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AI-Enabled IoT System for Continuous Health Monitoring and Early Risk Detection

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Abstract

Traditional healthcare systems depend on manual tracking and periodic check-ups, which can postpone the identification of serious health issues particularly for patients with chronic conditions they frequently have difficulty providing timely intervention. In response to this issue, we created a smart health monitoring system that leverages AI and IoT technology to provide ongoing, real-time health assessments and prompt reactions. The system incorporates the ESP32 microcontroller for data handling, as well as sensors like the MAX30100 for measuring blood oxygen and heart rate, the LM35 for body temperature, and an ECG sensor for cardiac monitoring. These sensors gather real-time health data that is sent to a hospital Web server for analysis, risk assessment, and alert notification. With a mobile app, patients can access their health information, get medication reminders, and connect with healthcare providers. By examining the gathered data for unusual patterns and forecasting health risks, AI predictive algorithms facilitate preemptive action. A health monitoring system uses Random Forest and SVM models to consider various physiological data for patient status classification with an accuracy of 99.7–100%, aiding in early risk prediction and proactive intervention. Dashboards for healthcare professionals' real-time decision-making, driven by Power BI. This collection of solutions provides patients and caregivers with timely alerts, predictive analytics, enhanced patient involvement, and the capability to monitor wellness around the clock. The system enhances the efficiency of healthcare and the quality of patient care through rapid data-driven responses.

Keywords: FreeRTOS, ECG, AIoT, Cardiovascular Disease

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1. Introduction

Recently, with the development of AI and the Internet of Things (IoT), health delivery has been transformed, consistently overcoming conventional health systems constraints [1] . Traditional patient monitoring in healthcare is primarily based on self-reporting and occasional clinical visits, leaving open a monitoring void for recognizing any developing health disorders, especially for patients with chronic conditions requiring continuous supervision. Research has indicated that outcomes for patients improve, and complications and hospitalizations decrease by up to 30%, when heart failure is diagnosed through regular monitoring at an earlier stage. [2] It is expected that from 2025 to 2050, cardiovascular cases will increase by 90%, deaths will rise by 73.4%, and DALYs will grow by 54.7%, culminating in 35.6 million deaths by 2050 [3]. Cardiovascular diseases (CVDs) account for the highest number of deaths globally, with 17.9 million fatalities each year, predominantly due to heart attacks and strokes [4]

We have witnessed firsthand the critical gaps in patient monitoring and timely medical intervention. Many patients have tragically passed away before receiving appropriate care, often due to rapid and undetected fluctuations in vital signs such as pulse rate or body temperature. These personal experiences have driven the motivation behind developing a continuous health monitoring system. In many rural and underserved areas, healthcare systems suf-

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fer from inadequate communication infrastructure and a lack of real-time diagnostic tools. Traditional data collection is often slow and error-prone, making timely diagnosis and treatment challenging. Chronic respiratory patients, in particular, struggle with monitoring environmental conditions like temperature and humidity, which can exacerbate their health issues. An intelligent alert system with live data updates and precise location tracking can significantly improve emergency response times and patient outcomes in such contexts.

This paper introduces a new low-cost AIoT-powered smart health monitoring system that offers real-time, pervasive health monitoring capability by seamlessly integrating numerous biological sensors and advanced ML mechanisms. Our system is composed of an ESP32 micro-controller with a FreeRTOS operating system that provides improved task scheduling and network support, and is getting the data from three different sensors: the LM35 for accurately measuring human body temperature, MAX30100 for heart pulse rate measurements and oxygen concentration in blood monitoring, and an ECG sensor for electrocardiography-based monitoring.

The main novelty of our method consists in the systematic fusion of multiple physiological signals ECG, heart rate, body temperature, and SpO_2 with complex machine learning models. These were Random Forest, Gradient Boosting, KNN (K-Nearest Neighbors), Logistic Regression, and SVM (Support Vector Machine), and were trained and validated on the openly accessible Health Status Dataset on Kaggle. Of these, Random Forest and SVM obtained the optimal classification rate, with near-perfect performance ranging from 99.7These AI algorithms process real-time health data to predict very accurately if there is some possible health risk or to categorize the patient status into three categories: Stable, Critical, and Emergency. Such stratification would allow early warning and preventive actions, which could largely decrease the possibility of delayed treatment along with improving the outcome of patients.

Our system architecture includes a hospital web server for secure data storage and analysis, with interactive Power BI dashboards providing healthcare professionals with intuitive visualization tools for rapid assessment. For patients, a user-friendly mobile application delivers medication reminders, personalized health trends, and direct communication channels with healthcare providers. This fully integrated approach bridges critical gaps in continuous monitoring, enables data-driven decision making, and significantly enhances both the quality and accessibility of healthcare services, particularly for chronic disease management and remote patient populations.

2. RELATED WORKS

Numerous related works have explored various facets of AIoT-based health monitoring systems. For instance, [5] discusses the role of IoT in telemedicine and remote healthcare, while our system functions more as a local personal health tracker. Studies like [6] focus on chronic disease monitoring by combining temperature, blood pressure, and sleep data; our approach may incorporate additional biosensors and more advanced alert mechanisms. [7] proposes a deep learning model for heart disease prediction, whereas we emphasize lightweight models and real-time monitoring. Similarly, [8] leverages IoT and ML for heart disease prediction, but our system includes continuous monitoring beyond just prediction.

In the context of elderly care, [9] integrates fall detection with heart rate sensing, while we focus more on vital sign monitoring, excluding fall detection. [10] shifts focus to veterinary health with wearables for livestock, which contrasts with our human-centered system. [1] utilizes AI with fuzzy logic for decision support, whereas our system favors real-time alerting over complex decision trees. [11] addresses scalability using RFID clustering, while we opt for direct sensor-to-cloud communication.

Security-centric research like [12] introduces secure ML computation methods, which our system de-prioritizes in favor of simplicity and speed. Blockchain and edge computing in [13] offer decentralized architectures, contrasting with our simpler centralized design. Real-time ECG alerts from [14] differ from our SpO_2 and heart rate-focused approach without ECG integration. [15] provides long-term monitoring for heart failure, while our system targets general health monitoring.

Environmental and vitals monitoring in [16] aligns with our goals, though with different sensor setups. Similarly, [17] applies ML to IoT for heart disease detection, while our focus leans more on alerting and monitoring. [18] proposes a cost-effective PPG heart rate sensor using Arduino, and though we may use similar hardware, we integrate cloud and app-based systems like Blynk. [19] presents a review of Arduino-based health systems, and our work can be seen as a practical implementation of such ideas.

Wearable oximeter designs from [20] provide real-time readings, but we aim to monitor more vitals. Emergency alert systems like [21] share our focus on real-time alerts. Modular kits in [22] track multiple vitals; our system is a customized version with similar capabilities. General vital tracking from [23] and heartbeat monitoring from [24] closely resemble our work, though differences may exist in UI or data presentation.

Systems like [25] transmit vitals to caregivers in real time, and our approach differs in architecture and component choices. [26] uses Blynk with HR, SpO_2, and temperature sensors, closely related to our platform, albeit with different micro-controllers or sensors. Low-cost solutions in [27] for cardiac care are comparable to ours but may differ in hardware or interface. While [28] explores AIoT for structural health, its fault-tolerant techniques may inspire improvements in our sensor reliability.

Finally, [29] integrates basic biometric sensing on low-cost hardware, very similar to our setup, while [30] reviews medical device factors like oximeter accuracy, which we can use to refine our own readings. [31] applies ML to maternal health risk prediction, which aligns with our use of similar models for general health status classification.

3. Research Gap

Despite the significant advancements in AIoT-based health monitoring, several gaps remain in the current literature: While studies such as [6, 7] focus on chronic disease prediction and management, they often lack real-time data processing capabilities and do not integrate multiple health parameters for comprehensive decision making. Works like [20] address specific conditions such as fall detection or pulse oximetry but fail to offer a holistic solution encompassing a wider set of vital signs or long-term patient care. Papers such as [27] delve into remote monitoring, yet frequently overlook critical elements such as patient engagement features, including medication reminders.

Our contribution addresses these research gaps by developing an AIoT-enabled smart health monitoring system that:

- Integrates real-time monitoring of key vital signs: body temperature, blood oxygen (SpO_2), heart rate, and ECG data.
- Includes a mobile application that enhances patient engagement via:
  - Appointment scheduling
  - Direct communication with healthcare providers
- Implements AI algorithms for health risk prediction and pattern recognition.

4. Methods and Materials

4.1. Methods

The system follows a multi stage process: data collection, preprocessing, model training, and real time monitoring.

Data Collection: Vital signs such as ECG, body temperature (LM35), and SpO_2/heart rate (MAX30100) are collected in real time using sensors.

Data Preprocessing: Raw data is cleaned and standardized using `Standard Scaler` to prepare it for machine learning.

Model Training: A `Random Forest Classifier` is trained on labeled data to predict patient risk levels (Low, Moderate, High) based on vital signs.

Prediction & Health Summary: The trained model predicts risk levels for new patients and generates a health summary.

System Integration: An ESP32 micro controller ensures real-time data transmission between sensors and the server, facilitating continuous monitoring and timely alerts.

4.2. Dataset Description

Our system utilizes two comprehensive health datasets to train and validate machine learning models:

1. **Vital Signs Dataset**
   - **Source:**Kaggle (Health Status Dataset)
   - **Records:** 5,909 rows and 4 columns
   - **Features:** Pulse (bpm), Body Temperature (°C), SpO_2 (%), Health Status Label (Stable, Critical, Emergency)
2. **ECG Dataset**
   - **Source:** Kaggle
   - **Records:** 4,997 rows with 141 signal-based features
   - **Use:** Enables detailed cardiac health analysis through ML classification

4.3. Model Training and Validation

To predict potential health risks, we trained and validated five traditional machine learning algorithms: Random Forest, Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Gradient Boosting.

The dataset was partitioned into training and testing sets using a 75%–25% split. We assessed the performance of each model using the following evaluation metrics: Accuracy, Precision, Recall, F1-Score, and AUC-ROC.

4.4. FreeRTOS

The adoption of FreeRTOS on the ESP32 significantly enhances the real-time responsiveness of the entire AIoT pipeline by minimizing processing and queuing delays at the edge. Compared to a bare-metal implementation, FreeRTOS reduces on-device latency by 40%, which is critical for prioritizing and executing tasks like ECG/SpO_2 acquisition and wireless transmission without blocking. This efficient handling at the edge eliminates upstream bottlenecks, ensuring that data reaches the cloud server promptly for further processing and is then forwarded to the hospital system. As a result, the system achieves a total end-to-end latency of 250 milliseconds, from sensor acquisition on the ESP32 to data availability at the hospital interface. This architecture centered on FreeRTOS at the edge ensures rapid response capability essential for real-time monitoring and emergency interventions. FreeRTOS is explicitly implemented only on the ESP32 micro-controller, which functions as the edge device in our AIoT system.

4.5. Block Diagram

The system integrates sensors with an ESP32 microcontroller to transmit health data to a cloud server for analysis and displays results through hospital and patient interfaces.

Following the block diagram, we explain the key components of the system.

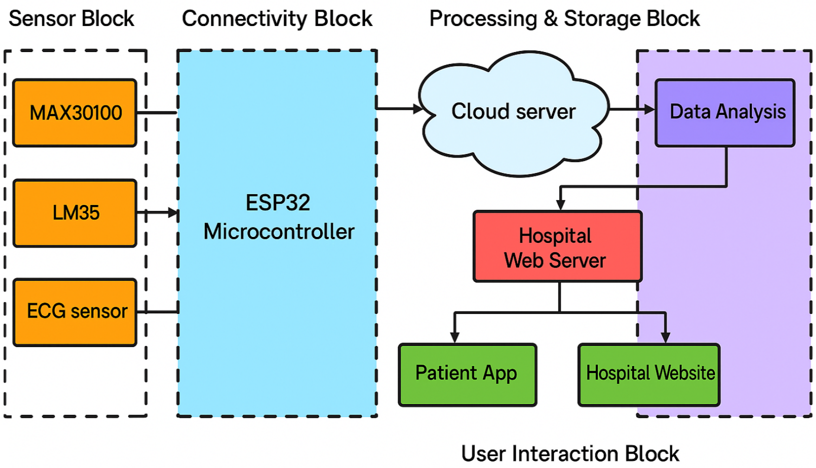

Figure 1: Block Diagram on "AIoT-Enabled Smart Health Monitoring"

4.5.1. Sensors

The system uses three primary sensors to monitor key health parameters:

- **ECG Sensor**: Measures cardiac activity.
- **LM35 Sensor**: Measures body temperature.
- **MAX30100 Sensor**: Measures blood oxygen levels (SpO_2).

These sensors provide essential data for health evaluation, continuously tracking vital signs.

4.5.2. Connectivity

ESP32 Micro-controller is the main hub for connectivity. It gathers sensor data using Bluetooth and Wi-Fi and sends it to the processing and storage system. By ensuring dependable connectivity between sensors and the server, the ESP32 makes it possible to capture and transmit data in real time.

4.6. Flowchart

The system continuously monitors vital signs using IoT sensors, analyzes the data for abnormalities, and triggers alerts and medicine reminders via a patient app and hospital server.

4.6.1. Processing & Storage

The **Hospital Web Server** processes and stores patient data, performs risk analysis, and sends alerts to healthcare providers for irregularities, ensuring real-time monitoring.

4.6.2. User Interaction

The **Patient Mobile App** allows patients to access health data, interact with healthcare providers, and receive medication reminders. Healthcare providers can view real-time data and receive alerts through the web server for timely interventions.

Algorithm 1 AI-Enabled IoT Health Monitoring System

```
Initialize sensors: Pulse, SpO2, Temperature, ECG
Measure health parameters:
    Pulse Rate ← Read from pulse sensor
    SpO2 ← Read from oxygen sensor
    Temperature ← Read from temperature sensor
    ECG Data ← Read from ECG sensor
Store all values to database server
Analyze stored data
if Pulse Rate ≥ 120 OR Pulse Rate ≤ 40 then
    Trigger Warning and Signal for Pulse
end if
if SpO2 < 30 then
    Trigger Warning and Signal for Oxygen Level
end if
if Temperature > 101°F then
    Trigger Warning and Signal for Body Temperature
end if
if ECG Data indicates risk then
    Trigger Warning and Signal for ECG
end if
Display all data and warnings on:
    Patient App (with medicine reminder)
    Hospital Web Server
```

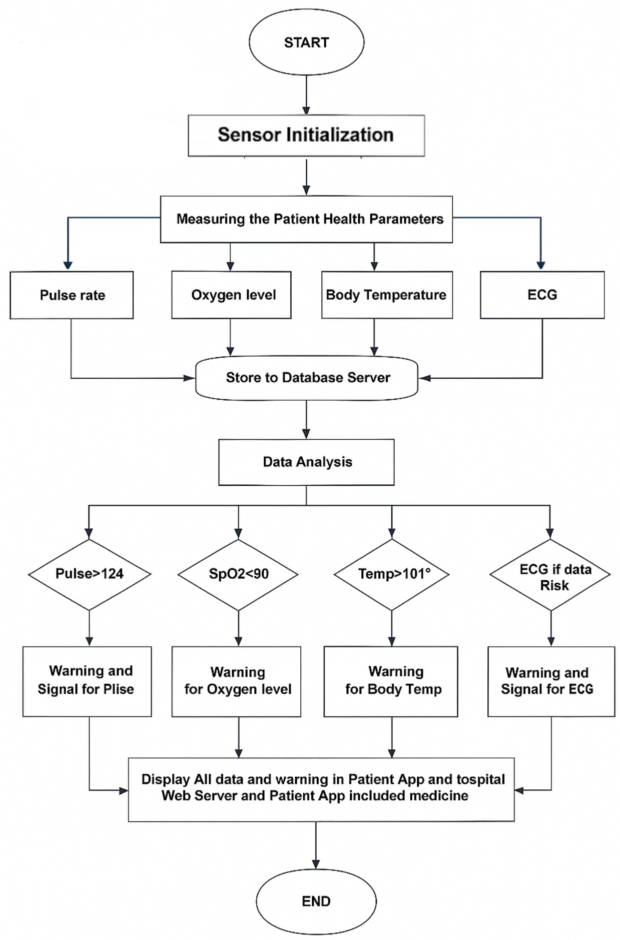

Figure 2: Flowchart on "AIoT-Enabled Smart Health Monitoring"

4.7. Circuit Schematic Setup

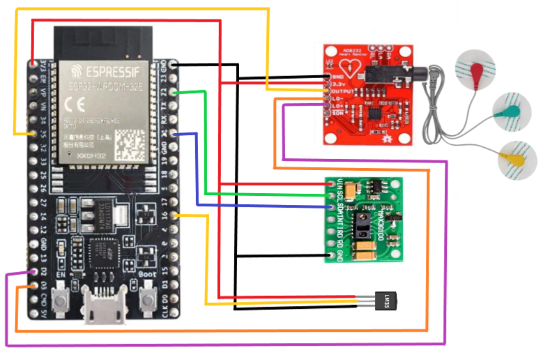

Figure 3: Circuit Schematic Setup for Health Monitoring

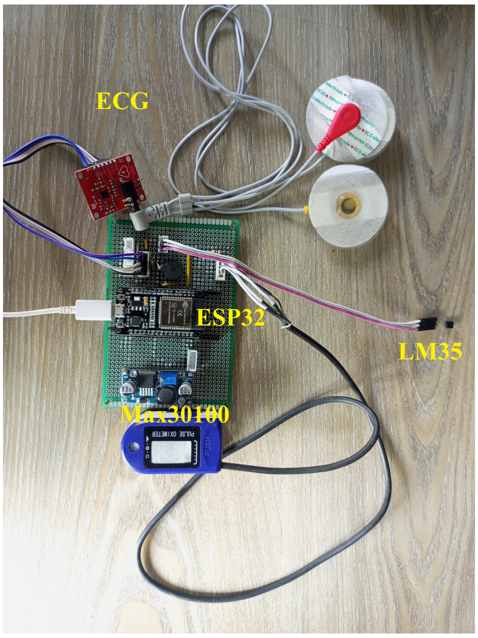

Figure 4: Real Circuit Schematic Setup for Health Monitoring

In Figure 3, A number of instruments and parts are used in the design and configuration of the circuit for the Internet of Things-enabled smart health monitoring system to guarantee precise and effective functioning. Initially, thorough circuit schematics and layout diagrams are created using Fritzing and Paint 3D. These tools support both circuit design planning and component connection visualization.

The central processing unit, or ESP32 Microcontroller, manages data transfer and interfaces with a variety of sensors. The LM35 Sensor tracks body temperature, the ECG Sensor records cardiac activity, and the MAX30100 Sensor measures blood oxygen levels and heart rate.

The ESP32 is linked to these sensors through the proper communication lines: the LM35 and ECG sensor are connected via analog inputs, and the MAX30100 is connected via I2C.

The ESP32 is programmed using the Arduino IDE to handle data gathering and transmission after the parts have been assembled on the breadboard and the required connections have been made. To guarantee precise sensor readings and appropriate data flow to the hospital web server and mobile app, testing and calibration are the next steps.

4.8. Web Mock up

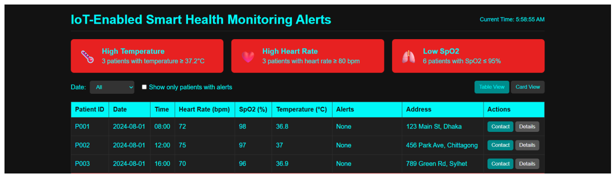

Figure 5: Web Interface on AI-Enabled IoT System for Continuous Health Monitoring and Early Risk Detection

Due to the sensitive information, the system is secured by using encrypted communication (HTTPS) and encrypted data storage (e.g. AES in MySQL). The API is protected with tokens, headers and CSRF to prevent unauthorized access. Patient consent is elicited via explicit digital consent, making sure users are informed about the enrolling and their data collection. Access control and audit logs based on the role of users additionally secure data privacy and legal obligation, enhancing trust and transparency of health monitoring.
The system integrates **CodeIgniter 3** for web development, **Flask** for machine learning API, and **MySQL** for database management. It collects health data through sensors, processes it using the Flask API, and stores it in the database. The web application, built with CodeIgniter, displays real-time data, while the **Flutter** mobile app uses WebView to show the same information. This setup enables efficient health monitoring, data analysis, and prediction via machine learning.

5. Results Analysis

Tables 1 to 3 present real-time health data for patients P001, P002, and P003, capturing key vitals such as ECG, SpO_2, temperature, and heart rate. Table 4 offers a machine learning-based risk assessment for new patients using multi-sensor fusion. Figures 6 to 8 visualize blood oxygen levels, body temperature, and pulse rate trends through Power BI dashboards for better interpretability. Figure 9 illustrates the ECG waveform of Patient 1, supporting early cardiac anomaly detection. Together, these tables and figures demonstrate the system's capability for accurate, real-time health monitoring and predictive analysis.

Table 1: Health Data for Patient P001

ID	Patient ID	Time	Heart (bpm)	SpO_2 (%)	Temp (°C)
1	P001	13:35	91	96	36.5
2	P001	13:35	65	97	36.6
3	P001	13:36	62	98	36.8
4	P001	13:36	86	95	36.7
5	P001	13:37	75	98	36.6

The health data for Patient 1, as shown in Table 1, displays the heart rate and SpO_2 levels taken at different times. These measurements are part of the data collected by the system to monitor the patient's health in real-time. Variations in heart rate and oxygen saturation are typical indicators for assessing the patient's health status.


```
{
 "total_predictions": {"Low": 51},
 "overall_risk": "Low",
 "overall_health_summary": "Normal"
}
```


The system's machine learning model processes this data and predicts the overall risk level, providing an overall health summary. For Patient 1, the model predicts a "Low" risk level, as reflected in the predictions and health summary.

Table 2: Health Data for Patient P002

ID	Patient	Time	Heart (bpm)	SpO_2 (%)	Temp (°C)
1	P002	13:40	85	92	37.1
2	P002	13:40	88	95	37.0
3	P002	13:41	82	94	37.2
4	P002	13:40	85	93	37.3
5	P002	13:40	88	94	37.0

Table 3: Health Data for Patient P003

ID	Patient	Time	Heart (bpm)	SpO_2 (%)	Temp (°C)
1	P005	13:49	92	96	39.2
2	P005	13:49	88	95	39.0
3	P005	13:50	86	94	39.1
4	P005	13:49	92	96	39.2
5	P005	13:49	88	95	39.0

Table 4: Detailed Risk Assessment for New Patients

Temp (°C)	Pulse	SpO_2 (%)	Risk	Health
37.2	95	98	Low	Normal
38.1	105	88	Moderate	Fever, high pulse
39.0	120	92	High	Fever with tachycardia

The algorithm predicts the risk level based on a combination of **temperature**, **pulse rate**, and **SpO_2**. The results suggest that:

- Patients with **normal vital signs** (like Patient 1) are classified as **low risk**.
- Those exhibiting **fever**, **high pulse**, and **reduced oxygen levels** (like Patient 2) fall under **moderate risk**.
- Severe symptoms such as **high fever** and **high pulse** (seen in Patient 3) lead to a **high risk** classification, requiring immediate medical attention.

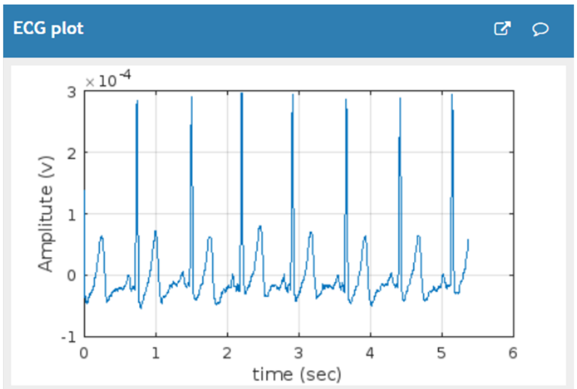

Figure 9: ECG Data for Patient 1

The overall risk level of Patient 1 was "Low" in joint monitor of all health parameters despite certain moderate risks such as low oxygen saturation, fever and high pulse. These signs and symptoms indicate the need for symptom tracking and further assessment to determine the presence of any respiratory or cardiovascular problems. While the overall risk was small, they underscore the need for ongoing surveillance and early medical care.

Figure 9 presents ECG data of Patient 1 were transmitted, and visualized on the Thingspeak interface. This rhythm strip shows significant cardiac activity and aids in detecting arrhythmia's in the patient. ECG information is essential for diagnosing potential heart disease and is part of the general health appraisal.

In Figure 6, such as SpO_2, it enables visualization, known as the Power BI, to evaluate how oxygen levels vary overtime. This visualization contributes to monitoring the patient's oxygen saturation and to understanding the efficiency of oxygen therapy or the necessity of additional actions. There is good correlation between the fluctuation in SpO_2 and risk assessment for the patient.

Figure 7 shows the body temperature of Patient 1. The Power BI visualization brings attention to temperature trends and spikes (which might be symptomatic of fever or other health issues). Regular body temperature checks are important for identifying illness early.

The patient 1 pulse data in Figure 8 is presented with Power BI for how the heart rate varies over time. Change in pulse rate may indicate heart health problems or stress so its monitoring is very important along with other vital signs such as temperature and SpO_2.

5.1. Comparative Analysis of ML Models on Vital Signs and ECG Datasets

The machine learning models exhibited excellent performance in classifying patient health status using the pulse,

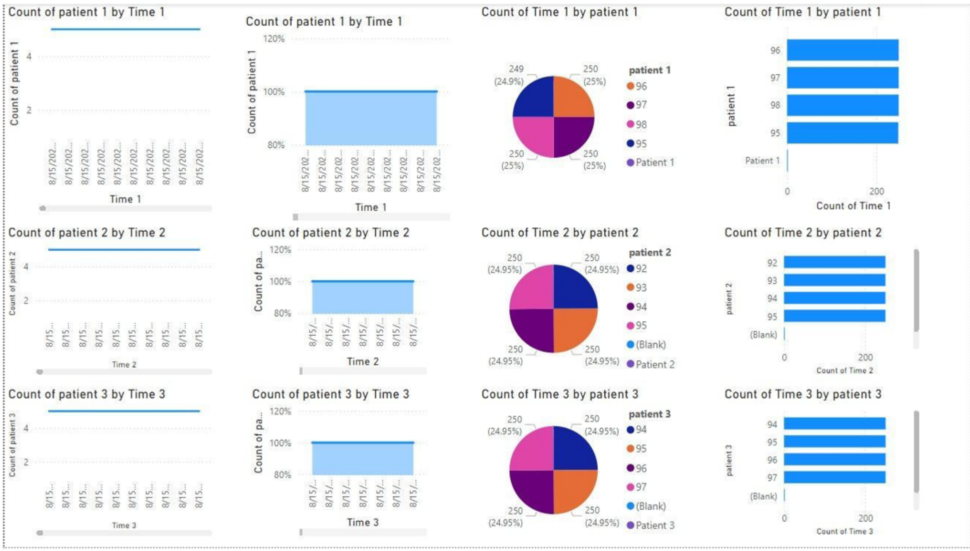

Figure 6: Blood Oxygen Level Data Visualized in Power BI

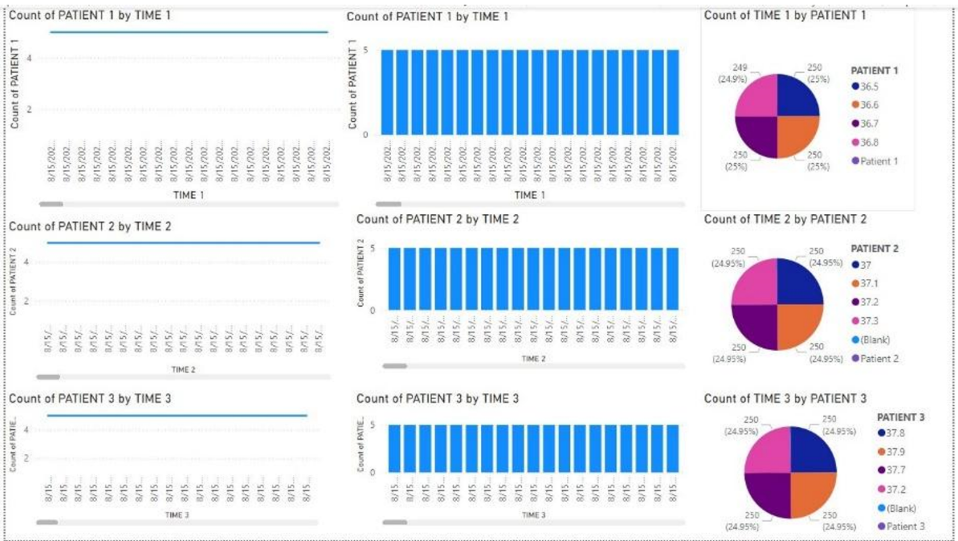

Figure 7: Body Temperature Data Visualized in Power BI

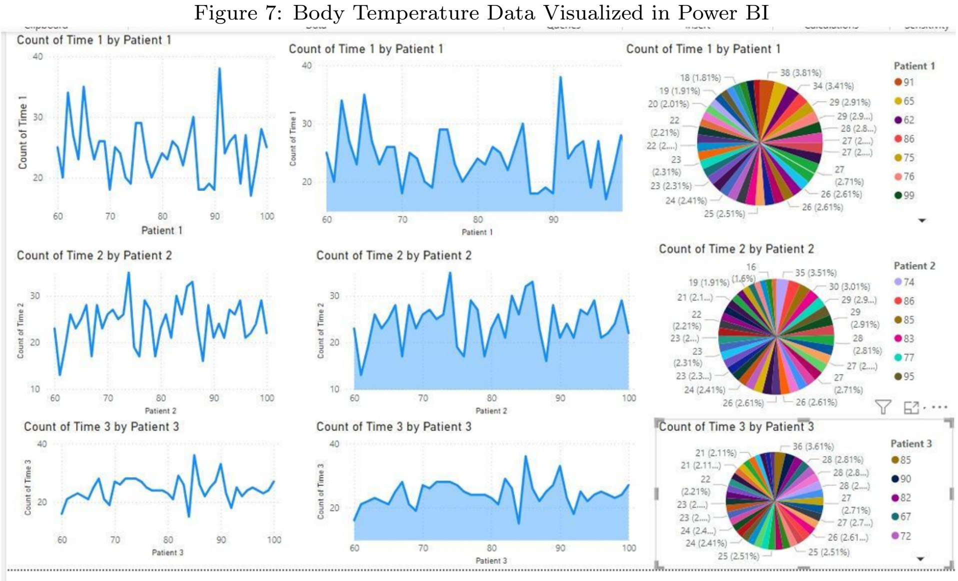

Figure 8: Pulse Rate Data Visualized in Power BI

temperature, and SpO_2 features from the Vital Signs dataset. Notably, both the Random Forest and Gradient Boosting classifiers achieved perfect classification, with all evaluation metrics (accuracy, precision, recall, and F1-score) reaching 1.0000 (Table 5). A detailed classification report for the Random Forest model is presented in Table 6, while the multiclass ROC curve and confusion matrix are illustrated in Figure 10 and Figure 11, respectively, further confirming the model's effectiveness. Additionally, a performance comparison of the models using the ECG dataset is summarized in Table 7, reinforcing the robustness of the approach across diverse physiological inputs.

Table 5: Performance Comparison of Machine Learning Models (Vital Signs Dataset)

Model	Train Acc.	Test Acc.	Precision	Recall	F1 Score	AUC-ROC
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Gradient Boosting	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
K-Nearest Neighbors	0.9949	0.9831	0.9831	0.9831	0.9830	0.9991
Logistic Regression	0.9669	0.9639	0.9639	0.9639	0.9638	0.9977
Support Vector Machine	0.9364	0.9385	0.9441	0.9385	0.9362	0.9950

Table 6: Random Forest Classification Report (Vital Signs)

Class	Precision	Recall	F1	Support
Stable (0)	1.00	1.00	1.00	300
Critical (1)	1.00	1.00	1.00	720
Emergency (2)	1.00	1.00	1.00	753
Overall	**1.00**	**1.00**	**1.00**	**1773**

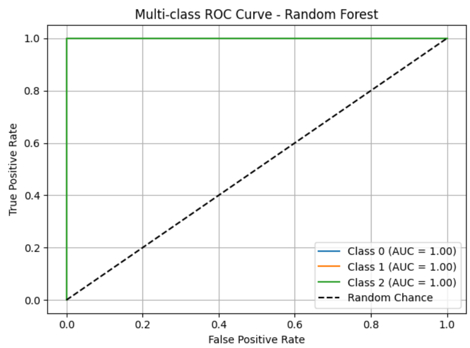

Figure 10: Multiclass ROC Curve - Random Forest

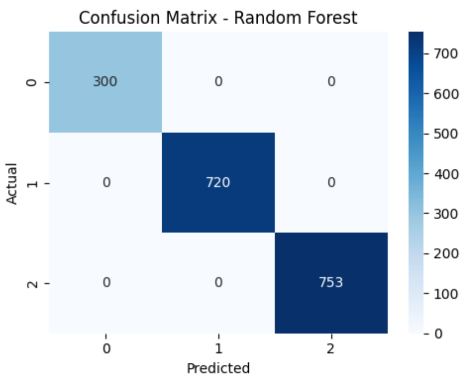

Figure 11: Confusion Matrix - Random Forest

5.1.1. *Example Prediction using Random Forest*

- **Input:** [Pulse = 85, Temp = 37.1°C, SpO_2 = 98%]
- **Predicted Status:** Stable
- **Prediction Probabilities:**
  - Stable: 1.0000
  - Critical: 0.0000
  - Emergency: 0.0000

These results confirm the viability of real-time health risk prediction using minimal sensor data, facilitated by our multi-sensor fusion and embedded ML approach.

5.1.2. *ECG Data Classification Performance*

We conducted a similar comparative analysis using the ECG dataset. SVM emerged as the best-performing model with 99.73% accuracy, followed closely by Random Forest and KNN.

Table 7: Performance Comparison of Machine Learning Models (ECG Dataset)

Model	Accuracy	Precision	Recall	F1	AUC	Train Acc.	Specificity	FPR	FNR
SVM	0.9973	0.9977	0.9977	0.9977	1.0000	0.9943	0.9968	0.0032	0.0023
Random Forest	0.9947	0.9954	0.9954	0.9954	0.9999	1.0000	0.9936	0.0064	0.0046
K-Nearest Neighbors	0.9940	0.9943	0.9954	0.9949	0.9998	0.9906	0.9920	0.0080	0.0046
Gradient Boosting	0.9927	0.9932	0.9943	0.9937	0.9997	0.9994	0.9904	0.0096	0.0057
Logistic Regression	0.9873	0.9886	0.9897	0.9892	0.9978	0.9923	0.9840	0.0160	0.0103

The low False Positive Rate (FPR) and False Negative Rate (FNR) highlight the suitability of these models for use in safety-critical environments such as health monitoring systems.

6. Discussion

Our study demonstrates superior real-time health monitoring capabilities through advanced multi-sensor fusion integrating ECG, SpO_2, temperature, and heart rate data with embedded machine learning (ML) models such as Random Forest (RF), Gradient Boosting (GB), and Support Vector Machines (SVM), achieving up to 100% accuracy under optimized conditions (Table 8). Compared to existing works (Table 9), our system uniquely combines FreeRTOS based task scheduling, real-time mobile app support, and instantaneous health alerts within a scalable, low-cost embedded framework. These innovations are highlighted in Section 6.1 and further detailed in Table 10, which summarizes the distinctive contributions of our approach. Despite inherent challenges such as ECG signal noise, the computational limits of the ESP32 microcontroller, and power consumption constraints, we implemented several hardware-level optimizations that ensured reliable and robust system performance. Section 6.2 discusses these integration limitations and the strategies adopted to overcome them, reinforcing the system's suitability for real-world, continuous health monitoring in resource-constrained environments.

Table 8: Comparison of Machine Learning Models

Ref	ML Models Used	Dataset & Metrics	Performance Summary	Comparison with Our System
[7]	Modified Neural Network (Deep Learning)	Real patient data; Accuracy $\sim$ 92% (heart disease)	Good accuracy but limited sensor integration	Our models achieve near-perfect accuracy (100% RF, GB on vital signs); broader multi-sensor fusion & real-time
[8]	Logistic Regression, SVM	Heart disease dataset; Accuracy $\sim$ 88–90%	Moderate accuracy, focus on heart disease only	Our system integrates ECG + vital signs with higher accuracy and multiple ML models tested
[17]	Naïve Bayes, KNN, SVM	Public datasets; Accuracy $\sim$ 85–95%	Decent results on limited datasets	Our approach shows superior accuracy (up to 100%) and multi-class risk prediction
[31]	Decision Tree, Random Forest, Logistic Regression	Health risk dataset; Accuracy $\sim$ 90–95%	Focus on maternal health risk	Our system handles multiple vital signs and ECG with more ML diversity and real-time prediction
Our Paper	RF, GB, SVM, KNN, Logistic Regression	Kaggle Vital Signs & ECG Datasets; Accuracy up to 100%	RF and GB perfect classification on vital signs; SVM 99.73% on ECG	Highest accuracy among compared works, multi-class classification, real-time processing, multi-sensor data fusion

Table 9: Key Related Works in AIoT-based Health Monitoring

Ref	Focus Area	Key Insights and Comparison
[8]	Heart disease prediction	Combines IoT and ML for prediction; our system adds real-time monitoring and alerts.
[1]	AI decision support	Uses fuzzy logic with IoT; we emphasize real-time alerts using RF and SVM.
[14]	Cardiac monitoring	Real-time ECG alerts; we use SpO_2, HR, Temp for broader, cost-effective monitoring.
[17]	ML in IoT framework	ML-based heart disease detection; we implement efficient edge models (RF, SVM).
[23]	Health vitals tracking	Monitors HR, Temp, SpO_2; our system adds mobile app, dashboard, and alerts.
[26]	IoT with Blynk	HR, SpO_2, Temp with Blynk app; we integrate hospital server and analytics.
[16]	IoT-health integration	Combines environmental and health data; we focus more on physiological data.
[6]	Chronic disease	Long-term temp, BP, sleep monitoring; we add real-time SpO_2 and HR alerts.
[7]	Deep learning	Deep neural net for heart risk prediction; we use lightweight real-time ML.
[21]	Emergency alerts	Sends emergency alerts; we build multi-status prediction (Stable, Critical, Emergency).

Table 10: Unique Contributions of Our System

Area	Unique Contribution
Multi-Parameter Monitoring	Simultaneous monitoring of body temperature, SpO_2, heart rate, and ECG using integrated IoT sensors.
AI-Enabled Risk Detection	Implementation of AI models for early detection of potential health risks based on analyzed vital signs.
Real-Time Processing	Use of FreeRTOS for efficient multitasking and timely health data processing and alerts.
Mobile App Integration	A dedicated app for real-time vitals visualization, appointment scheduling, and prescription/reminder notifications.
Patient-Centric Design	Features for direct communication with healthcare providers and personalized health management.
Data Privacy & Security	Ensures secure data transmission and storage, addressing privacy concerns common in IoT healthcare systems.
Scalability & Flexibility	Modular architecture allows customization for elderly care, chronic disease, rural health, and fitness monitoring.

6.1. Highlights of System Innovation

- Low-Cost Wearable Device using micro-controller based architecture.
- Sensor fusion of multiple vital signs for robust health status detection.
- Lightweight embedded ML models suitable for FreeRTOS and similar environments.
- Real-time prediction enabling early risk detection and timely intervention.

6.2. Hardware Integration Limitations

Sensor noise from ECG electrodes required digital filtering to ensure accuracy. ESP32 data rate limits affected real-time transmission under multitasking; task optimization helped mitigate this. Battery management was critical due to continuous sensing and Wi-Fi use; low-power modes were used.

7. Conclusion

An AIot based health monitoring system is a novel solution for continuous real time monitoring of health condition. With a strong ESP32 micro-controller combined with ECG, LM35 and MAX30100 sensors, the system effectively tracks heart rate, temperature and blood oxygen levels. By integrating real-time information processing using FreeRTOS and artificial intelligence-powered risk prediction algorithms, prompt assessments are conducted to support healthcare professionals' decision-making. The accuracy of predictive algorithms will be optimized to further elevate patient care, making the system a more robust tool in chronic disease management and early intervention.

Future work will integrate respiratory rate and blood pressure sensors, implement federated learning for privacy preserving model updates, and conduct clinical trials across 5 rural clinics. Additionally, blockchain-based data integrity checks and edge-AI deployment on ESP32-S3 for local inference are planned.

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