduino processes the values and compares them against thresholds; the ESP8266 transmits the resulting status to the cloud; the dashboard displays the data and raises alerts; and the caregiver is notified through the application or the local buzzer.

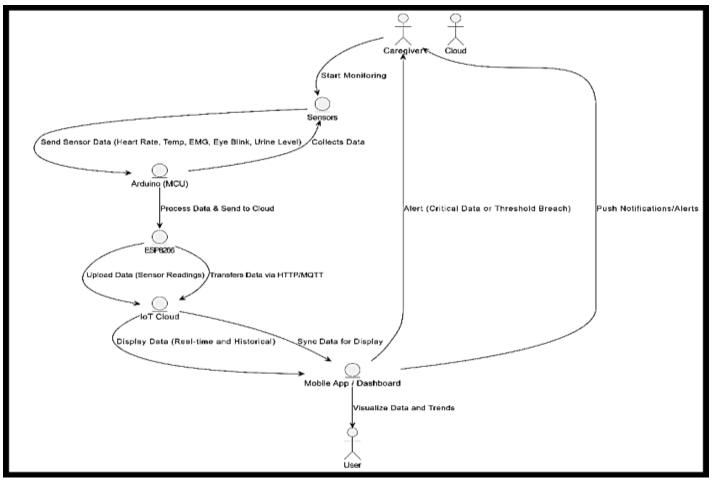

Figure 11: System data-flow diagram from sensor acquisition through cloud publication to caregiver notification.

5. Threshold Definition and Calibration

Threshold values are programmed for each parameter on the basis of accepted physiological ranges. During integration the sensors were calibrated against medical reference values and signal conditioning was applied to attenuate noise; real-time testing was then carried out with volunteers under safe conditions. The resulting calibration thresholds are given in Table 4.

Table 4. Calibration Thresholds for Alert Generation

Parameter	Normal range	Alert condition
Heart rate	60–100 bpm	< 60 or > 100 bpm
Temperature	36–37.5 °C	< 36 °C or > 38 °C
Blink count	10–15 per minute	> 25 blinks per minute
EMG voltage	< 0.05 V (idle)	Spikes > 0.2 V
Urine volume	< 80 % capacity	≥ 80 % triggers buzzer

6. Test Procedure

The system was exercised using controlled simulation rather than clinical subjects. Heart rate and temperature were varied by means of adjustable potentiometers; blink detection was exercised by manual blinking in front of the infrared sensor; and urine-level response was simulated using water-filled bags of known mass. Calibration was found to be essential for the EMG and urine channels in particular, in order to suppress noise and false positives.

Power and safety provisions

For home use the unit is powered from a portable 5 V battery pack. Sensors exposed to moisture, notably those at the urine bag, are fitted with insulated and waterproof housings. Sensor leads in contact with the skin, in particular the EMG electrodes, follow standard safety practice to preclude any electrical hazard.

Results

The assembled prototype is shown in Fig. 12. It comprises the Arduino Uno, the ESP8266 module and the five sensing channels, with the local buzzer and LED indicators mounted on the same board.

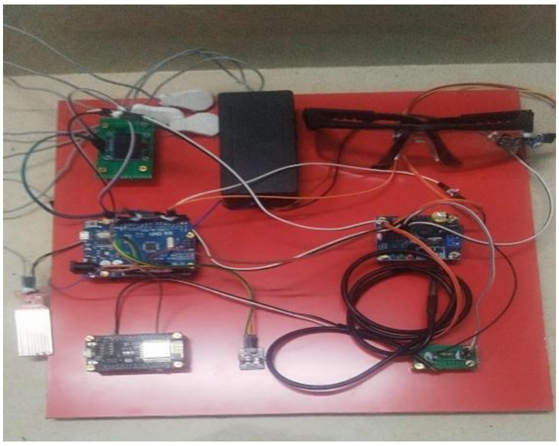

Figure 12: Experimental setup of the assembled prototype with all five sensing channels, the Arduino acquisition unit and the ESP8266 uplink.

1. Heart Rate Channel

Heart-rate output was compared against a commercially available pulse oximeter. Across the four comparison points recorded (Table V) the maximum deviation was 1 bpm, which is within the ±5 bpm band adopted as the acceptance criterion for this channel.

Table 5. Heart Rate Sensor Accuracy Against a Reference Pulse Oximeter

Sensor reading (bpm)	Pulse oximeter (bpm)	Difference (bpm)
72	72	0
88	89	1
96	95	1
102	101	1

2. Temperature Channel

The DS18B20 was calibrated against a mercury thermometer and returned readings consistently within ±0.5 °C of the reference across the tested range. No drift was observed over the duration of the trials.

3. EMG and Eye-Blink Channels

The EMG channel produced clear separation between muscle activity and baseline noise once the threshold of Table IV had been applied, and detected the minor spasms of interest in an unconscious patient. The infrared blink sensor detected eyelid movement reliably, including cases of minimal eye activity, provided that alignment with the face was maintained.

4. Urine Level Channel

The urine-level channel was tested by filling the collection bag with known volumes and recording the sensor output and alert state. The results are given in Table VI. Actuation occurred at the intended 80 % threshold and was sustained beyond it.

Table 6. Urine Bag Level Test Data

Urine volume (ml)	Sensor output (%)	Alert triggered
500	50	No
800	80	Yes
1000	100	Yes

5. Alert Generation

Alerts were raised reliably whenever a monitored parameter exceeded its threshold. Notifications were delivered to the mobile application and web dashboard, and were accompanied by the local visual and audible signals. Table 7 records the alert configuration and the corresponding response action.

Table 7. Alert Thresholds and Response Actions

Parameter	Threshold range	Alert type	Response action
Heart rate	< 60 or > 100 bpm	Red LED, buzzer	Notify caregiver
Temperature	< 36 °C or > 38 °C	Red LED, buzzer	Notify caregiver
EMG activity	Spikes detected	LED indicator	Notify caregiver
Eye blink	Irregular blinks	LED indicator	Notify caregiver
Urine level	> 80 % full	Buzzer	Notify caregiver

6. System-Level Performance

Overall performance was assessed against five criteria:

1. Measurement accuracy. All five channels showed deviations from reference values small enough for the intended supervisory role, and behaved consistently across repeated trials.
2. Real-time transfer. The ESP8266 uplink remained stable, and readings reached the cloud platform without observable delay for the duration of the tests.
3. Alert efficiency. Visual, audible and push notifications were generated correctly against the programmed thresholds.
4. Reliability. Over a continuous test period of several hours the system operated without major fault and without loss of data integrity.
5. Scalability. Additional sensing channels could be added without restructuring the existing hardware or firmware.

Discussion

The results confirm the central design objective: a five-parameter monitor for comatose patients can be assembled from commodity components and can deliver measurement accuracy adequate for supervisory alerting. The accuracy figures of Tables V and VI are the substantive outcome, since they place quantitative bounds on what the prototype can be trusted to report.

The decision to evaluate thresholds locally rather than in the cloud proved important in practice. Because the Arduino raises the buzzer and LED alerts directly, an interruption of the Wi-Fi link degrades the system to a local monitor rather than disabling it. This is a meaningful property in the rural and home-care settings that motivated the work, where connectivity cannot be assumed.

Two difficulties emerged during development. The EMG channel intermittently picked up background electrical noise, which required additional signal conditioning and threshold tuning before muscle activity could be separated reliably from the baseline. The eye-blink sensor proved sensitive to the position of the patient's face relative to the emitter, producing occasional false positives and missed blinks when alignment drifted. Neither difficulty prevented operation, but both constrain the confidence that can be placed in those two channels without periodic attention.

It should also be noted that the firmware implemented on the prototype (Appendix A) acquires the pulse signal on an analogue input with exponential smoothing, and drives an OLED bedside display, whereas the component specification of Table II lists an I^2C pulse-oximeter module. Both descriptions originate in the project record and are reported here as they stand; the analogue arrangement is the one exercised in the tests of Section V.

Limitations

The following limitations bound the claims made in this paper.

- Validation was performed by controlled simulation with volunteers under safe conditions, not on comatose patients. No clinical trial was undertaken and no clinical claim is made.
- The heart-rate comparison rests on four data points against a single reference

instrument, which is sufficient to bound the deviation observed but not to characterise the channel across its full range.
- EMG measurement remains susceptible to mains and motion-induced interference, and requires per-installation threshold tuning.
- Eye-blink detection depends on stable sensor alignment and controlled lighting; drift in either produces false positives or missed events.
- Cloud publication depends on Wi-Fi availability. Local alerting continues without it, but remote supervision and data logging do not.
- The system provides no diagnostic interpretation. It reports threshold breaches and is not a substitute for hospital-grade monitoring or clinical judgement.

Conclusion

A multi-parameter IoT monitoring system for comatose patients has been designed, implemented and tested. The system integrates heart-rate, body-temperature, EMG, eye-blink and urine-level sensing into a single unit built on an Arduino acquisition stage and an ESP8266 network stage, publishing to a cloud dashboard while retaining local alert actuation.

Bench testing gave heart-rate agreement within 1 bpm of a reference pulse oximeter across the recorded comparison points, temperature agreement within ±0.5 °C of a calibrated thermometer, and correct alert actuation at the 80 % urine-bag threshold. The prototype sustained continuous operation over a multi-hour trial without loss of data integrity, and its modular structure permits additional channels to be added without redesign.

The contribution lies in combining five parameters — including the two least commonly instrumented, eye-blink and urine output — at a cost compatible with rural and home-care deployment, and in reporting the two channels whose reliability remains conditional rather than presenting uniform success. On this basis the system is offered as a complementary early-warning aid that shortens the interval between a physiological change and the caregiver becoming aware of it.

Future Work

Several extensions follow directly from the limitations above.

- Predictive analysis-Machine-learning analysis of accumulated sensor histories would allow deterioration to be anticipated rather than merely detected at the threshold, supporting proactive rather than reactive intervention.
- Additional physiological channels-Pulse oximetry for oxygen saturation, electrocardiography for cardiac rhythm and a camera module for facial-expression analysis would broaden the physiological picture available to the caregiver.
- Communication resilience-A GSM or GPRS fallback path would preserve remote notification when Wi-Fi is unavailable, closing the gap identified in Section VII.
- Power and portability-Battery optimisation and an optional solar-charging module would extend unattended operation in remote or rural deployments.
- Software and integration-A dedicated mobile application with multilingual support would widen accessibility. Encrypted transport and privacy-compliant storage should be adopted before any deployment involving identifiable patient data, and integration with electronic medical records would automate documentation and support clinical decision-making.

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