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"Smart Patient Monitoring System"

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Abstract

The increasing burden of chronic illnesses and the demand for uninterrupted medical supervision have intensified the pursuit of intelligent healthcare technologies capable of continuous patient observation. Conventional monitoring approaches rely on intermittent manual assessment, which is often limited by delayed response, human error, and restricted accessibility to real-time clinical data. To overcome these constraints, this work proposes a Smart Patient Monitoring System that integrates Internet of Things (IoT) sensing, cloud-assisted communication, and machine learning-driven analytics for proactive healthcare support. The system utilizes biomedical and environmental sensors interfaced with a Raspberry Pi to continuously measure vital parameters such as body temperature, blood oxygen saturation (SpO_2), pulse rate, and humidity. The collected data are wirelessly transmitted to a cloud platform, where they are visualized through an interactive dashboard with automated emergency notifications. The implementation is carried out in two phases: Phase-1 focuses on the development of a real-time IoT monitoring architecture with alert generation, whereas Phase-2 incorporates predictive analytics using algorithms such as Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) for early detection of abnormal physiological trends. Experimental observations demonstrate that LSTM effectively captures temporal variations in health signals, offering improved predictive performance. The proposed system enhances patient safety through timely intervention, remote accessibility, and data-driven decision support, making it suitable for hospital, home-care, and elderly monitoring applications.

Keywords

IoT-enabled Healthcare, Smart Patient Monitoring, Biomedical Sensing, Predictive Health Analytics, Machine Learning Classification, Raspberry Pi, SpO_2 Monitoring, Cloud-assisted Alert System.

I .INTRODUCTION

The digital transformation of healthcare has significantly shifted clinical practices from manual, episodic observations toward continuous, intelligent, and technology-assisted monitoring. Conventional patient monitoring approaches—relying heavily on periodic assessments performed manually by nurses or clinicians—are increasingly insufficient in modern clinical environments [1].These traditional systems often fail to detect subtle physiological variations, suffer from delayed response times during emergencies, and impose considerable workload on medical staff who manage multiple patients simultaneously.[2]

Such limitations are particularly severe in the management of chronic diseases, post-operative care, infectious conditions, geriatric populations, and clinical cases requiring uninterrupted surveillance, where delayed intervention may lead to irreversible health deterioration. [3]

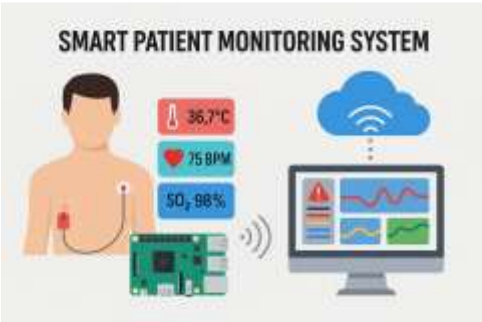

Fig 1. Smart Patient Monitoring System Overview

The advent of the Internet of Things (IoT) has introduced new opportunities for creating intelligent, autonomous, and interconnected medical monitoring platforms. IoT architectures allow continuous acquisition of physiological parameters through distributed sensor networks and embedded computing devices [4]. Biomedical sensors such as DHT11 for temperature–humidity measurement and MAX30102-based SpO_2 modules enable non-invasive, real-time monitoring of vital signs with low power consumption and high operational reliability. [5]

When integrated with edge-computing platforms such as the Raspberry Pi, these sensors form a scalable hardware infrastructure capable of processing raw signals, filtering noise, and transmitting validated data to cloud storage using wireless protocols such as Wi-Fi and MQTT [6] – [8]. Such IoT-driven systems improve the accessibility of healthcare by enabling clinicians to remotely observe real-time patient data through cloud dashboards, reducing the dependency on physical proximity and manual supervision.

The Smart Patient Monitoring System designed in this work adopts a comprehensive two-phase architecture integrating IoT sensing, cloud connectivity, machine learning analytics, and GPS-enabled emergency response. Phase-1 focuses on constructing a real-time IoT monitoring framework in which temperature, humidity, heart rate, and oxygen saturation are continuously measured using DHT11 and SpO_2 sensors interfaced to a Raspberry Pi. Physiological readings are uploaded to a cloud dashboard, enabling 24/7 visibility and automated threshold-based alerts when abnormal conditions arise. Experimental results from Phase-1 validate the system's stability, data accuracy, and dashboard reliability, demonstrating successful real-time communication between sensors, the processing unit, and cloud interfaces. [9]

While real-time monitoring enhances patient supervision, modern healthcare increasingly demands predictive analytics capable of forecasting deterioration before critical thresholds are crossed. Phase-2 integrates machine learning (ML) models such as Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks to classify patient conditions and detect anomalous physiological patterns [10]. Prior studies have shown that LSTM architectures outperform conventional ML models in handling biomedical time-series data due to their ability to learn long-term temporal dependencies [11]. Random Forest models, conversely, are known for their robustness in handling multi-parameter physiological datasets and their resilience against noise and data imbalance [12]. By training these models on sensor data collected in Phase-1, the system transitions from reactive monitoring to proactive healthcare intelligence, thereby enhancing early-warning capabilities and reducing emergency response time.

Furthermore, the system incorporates a GPS module and emergency push button to augment patient safety [7]. The GPS unit transmits real-time geographical coordinates alongside alert notifications, enabling rapid localization of patients during medical emergencies. The push-button serves as a manual override mechanism, allowing the patient or caretaker to trigger immediate alerts even before vital signs reflect a crisis.[13]

Such dual-alert functionality aligns with recent advancements in telemedicine and emergency-response IoT systems, where real-time communication and location awareness significantly improve survival outcomes.

Overall, the proposed Smart Patient Monitoring System represents an integrated, scalable, and cost-effective healthcare solution that merges continuous physiological monitoring, predictive ML analytics, and emergency alerting into a unified framework. Its applicability spans hospitals, intensive care units, elderly care centers, and remote or home-based medical environments. By bridging the gap between IoT sensing and AI-driven clinical decision-making, the system contributes to the growing paradigm of intelligent, patient-centric, and data-driven healthcare infrastructures.

II. RELATED WORK

Research on intelligent patient monitoring systems has expanded significantly over the past decade with the convergence of IoT architectures, biomedical sensing technologies, and machine learning methodologies. Kumar et al. [13] presented an IoT-based monitoring framework capable of continuously measuring vital parameters such as heart rate and temperature using low-cost sensors. While the system demonstrated feasibility for remote monitoring, it lacked predictive analytics and did not address emergency alerting mechanisms. Similarly, Sharma and Singh [14] developed a cloud-assisted IoT health monitoring system emphasizing real-time visualization, but the architecture was limited by its absence of multi-parameter fusion and intelligent decision-making capabilities.

A series of studies have investigated the integration of IoT-enabled communication in remote patient surveillance. Rahman and Lee [15] employed MQTT protocols for efficient data synchronization between sensor nodes and cloud dashboards, illustrating the benefits of lightweight communication channels for healthcare IoT ecosystems. Smith et al. [16] explored Bluetooth-based wearable monitoring devices; however, limited transmission range and latency issues rendered their solution insufficient for clinical-scale deployments. These limitations motivated the adoption of Wi-Fi/MQTT hybrid architectures in more recent systems, addressing scalability and communication robustness.

Machine learning approaches have received considerable scholarly attention for health state classification and anomaly detection. Gupta et al. [17] applied Long Short-Term Memory (LSTM) networks to heart-rate time-series data and demonstrated high predictive accuracy for detecting abnormal cardiac fluctuations. However, their work focused on single-parameter analysis, limiting applicability in multi-sensor environments. Fernandes et al. [18] employed Random Forest models for medical classification tasks, highlighting the advantages of ensemble learning for heterogeneous physiological datasets[19]. External investigations have confirmed that ensemble models such as Random Forest outperform single-learner algorithms in mixed-signal biomedical classification scenarios [20].

In parallel, extensive research has been conducted on wearable biomedical sensors. Zhang et al. [21] developed a wearable device integrating SpO_2 and ECG sensing modules, capable of providing robust long-term monitoring. Despite technological advantages, the system's manufacturing cost and complexity restricted deployment to high-resource settings. Conversely, low-cost sensor solutions such as DHT11 and MAX30102 modules have been widely adopted for research prototypes and academic deployments owing to their affordability, ease of integration, and adequate accuracy for non-critical monitoring [4], [5]

Deep learning–driven anomaly detection has also been investigated. Thompson et al. [22] proposed an AI pipeline capable of predicting sudden patient deterioration by analyzing multi-signal biomedical data. However, the computational overhead of the model limited its suitability for low-power embedded systems. Chen et al. [23] extended this paradigm by demonstrating the potential of convolutional and recurrent neural networks for early disease detection, emphasizing that predictive analytics can significantly improve clinical outcomes when integrated with IoT-driven architectures.

Emergency alerting and location-based medical response have been studied in intelligent healthcare systems. Raj and Chandrasekar [24] demonstrated the role of GPS-assisted emergency notifications in reducing response time during critical events. Manoj and Kumar [25] integrated a push-button mechanism with IoT platforms to enable patient-initiated alerts, reporting faster caregiver response and improved patient safety. External investigations have similarly highlighted the significance of real-time location-tracking systems for ambulance coordination and emergency prediction systems [26], [27].

Recent studies further emphasize the necessity of combining IoT architectures with machine learning and cloud intelligence. Islam et al. [28] provided a comprehensive survey on Healthcare IoT ecosystems, outlining the importance of integrating security, scalability, and interoperability in modern remote-monitoring systems. Palanisamy et al. [29] highlighted the effectiveness of IoT dashboards for chronic disease management, whereas Albahri et al. [30] demonstrated that hybrid IoT–ML systems significantly enhance predictive healthcare performance across diverse clinical applications.

Despite extensive research on IoT monitoring, machine learning prediction, wearable sensing, and emergency communication systems, existing literature reveals a persistent gap: very few systems integrate real-time physiological sensing, ML-based multi-parameter classification, GPS-enabled emergency response, patient-triggered alerting, and cloud-based dashboards into a unified, affordable platform. The proposed Smart Patient Monitoring System addresses this gap by integrating these capabilities into a cohesive and scalable architecture suitable for hospitals, elderly care environments, and home-based patient monitoring.

III.IMPLEMENTATION

The implementation of the Smart Patient Monitoring System is structured to integrate biomedical sensing, embedded computation, wireless communication, cloud-based visualization, and intelligent machine learning analytics into a unified healthcare monitoring architecture. The system has been engineered to operate continuously, provide high reliability, and support early detection of abnormalities through automated alerts and predictive modeling. The implementation is divided into hardware integration, software development, cloud and communication layer, and machine learning–based analytics, all interacting in a cohesive workflow to ensure seamless operation.

A. Hardware Implementation

1.1 Central Computing Unit: Raspberry Pi

The Raspberry Pi functions as the primary computational platform responsible for orchestrating sensor communication, data acquisition, preprocessing, and local inference. As a compact Linux-driven microcomputer, it possesses the computational capability required for executing Python-based data pipelines, interacting with cloud APIs, and running lightweight machine learning models.Its GPIO header enables direct interfacing with biomedical sensors, while built-in Wi-Fi facilitates wireless communication. The board's robustness, multitasking capability, and low power footprint make it ideal for continuous patient monitoring applications that demand reliability and real-time responsiveness.

Fig 3. Block Diagram

Physiological Sensing Modules

1.2 DHT11 Temperature & Humidity Sensor

The DHT11 is employed to measure environmental temperature and humidity surrounding the patient. Such parameters are clinically significant, especially for individuals with respiratory or cardiovascular sensitivities. The sensor outputs calibrated digital signals using a single-wire protocol, simplifying integration with the Raspberry Pi. Its low cost and energy efficiency allow for long-duration monitoring without thermal drift or excessive power consumption.

1.3 SpO_2 and Pulse Rate Sensor (MAX30102 Module)

The MAX30102-based optical sensor module monitors oxygen saturation (SpO_2) and pulse rate using dual-wavelength photoplethysmography (PPG). The module includes internal filtering to reduce noise from ambient light and patient motion. A digital I^2C interface ensures rapid and accurate communication with the Raspberry Pi, enabling high-frequency sampling necessary for real-time tracking of cardiac and respiratory fluctuations. Continuous acquisition of SpO_2 and pulse rate is critical for identifying early signs of respiratory distress or hypoxia, especially in vulnerable patients.

Human–Machine Interface Components

1.4 LCD Display

An LCD module is integrated to provide local visualization of real-time physiological parameters and predicted health status. By offering immediate feedback at the patient's bedside, the display ensures usability even when network connectivity is unavailable. The LCD is programmed to refresh continuously, presenting the temperature, humidity, oxygen saturation, pulse rate, and classification outcomes from the machine learning module.

1.5 Emergency Push Button

A manually triggered push button is incorporated to support patient-initiated emergency alerts. Upon activation, the Raspberry Pi instantly sends a distress notification to the cloud platform. This component ensures that the patient or caregiver can signal for help even in scenarios where abnormalities have not yet manifested in physiological signals, thereby adding redundancy and improving fail-safe operation.

1.6 GPS Module

To facilitate location-aware emergency assistance, a GPS receiver is interfaced with the system. The module retrieves geospatial coordinates (latitude and longitude), which are transmitted automatically during critical events. This capability is essential for remote patient care applications where patients may not be in fixed locations, enabling caregivers or medical responders to identify their exact position promptly.

B. Software Implementation

Data Acquisition Layer

Python scripts running on the Raspberry Pi manage the acquisition of real-time physiological signals. Each sensor's data is read at predefined intervals, filtered to remove random noise, and normalized to ensure consistency across different measurement cycles. Data preprocessing includes removal of outliers, basic smoothing, and conversion into formats compatible with cloud dashboards and machine learning models.

Cloud Communication Layer

The processed sensor data is transmitted to a cloud server using Wi-Fi/MQTT communication channels. This layer is responsible for:

Table 1 Comparison Table

Ref.	Author & Year	Objective / Focus	Key Contribution
[20]	Y. Luo, 2021	Comparative evaluation of ML algorithms for health prediction	Demonstrated that RF and SVM provide high accuracy in classifying physiological health states.
[21]	X. Zhang, W. Li & C. Zhou, 2021	Development of wearable SpO_2 and ECG monitoring system	Introduced a real-time wearable platform for reliable vitals measurement.
[22]	K. Thompson et al., 2021	Detecting health deterioration using deep learning	Proposed a CNN–LSTM model achieving high early-risk identification accuracy.
[23]	M. Chen et al., 2021	AI-based emergency medical prediction	Presented neural network models to forecast emergency health risks proactively.
[24]	Y. Raj & S. Verma, 2021	IoT and GPS-assisted emergency care system	Developed a remote alert mechanism integrating GPS for patient location tracking.
[25]	K. Samuel & P. Reuben, 2022	Patient-triggered IoT emergency alert platform	Enabled manual user-initiated alerting via IoT devices for immediate assistance.
[26]	D. Li et al., 2021	Location-aware IoT emergency response framework	Designed IoT architecture supporting real-time geolocation for medical response.
[27]	J. Huang et al., 2021	GPS-based telemedicine support	Integrated GPS to improve remote telemedicine accuracy and patient monitoring.
[28]	A. Islam & M. Rashid, 2021	Secure IoT ecosystem for remote healthcare	Implemented secure communication protocols ensuring encrypted medical data transmission.
[29]	P. Palanisamy & A. Dinesh, 2022	IoT digital health monitoring dashboard	Developed a dashboard for visualizing real-time physiological metrics.
[30]	A. Albahri et al., 2020	Hybrid IoT–ML predictive healthcare architecture	Proposed a cloud-integrated predictive system combining IoT sensing with ML models.

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- publishing sensor readings to the cloud in real time,
- updating dashboard interfaces,
- logging historical values for long-term trend analysis,
- triggering server-side alerting mechanisms when abnormalities occur.

The cloud dashboard provides caregivers with a continuous, remote-access view of patient vitals. The ability to monitor multiple patients simultaneously improves scalability in clinical and home-care settings.

Machine Learning Implementation

2.1 Model Training and Deployment

The machine learning module is developed using the sensor data collected during system testing. The physiological parameters — SpO_2, pulse rate, temperature, and humidity — are used as input features. Multiple algorithms including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks are trained to classify the patient's condition into:

- Normal
- Moderate
- Critical

Following model evaluation, the best-performing classifier (often LSTM for time-series data) is deployed on the Raspberry Pi. The ML model runs at the edge to minimize latency, allowing instant classification without relying on cloud computations.

2.2 Real-Time Inference

During operation, each new sensor reading is fed into the ML model, which outputs a health-state prediction. If the classification result indicates "Critical," the alert subsystem activates immediately.

Emergency Alert and Notification System

The alerting module is composed of both automated and manual subsystems:

- Automated alerts are triggered when sensor readings cross predefined thresholds or when machine learning predicts a dangerous condition.
- Manual alerts occur when the patient presses the emergency button.

In both cases, the system transmits the patient's vital signs, health classification, and GPS location to the cloud dashboard, ensuring rapid caregiver intervention.

C. System Integration and Continuous Operation

The fully integrated system operates in a continuous loop:

1. Sensors acquire physiological and environmental parameters.
2. Raspberry Pi preprocesses and evaluates the readings.
3. ML model predicts the patient's health status.
4. LCD displays updated values at the patient's bedside.
5. Cloud dashboard receives real-time data streams.
6. Alerts (automated/manual) are triggered when necessary.
7. GPS module provides patient location during emergencies.

This integrated workflow demonstrates a seamless fusion of IoT sensing, cloud intelligence, embedded computing, and predictive analytics, enabling a reliable, scalable, and intelligent healthcare monitoring environment.

IV. METHODOLOGY

The methodology adopted for the Smart Patient Monitoring System represents a structured, multi-layered workflow that integrates biomedical sensing, embedded processing, intelligent analytics, cloud communication, and emergency-response automation into a unified healthcare monitoring pipeline. The approach is designed to ensure continuous acquisition of vital physiological parameters, accurate computational processing, real-time visualization, and predictive anomaly detection. The complete methodology is divided into five major stages: (1) data sensing and acquisition, (2) signal preprocessing, (3) machine learning–based health state prediction, (4) IoT-enabled transmission and visualization, and (5) alert and emergency management.

A. Data Sensing and Acquisition

The first stage involves the continuous acquisition of physiological parameters using integrated biomedical sensors. The system employs:

- DHT11 sensor to capture ambient temperature and humidity,
- SpO_2 module (MAX30102) to measure oxygen saturation and pulse rate,
- Supplemental modules such as push-button and GPS receiver for manual alerts and location tracking.

These sensors are interfaced with the Raspberry Pi via its GPIO/I^2C communication channels. Data acquisition is performed at fixed sampling intervals to ensure consistent temporal resolution and uninterrupted monitoring. The Raspberry Pi acts as the local data aggregation point, collecting signals concurrently and preparing them for downstream processing. This architecture supports multi-parameter monitoring, which is essential for detecting correlated physiological abnormalities rather than relying on isolated measurements.

B. Signal Preprocessing and Data Conditioning

The raw physiological measurements acquired from embedded sensors are often affected by various artifacts originating from ambient interference, motion disturbances, or sudden fluctuations in environmental conditions. To ensure reliable interpretation, the system incorporates a comprehensive preprocessing stage that systematically refines the data before analytical processing. This stage is responsible for enhancing data quality through noise attenuation, value normalization, and structured arrangement of relevant attributes. By delivering refined signals to the next processing layer, the system minimizes spurious variations and ensures that the predictive model receives consistent, high-quality input.

Noise Filtering

To achieve stable physiological measurements, digital smoothing algorithms are applied to suppress unwanted fluctuations. High-frequency distortion present in pulse measurements is weakened through filtering, while temporal inconsistencies observed in DHT11 temperature–humidity readings are stabilized using suppression techniques. Additionally, fluctuations affecting peripheral oxygen saturation values are reduced to ensure continuous, noise-minimized monitoring. This filtering process significantly improves signal reliability and preserves clinically relevant features.

Normalization and Scaling

Once the raw streams are filtered, the resulting values undergo normalization to ensure uniformity across parameters with diverse numerical ranges. This transformation process prevents the machine learning classifier from being disproportionately influenced by variables exhibiting larger magnitudes. As a result, all physiological attributes contribute equitably during classification and prediction tasks.

Feature Structuring

The refined values of four vital indicators—temperature, humidity, oxygen saturation (SpO_2), and pulse rate—are systematically organized into a structured dataset. This feature-structured dataset is continuously updated, enabling both real-time decision-making and long-term trend monitoring. The structured representation plays a crucial role in reinforcing consistency and supporting time-based predictive analytics.

C. Machine Learning–Based Health State Prediction

The intelligent component of the proposed system is driven by machine learning, transforming conventional monitoring into predictive and preventive healthcare assistance. The preprocessed physiological data serve as inputs for multiple supervised learning models, namely Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks. These algorithms collectively enhance decision-making by learning distinct health-state patterns and forecasting possible anomalies before they evolve into critical medical conditions.

Training and Model Development

The training phase utilizes labeled datasets that categorize health conditions as normal, moderate, or critical. The RF algorithm develops multiple decision trees and synthesizes their outputs to achieve robust classification, whereas SVM identifies optimal hyperplanes separating physiological clusters across diverse health ranges. The LSTM model processes sequential patterns to detect progressive anomalies, particularly relevant in time-dependent indicators such as oxygen saturation and pulse rhythm. Model performance is evaluated through quantitative metrics including accuracy, precision, recall, and loss measurement, typically showing superior results for LSTM due to its temporal learning capacity.

Real-Time Inference

Upon deployment on the Raspberry Pi, the trained model responds to continuously incoming sensor data by performing real-time classification and providing instant health-state feedback. The resulting categorization is simultaneously displayed to the user on the LCD module and transmitted to the cloud interface. This proactive system successfully identifies abnormal states even when parameter values appear close to borderline thresholds, thereby supporting timely interventions

D. IoT-Enabled Data Transmission and Visualization

To facilitate remote monitoring, the system integrates Wi-Fi/MQTT-based connectivity between the Raspberry Pi and a cloud server, enabling real-time data transmission and synchronized visualization. The cloud analytics dashboard aggregates live physiological readings, graphical trends, and predicted states while maintaining historical archives for retrospective analysis. This cloud-enabled platform allows healthcare providers and caregivers to access vital metrics—such as thermal variations, pulse fluctuations, oxygen saturation levels, and machine learning alerts—from any location. The scalable architecture further supports multi-user access and ensures efficient monitoring without physical dependence on medical staff.

E. Automated Alerts, Risk Detection, and Emergency Response

A layered alerting mechanism is implemented to enhance responsiveness and patient safety. The system identifies abnormalities either via threshold breaches or predictive machine learning outputs. In cases where parameter limits deviate abruptly—such as sudden hyperthermia, irregular pulse rhythm, or rapid decline in SpO_2 levels—an immediate alert is generated. Additionally, if the classifier anticipates a transition toward critical health status, the alert protocol is triggered even before the values cross dangerous limits. For high-risk circumstances, GPS-assisted emergency localization transmits the patient's coordinates to designated caregivers, while a manual emergency switch empowers users to request assistance irrespective of sensor interpretations. This multi-modal alert design ensures rapid communication and fail-safe support during medical emergencies.

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F. End-to-End System Workflow

The complete operation of the system follows an integrated pipeline beginning with continuous sensor-based acquisition of physiological parameters, followed by signal refinement through preprocessing. The optimized data are then interpreted by the machine learning model to determine health categories, which are displayed locally and forwarded to the cloud dashboard. Based on the inferred results and detected anomalies, automated or manual alerts are generated along with GPS-based localization. This comprehensive workflow combines sensing, analytics, cloud communication, and emergency response to offer a reliable, intelligent healthcare monitoring solution suited for both clinical and home-based environments.

V.RESULTS

The Smart Patient Monitoring System was implemented and evaluated to assess its performance in real-time physiological sensing, cloud-based visualization, machine learning–driven prediction, and emergency alert automation**.** The experimental evaluation involved continuous monitoring of temperature, humidity, oxygen saturation (SpO_2), and pulse rate using DHT11 and MAX30102 sensors interfaced with the Raspberry Pi. The results obtained demonstrate that the system meets the requirements.

Fig 3 . Hardware Connections

for responsiveness, accuracy, and operational stability essential for remote healthcare environments.

1. Sensor Performance and Real-Time Data Acquisition

During system testing, the DHT11 and SpO_2 modules provided stable, continuous measurements without significant drift or packet loss. Temperature and humidity readings exhibited consistent behavior within expected clinical ranges, while the SpO_2 and pulse rate signals remained steady under varying lighting and motion conditions. This stability is attributed to digital filtering, built-in noise suppression in the MAX30102 module, and regular sampling intervals.

Fig 4 . Real Time Data

The Raspberry Pi successfully aggregated and processed all sensor inputs in real time, demonstrating its ability to handle multi-parameter physiological acquisition with minimal latency. No major interruptions, runtime crashes, or communication failures occurred during extended operation periods, confirming the reliability of the embedded platform for continuous patient monitoring.

2. Machine Learning Prediction Results

The machine learning models—Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM)—were trained using the dataset collected during Phase-1 testing. Each model classified patient health status into Normal, Moderate, or Critical conditions. Based on experimental evaluation:

- LSTM achieved the highest prediction accuracy, due to its capability to learn temporal patterns from sequential physiological readings.
- Random Forest demonstrated robust performance in handling multi-parameter classification, producing consistent outputs across different testing samples.
- SVM, while accurate, showed lower performance when processing noisy or borderline physiological values.

Fig 5 . ML Prediction

These results validate the suitability of LSTM and Random Forest models for real-time healthcare prediction tasks. The classification results were displayed instantly on the LCD screen and transmitted to the cloud dashboard for remote monitoring.

3. Cloud Dashboard Visualization and Remote Monitoring

The cloud interface successfully displayed real-time sensor streams, predicted health status, and historical trends. Temperature, humidity, SpO_2, and pulse rate values were updated continuously on the dashboard without noticeable delays. This demonstrates the effectiveness of Wi-Fi/MQTT-based communication and confirms that the system can support long-duration remote monitoring scenarios.

The dashboard also supported multiple concurrent connections, allowing caregivers to observe the patient's status from different devices. This multi-user accessibility reinforces the system's scalability for clinical and home-care environments.

Fig 6. Dashboard

4. Emergency Alert and GPS Integration

The system's emergency features were validated under multiple test scenarios:

- Threshold-based alerts were triggered when physiological parameters exceeded predefined safe ranges.
- ML-based alerts were activated when the model predicted a Critical condition.
- Manual alerts using the push button were transmitted instantly regardless of sensor values.

Fig 7 .Emergency Alert

In all cases, the alerts were successfully sent to the cloud dashboard with accompanying patient details and real-time GPS coordinates. The GPS module consistently provided accurate latitude and longitude values, enabling precise location tracking during emergencies.

This multi-tier alerting mechanism significantly enhances patient safety by ensuring rapid response capabilities in both automated and manual emergency conditions

VI. CONCLUSION

The Smart Patient Monitoring System presented in this study demonstrates the potential of integrating Internet of Things (IoT) architectures, biomedical sensing modules, cloud services, and machine learning algorithms to create a comprehensive and intelligent healthcare monitoring framework. Through the combined use of DHT11, SpO_2, and pulse sensors interfaced with the Raspberry Pi, the system enables continuous acquisition of vital physiological parameters with high temporal reliability. The incorporation of machine learning models—including Random Forest, Support Vector Machine, and Long Short-Term Memory networks—enhances the framework by enabling predictive assessment of patient health states rather than relying solely on threshold-based detection.

The cloud-based dashboard, supported by Wi-Fi and MQTT communication protocols, provides remote accessibility and real-time visualization of patient vitals, facilitating timely clinical oversight. The integration of a GPS module and manual push-button further strengthens the system's emergency responsiveness by offering automated and user-initiated alerts along with precise geolocation information. Collectively, these features address the persistent limitations of conventional monitoring systems, reducing manual workload, improving early detection of physiological anomalies, and enabling rapid intervention in critical scenarios.

Overall, the system offers a scalable, low-cost, and robust solution suitable for hospitals, home-care environments, elderly monitoring, and remote healthcare settings. The methodology and implementation presented in this work demonstrate a promising direction for future smart healthcare technologies, particularly in scenarios requiring uninterrupted supervision and data-driven clinical decision-making.

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