Design and Implementation of a Standalone Multi-Parameter Clinical Health Monitoring and Alert System

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DOI: https://doi.org/10.51244/IJRSI.2026.1309000153

Received: 21 September 2026; Accepted: 26 September 2026; Published: 14 October 2026

ABSTRACT

Continuous monitoring of patient health parameters is important for identifying abnormal conditions as early as possible. Conventional monitoring methods usually depend on measurements taken at specific times, which may not detect sudden changes between measurements. This project presents a standalone clinical health monitoring and alert system designed to continuously monitor several health-related parameters and provide immediate local warnings. The proposed system uses a NodeMCU ESP8266 as the main processing unit. It is connected to a DS18B20 temperature sensor, a pulse oximeter for heart rate and blood oxygen saturation (SpO_2), an AD8232 ECG sensor, and an MPU6050 sensor for fall detection. The collected readings are processed by the NodeMCU and displayed through a 16×2 I2C LCD. A red LED and an active buzzer are used to indicate abnormal conditions, while a green LED indicates normal operation. The implemented system uses predefined threshold values and a state-based control method to identify conditions such as abnormal temperature, low oxygen level, abnormal heart rate, ECG lead disconnection, and falls. Testing was performed under normal and simulated abnormal conditions. The results showed that the system successfully detected the tested conditions and generated the corresponding visual and audible alerts. The prototype provides a low-cost and portable solution for local health monitoring.

Keywords: NodeMCU ESP8266, DS18B20, MAX30102, AD8232 ECG, MPU6050, SpO2.

INTRODUCTION

Continuous observation of patient health is important because some changes in physiological condition can happen quickly. Periodic measurements may not always be sufficient to identify these changes immediately. This creates a need for simple monitoring systems that can continuously observe important health parameters and provide a warning when an abnormal condition occurs. The proposed project is a clinical health monitoring and alert system that combines several sensors with a NodeMCU ESP8266 microcontroller. The system monitors body temperature, heart rate, blood oxygen saturation, ECG activity, and physical movement. The measured information is processed locally and displayed to the user through an LCD. The system is designed to operate as a standalone platform without depending on an internet connection or cloud service. When a monitored value moves outside the predefined limits, the controller changes the system status and activates an appropriate alert using LEDs and a buzzer. The main purpose of the project is to provide a low-cost prototype capable of continuous monitoring and immediate local notification. The system can potentially be useful in places such as hospitals, clinics, nursing homes, ambulances, and home environments.

LITERATURE SURVEY

The study *"*Health Monitoring System Using Machine Learning Techniques Algorithm*"* presents a Flask-based health monitoring system using Decision Tree classification to predict health risks from parameters such as BMI, age, blood pressure, and lifestyle factors. The model achieved 99% accuracy, demonstrating its potential for early risk prediction and clinical decision support. However, system complexity and cost remain limitations [1].

Manjhi and Sinha (2025) proposed an IoT-based health monitoring framework integrating wearable sensors with machine learning models. The LSTM model achieved 96.8% accuracy and an AUC of 0.98, enabling real-time detection of physiological abnormalities. The system supports timely alerts and remote patient monitoring [2].Hunsigi, Patil, and Kumar (2025) developed an AI-based predictive framework for early detection of patient deterioration using vital signs, laboratory results, and electronic health records. The models achieved AUC values of 0.92 for sepsis and 0.89 for cardiac arrest prediction, highlighting the potential of AI for proactive clinical intervention [3].

Al-Nafjan et al. (2025) systematically reviewed 147 studies on AI-driven predictive healthcare. The review identified Random Forest, XGBoost, LSTM, and CNN as widely used approaches. Key challenges include data heterogeneity, limited interpretability, and difficulties in clinical deployment [4].The study *"*IoT Based Patient Health Monitoring System*"* (IJRASET, 2023) presents an Arduino-based system using heartbeat, temperature, ECG, and saline-level sensors. Data is transmitted to ThingSpeak and a mobile application for remote monitoring, with alerts generated when predefined thresholds are exceeded [5].

Wai, Aung, and Htay (2019) proposed an IoT-based healthcare monitoring system using Arduino Uno, NodeMCU, and physiological sensors. The system transmits patient data to the cloud and sends notifications when measurements exceed predefined thresholds, supporting continuous remote monitoring [6].Yang, Liu, and Zhang (2025) introduced a transformer-based model for predicting sepsis using longitudinal electronic health records. The model achieved an AUC of 0.94 for predicting sepsis up to 12 hours before clinical recognition, demonstrating the potential of time-series deep learning for early intervention [7].Kwon, Lee, and Park (2022) developed an explainable machine learning framework for predicting patient deterioration using vital signs and laboratory data. The model achieved an AUC of 0.91 and provided feature importance scores to improve the interpretability of clinical alerts [8].

Nnamdi et al. (2024) developed a wearable health monitoring system that transmits temperature and pulse-rate measurements to ThingSpeak. The system enables remote access to patient data through web and mobile platforms, supporting continuous monitoring and timely healthcare intervention [9].Mounika and Akram (2026) proposed an ESP32-based ECG monitoring system integrating the AD8232 sensor with ThingSpeak. The system achieved a mean transmission latency of 0.35 seconds and examined heart rate and variability across age groups and daily time intervals, demonstrating its potential for continuous cardiac monitoring [10].

COMPONENT SURVEY

A. Node MCU (ESP8266)

The NodeMCU is the main development board used to control the health monitoring system. It is based on the ESP8266 System-on-Chip, which combines processing capability, memory, wireless communication, and networking functions on one device. The board provides several GPIO pins for connecting sensors and output devices. It can be programmed using the Arduino IDE with C/C++.In this project, the NodeMCU acts as the central unit. It receives information from the connected biomedical sensors, processes the incoming signals, applies the programmed decision conditions, and controls the LCD, LEDs, and buzzer according to the detected system condition.



Fig 1: ESP8266

B. Temperature Sensor (DS18B20)

The DS18B20 is a digital temperature sensor used to measure temperature and provide the measurement as digital data. It uses the One-Wire communication protocol, requiring only one data line for communication with the controller. The sensor has VDD, GND, and DQ connections. In this project, it measures the patient's temperature and sends the information to the NodeMCU for display and monitoring.



Fig 2: DS18B20

C. I2C LCD Display

The 16×2 I2C LCD is used to display text, numerical values, sensor information, and system status. Its I2C interface uses SDA and SCL communication lines, which reduces the number of GPIO connections required. The module also includes VCC and GND connections. In this system, the LCD provides a local display of the monitored information and the current condition of the patient.



Fig 3: LCD

D. ECG Sensor (AD8232)

The AD8232 is an ECG signal-conditioning module designed to measure the electrical activity of the heart. It receives signals from body electrodes and conditions them to produce an analog ECG waveform suitable for processing. The module includes filtering to reduce noise and motion effects, as well as LO+ and LO− connections for lead-off detection. In this project, it provides ECG information to the NodeMCU for heart-rhythm monitoring.



Fig 4: AD8232

E. Pulse Oximeter (MAX30100)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

The MAX30102 is a non-invasive sensor used for measuring blood oxygen saturation (SpO_2) and pulse rate. It uses red and infrared LEDs with a photodetector to detect changes related to blood circulation. The sensor communicates with the NodeMCU through I2C using SDA and SCL lines. In this project, it provides pulse and oxygen-saturation information for health monitoring.



Fig 5: MAX30100

F. Fall Detection Sensor (MPU6050)

The MPU6050 combines a three-axis accelerometer and a three-axis gyroscope to measure linear acceleration and angular movement. It communicates with the NodeMCU through the I2C protocol and can detect changes in movement, tilt, vibration, and acceleration. In this project, it is used to monitor patient movement and identify sudden motion that may indicate a fall or abnormal activity.



Fig 6: MPU6050

G. Buzzer

The active buzzer is the audio alert component of the system. It contains an internal oscillator and produces a sound when DC power is applied. In the health monitoring system, the NodeMCU activates the buzzer when an abnormal physiological condition is detected, providing an audible warning to a nearby caregiver.



Fig 7: Buzzer

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

H. Light Emitting Diode (LED)

LEDs are semiconductor devices that produce visible light when current flows through them. They are used as visual indicators in electronic systems. In this project, the LED indicators are controlled by the NodeMCU to show the operating condition of the health monitoring system and provide a visual warning when an abnormal condition is detected.



Fig 8: LED

BLOCK DIAGRAM

Figure no 9 presents the detailed architecture of the proposed Health Monitoring and Alert System. The NodeMCU serves as the central control and processing unit of the entire system. The operation of the system begins when the biomedical sensors are connected to the patient. The temperature sensor continuously measures body temperature, while the pulse oximeter tracks pulse rate in beats per minute. At the same time, the ECG sensor captures the electrical activity of the heart to monitor rhythm patterns. Additionally, the fall detection sensor detects unusual body movements that may indicate physical instability or discomfort. The signals generated by these sensors are transmitted to the NodeMCU through its input pins. The microcontroller reads and processes the incoming data, converting analog signals into digital values when necessary. The programmed algorithm compares the measured parameters with predefined normal threshold limits stored in the system. If all values remain within the safe range, the system continues monitoring without interruption. However, when any parameter exceeds or drops below the acceptable limits, the NodeMCU immediately initiates the alert sequence. The buzzer is activated to generate an audible warning signal. Simultaneously, the LED indicator provides a visual alert. The I2C LCD module displays the real-time sensor readings along with the system status (Normal or Abnormal).

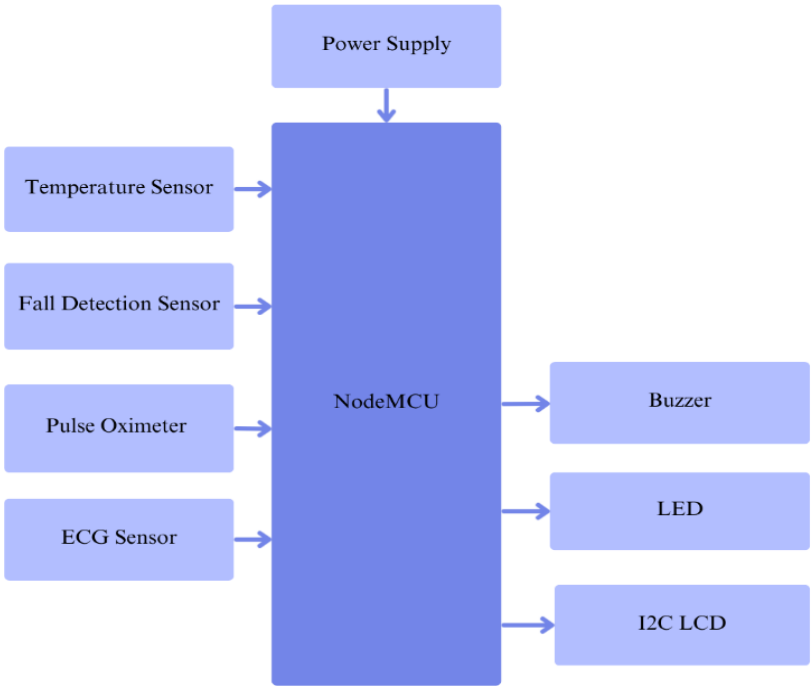


Fig 9: Block Diagram

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

RESULTS AND DISCUSSION

A. Circuit Diagram

The circuit diagram of a standalone multi-parameter health monitoring and alert system is shown below.

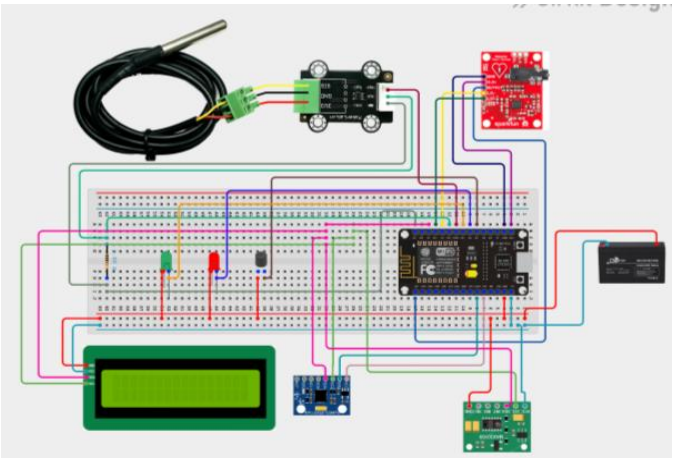


Fig 10: Circuit Diagram

B. Circuit diagram explanation

The proposed health monitoring system was tested under two primary conditions: normal physiological parameters and simulated abnormal conditions. All tests were conducted with the NodeMCU (ESP8266) connected to the DS18B20 temperature sensor, MAX30100 pulse oximeter, AD8232 ECG sensor, and MPU6050 fall detection sensor. The I2C LCD display, red and green LEDs, and active buzzer served as the output feedback mechanisms. The results from both test conditions are presented below.

Normal Condition Test

In the normal condition test, the system was operated within the predefined safe thresholds programmed in the NodeMCU. The following conditions were verified during this test:

The body temperature measured by the DS18B20 sensor was 29.3°C. Since the firmware triggers a temperature alert only when the reading exceeds 36.0°C (the upper threshold defined in the code as TEMP_MAX), this value did not activate any alert. It is shown below.

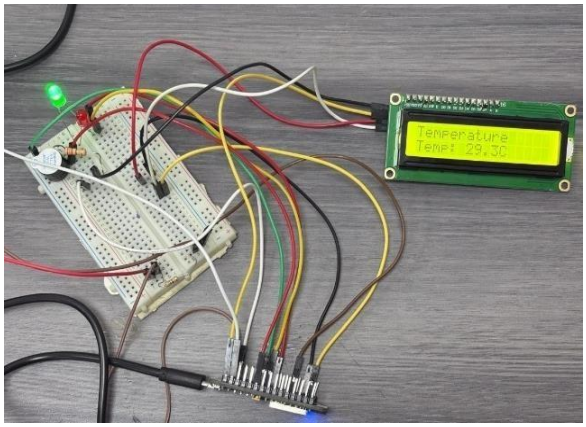


Fig 11: Displays normal temperature reading

The SpO_2 level obtained from the MAX30100 pulse oximeter was 97%, which is well above the critical lower limit of 90% defined in the program. It is shown in the below figure.

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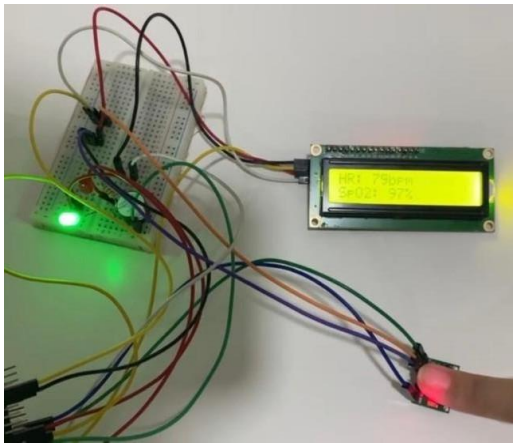


Fig 12. Shows normal pulse oximeter reading

The ECG sensor (AD8232) detected a normal sinus rhythm with both lead-off detection pins (LO+ and LO−) reading LOW, confirming that the electrodes were properly attached. The measured heart rate (BPM) was 79 BPM, comfortably within the programmed safe range of 40 to 150 BPM. The reading and the graph is shown below.

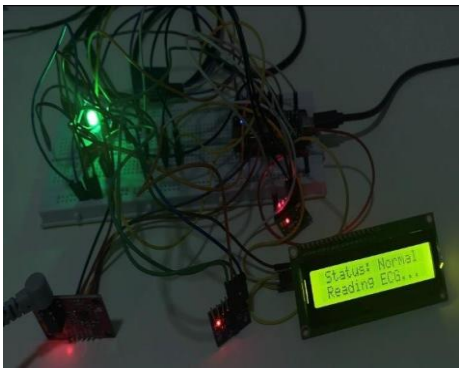


Fig 13. Shows normal ECG reading

The MPU6050 accelerometer recorded an acceleration magnitude of approximately0.98 g, which falls within the normal movement range of 0.6 g to 2.0 g, so no fall event was triggered as shown in figure given below.

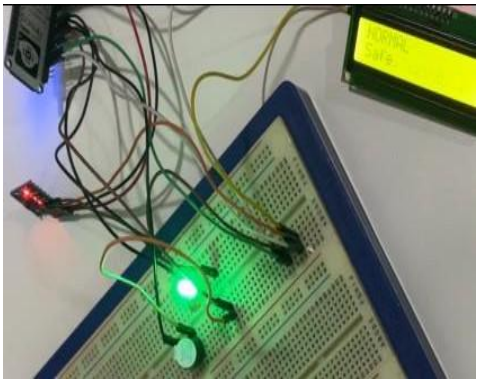


Fig 14. Shows person in safe

Under these conditions, the system responded as follows: the green LED remained continuously ON, the red LED and buzzer remained OFF, and the I2C LCD displayed "Status: Normal" on the first row along with the current BPM reading on the second row. The Serial Monitor output confirmed normal readings for all parameters with no alert flags raised. Table 1 summarizes the sensor readings and system responses recorded during the normal condition test.

Parameter	Measured Value	Safe Threshold	System Response
Body Temperature	29.3°C	≤ 36.0°C	GREEN LED ON,
			Buzzer OFF
SpO_2	97%	≥ 90%	GREEN LED ON,
			Buzzer OFF
Heart Rate (BPM)	78 BPM	40 – 150 BPM	GREEN LED ON,
			Buzzer OFF
ECG Waveform	Normal Sinus Rhythm	No lead-off detected	Status: Normal on LCD
Accelration	0.98 g	0.6 g – 2.0 g	No fall alert triggered
ECG Lead Status	Leads Connected	LO+, LO− = LOW	Reading ECG… on LCD

Table 1: Normal Condition Test Results

Abnormal Condition Tests

The abnormal condition test was performed by simulating various out-of-range physiological scenarios. Each condition was tested individually and in combination to verify that the system correctly identifies the abnormality, activates the appropriate alert output, and displays the correct status message on the LCD. Seven distinct abnormal test cases were evaluated based on the system states defined in the firmware: SYS_TEMP_ABNORMAL, SpO_2low, S_ECG_ABNORMAL, SYS_FALL, SYS_LEADS_OFF, and SYS_FALL_AND_ECG. High Temperature: The DS18B20 sensor recorded a value of 37.5°C, which exceeded the programmed threshold of 33.0°C. The system immediately activated the red LED continuously and turned on the buzzer. The LCD displayed "TEMP ALERT TRIGGERED" and the Serial Monitor printed the alert message. The green LED was turned off.It is shown in below figure.

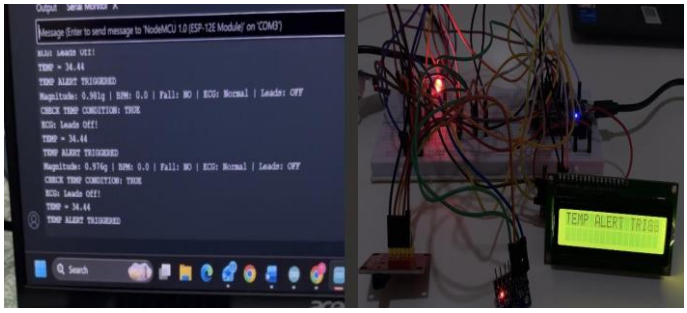


Fig 15. Shows an abnormal temperature reading

Low Blood Oxygen (SpO_2): The MAX30100 pulse oximeter returned an SpO_2 reading of 87%, which is below the critical threshold of 90% defined in the main loop. The system activated the red LED and printed "Oxygen level danger" to the Serial Monitor output.

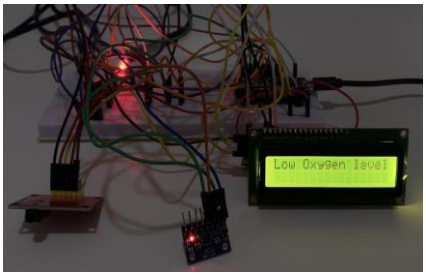


Fig 16. Shows an abnormal oxygen level

Low Heart Rate: By simulating a slow ECG signal, the calculated average BPM dropped to 35 BPM, which is below the BPM_LOW threshold of 40 BPM. The system transitioned to the SYS_ECG_ABNORMAL state. The red LED was activated, the buzzer beeped at 800 ms intervals, and the LCD displayed "ECG ABNORMAL!" on the first row and "Low BPM: 35" on the second row.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

High Heart Rate: A rapid simulated ECG signal caused the average BPM to reach160 BPM, exceeding BPM_HIGH of 150 BPM. The system again entered the SYS_ECG_ABNORMAL state, activating the red LED and the 800 ms buzzer beep pattern. The LCD displayed "ECG ABNORMAL!" and "High BPM: 160".It is shown in figure.



Fig 17. Shows an abnormal Heart Rate

Fall Detection: The MPU6050 sensor was subjected to a sudden impact, resulting in an acceleration magnitude of 2.5 g, which exceeds the FALL_MAGNITUDE_HIGH threshold of 2.0 g. The system immediately transitioned to SYS_FALL, activating the red LED and triggering the buzzer to beep every 500 ms for a duration of 5 seconds (FALL_ALERT_DURATION). The LCD displayed "!! FALL !!" and "Patient Fell!". The fall alert was automatically cleared after 5 seconds.

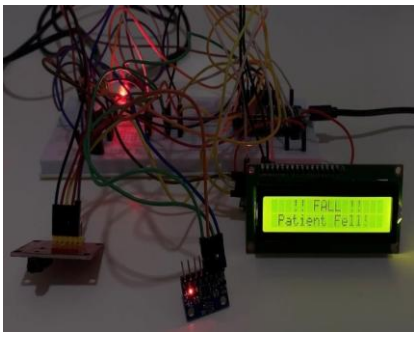


Fig 18. Shows an patient fell

ECG Leads Disconnected: When the ECG electrode leads were physically disconnected, both LO+ and LO− pins returned HIGH. The system entered the SYS_LEADS_OFF state, turned off the buzzer and the red LED, and instead began slow-blinking the green LED at 1-second intervals as a warning indicator. The LCD displayed "ECG Warning!" and "Check Leads!".

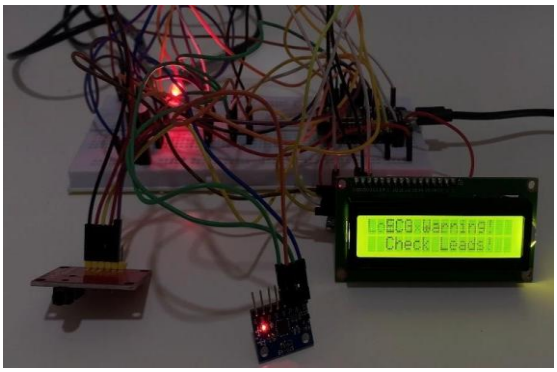


Fig 19. Shows an "ECG Warning!" and "Check Leads!".

DISCUSSION

The results demonstrate that the developed system successfully performs continuous, real-time monitoring of multiple physiological parameters and responds correctly to both normal and abnormal conditions. The system's

state machine architecture comprising six defined states (SYS_NORMAL, SYS_FALL, SYS_ECG_ABNORMAL, SYS_LEADS_OFF, SYS_FALL_AND_ECG, and SYS_TEMP_ABNORMAL) ensures that each type of abnormality triggers a distinct and appropriate alert pattern, preventing alert ambiguity. The buzzer beep frequency was intentionally varied across states: 800 ms intervals for ECG abnormalities, 500 ms for fall detection, and a rapid 300 ms pattern for the combined emergency scenario. This graduated alert design allows caregivers to distinguish the severity of the event based on sound alone, which is consistent with established principles of clinical alarm design. The temperature threshold is set to TEMP_MAX = 33.0°C, which aligns with the lower boundary of the standard normal adult body temperature range of 36.1°C to 37.2°C. Any reading exceeding this value is correctly treated as a potential fever or abnormal condition, ensuring timely detection of elevated body temperature in patients. Overall, the system achieved its primary objectives: real-time data acquisition from multiple biomedical sensors, immediate local alert generation without internet dependency, and clear visual feedback through the LCD display validating the design as a functional standalone health monitoring and alert platform

CONCLUSIONS AND FUTURE SCOPE

The developed prototype demonstrates a practical standalone approach for monitoring several patient-related parameters in real time. The integration of the NodeMCU with temperature, pulse oximetry, ECG, and fall detection sensors allowed the system to collect different types of health information using one central controller. The LCD provided local feedback, while the LEDs and buzzer supplied immediate visual and audible warnings when abnormal conditions were detected. Testing under normal and simulated abnormal conditions confirmed that the implemented system could respond to the tested temperature, oxygen, heart-rate, fall, and ECG lead conditions. The current prototype is based on fixed thresholds and programmed system states rather than an implemented machine-learning prediction model. This provides a functional foundation for the project while leaving room for more advanced analysis. The report identifies several limitations, including the absence of historical data storage, remote notifications, adaptive patient-specific thresholds, and battery backup.

Future development can focus on integrating machine-learning algorithms so that the system can analyze patient data and move from simple threshold detection toward predictive health assessment. Remote monitoring could also be added through a web dashboard or mobile application, together with SMS or email notifications. A backup battery could improve reliability during power interruptions. The fixed limits could be replaced with patient-specific adaptive values based on individual health history. Further improvements may include wearable implementation and the addition of sensors for blood pressure and respiratory rate.

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ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

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