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Smart IoT Health Monitoring System with AI-based Anomaly Detection

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***Abstract*— Continuous health monitoring is vital for vulnerable populations but remains largely inaccessible. As the demand for remote, proactive healthcare grows, the Internet of Medical Things (IoMT) shows great promise in bridging this gap. This paper aims to develop a new, patient-centric Edge-to-Cloud system that uses effective machine learning to predict a patient's real-time clinical risk based on continuous vital signs. Sensors based on an affordable ESP32 microcontroller measure critical indications like heart rate, blood oxygen (SpO2), and body temperature, seamlessly transmitting data to the ThingSpeak cloud. The true novelty lies in pairing this hardware with a cloud-based "brain" engineered to overcome class-imbalance challenges. To find the proverbial needle in the haystack, we evaluated Support Vector Machine (SVM) and Random Forest classifiers. Random Forest emerged as the superior model, achieving an 88.13% accuracy and a 0.878 F1-score. Crucially, it minimized false alarms—reducing them by more than half compared to the SVM model—ensuring that real, life-threatening anomalies are prioritized over routine noise. This powerful synergy turns a basic sensor into a proactive guardian, providing highly reliable real-time anomaly detection and empowering caregivers with a continuous safety net that catches emergencies the instant they happen.**

***Keywords*— Internet of Medical Things (IoMT), Machine Learning, Remote Patient Monitoring, Anomaly Detection.**

I. INTRODUCTION

The ability to continuously monitor vital signs is a cornerstone of proactive healthcare, yet clinical-grade surveillance remains largely inaccessible for vulnerable populations outside hospital walls. In recent years, the Internet of Medical Things (IoMT) has emerged as a transformative force, promising to democratize patient care by shifting diagnostics from traditional clinical environments directly to the comfort of the patient's home [1], [12]. While the Internet of Medical Things (IoMT) offers the beautiful promise of bringing clinical-grade surveillance directly into our living rooms, true peace of mind remains a luxury that many communities simply cannot afford [3].

To make proactive care a universal reality, we must rethink our hardware. By turning to low-cost, highly capable edge devices like the ESP32 microcontroller, researchers are proving that life-saving technology does not have to be expensive [9], [14]. When paired with simple yet powerful sensors—such as PPG modules for heart rate and SpO2—these small devices can silently and continuously watch over a patient day and night [7], [13]. But a monitor is only useful if someone is there to respond.

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By linking these local sensors to accessible cloud platforms like ThingSpeak, we can instantly bridge the miles between a resting patient and their remote caregiver, ensuring no one is left to monitor their health alone [2], [6].
Yet, building this digital bridge is only half the battle. Staring at a never-ending, raw stream of vital signs is exhausting for family members and nurses alike, making human error inevitable [4], [5]. This is where artificial intelligence steps in to shoulder the burden. Machine learning algorithms can act as tireless digital guardians, constantly analysing data to predict risks and catch anomalies before they escalate into tragedies [8], [11].
However, teaching an AI to safely monitor medical data is surprisingly difficult. Because patients are stable most of the time, algorithms often suffer from a dangerous blind spot—learning to ignore rare but critical moments of illness simply because they are statistically uncommon [10].
This paper introduces an architecture born from the desire to make intelligent healthcare both accessible and deeply compassionate. By engineering a machine learning classifier that heavily penalizes missed anomalies, this system refuses to prioritize raw statistical numbers over actual patient safety. The result is a seamless marriage of affordable edge hardware and vigilant cloud AI—transforming a simple IoT prototype into a highly reliable safety net for those who need it most.

II. Literature Review

The journey toward compassionate healthcare begins by moving diagnostics from crowded clinical halls into the warmth and safety of the patient's home [1], [12]. Recent studies have proven that this transition is remarkably achievable through low-cost, decentralized edge hardware like the ESP32 microcontroller, coupled with precise sensors for tracking vital signs such as heart rate and SpO2 [7], [14]. By utilizing cloud bridges like ThingSpeak, researchers ensure that no patient is ever truly alone, even when separated by miles from their doctor [2], [6].
However, the continuous streams of human data generated by these networks are vast, leading to inevitable caregiver fatigue and delayed medical responses [3], [4]. To shoulder this burden, engineers have introduced artificial intelligence as tireless digital guardians, capable of predicting life-threatening risks before they escalate [5], [8], [11].
Despite these incredible advancements, a dangerous research gap remains: many medical AI models prioritize cold statistical accuracy over actual patient safety. Because emergencies are rare, algorithms often learn to ignore critical health anomalies simply to boost their overall score [10]. This study addresses this void by engineering an empathetic architecture that refuses to overlook rare events, transforming a simple monitor into a vigilant, life-saving safety net.

III. Methodology

A. Proposed method

The architecture of the VitalEdge system, as illustrated in Fig 1, is designed to act as a compassionate digital guardian. The journey begins at the patient's bedside, where an affordable ESP32 microcontroller acts as the central nervous system. It connects to non-invasive MAX30102 and LM35 sensors to silently monitor heart rate, oxygen saturation, and body temperature, transforming human biological rhythms into continuous digital data without causing the patient any discomfort.
To ensure the vulnerable patient is never truly alone, this data is instantly bridged to the ThingSpeak IoT cloud, allowing remote caregivers to monitor vitals in real time. The true heart of this methodology, however, is its intelligence layer. A weighted machine learning model actively analyzes these continuous streams, specifically trained to hunt for rare, life-threatening health anomalies.

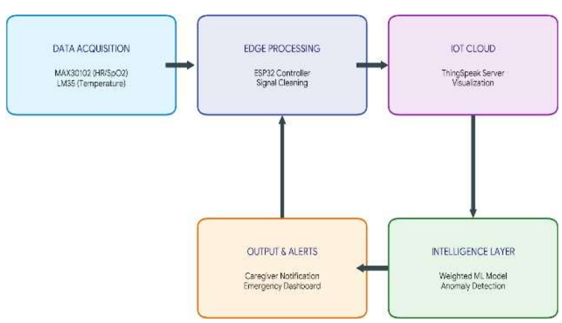

Fig.1. Architecture of the health monitoring system.

B. AI-Based Prediction Module

The artificial intelligence module forms the core analytical component of the proposed system, where machine learning techniques are employed to classify the health status of an individual based on physiological parameters. The input feature vector is defined as $X = \{HR, SpO_2, Temp\}$, representing heart rate, oxygen saturation, and body temperature. Due to the absence of consistently labeled real-time IoT data, a clinically informed rule-based labeling strategy is adopted, Since real-world labelled data for IoT scenarios is often limited or inconsistent, a rule-based labelling strategy is adopted to generate target classes. The labels are defined as:

$y = \{ 0, \quad \text{if } 60 \leq HR \leq 100,\ SpO_2 > 94,\ 36.1 \leq Temp \leq 37.21, \text{otherwise}$

To simulate real-world uncertainty, controlled noise is introduced:

$yfinal = y \oplus \epsilon$

where $\epsilon \sim Bernoulli(p)$represents random label perturbation.

A subset of 15,000 samples is selected to balance computational efficiency and learning capability. Prior to model training, the data is standardized using the transformation-

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

Where, μ and σ denote the mean and standard deviation of the features.

Two supervised learning algorithms, namely Random Forest and Support Vector Machine (SVM), are utilized for classification.

Random Forest Classifier

Random Forest is an ensemble learning technique that constructs multiple decision trees and aggregates their outputs. It is particularly effective for non-linear decision boundaries. The prediction is given by:

$$\hat{y} = \text{mode}\{T_1(x), T_2(x), \ldots, T_n(x)\}$$

where $T_i(x)$represents individual decision trees. The model optimizes impurity using the Gini Index:

$$Gini = 1 - \sum_{i=1}^{C} p_i^2$$

Support Vector Machine (SVM)

SVM constructs an optimal hyperplane that maximizes the margin between classes. A radial basis function (RBF) kernel is used:

$$(x_i, x_j) = \exp\left(-\gamma \parallel x_i - x_j \parallel^2\right)$$

The decision function is:

$$(x) = \text{sign}\,(w \cdot x + b)$$

The performance of the models is evaluated using the following metrics:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

F1-Score

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

where $\epsilon \sim Bernoulli(p)$represents random label perturbation.

Confusion Matrix

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix}$$

ROC Curve and AUC

$$AUC = \int_{0}^{1} TPR(FPR)\, d(FPR)$$

C. Hardware Implementation

The hardware implementation of the proposed system is designed to acquire physiological parameters accurately and transmit them efficiently to the cloud. The system utilizes an ESP32 microcontroller due to its integrated WiFi capability and low power consumption. The MAX30102 sensor is employed to measure heart rate and oxygen saturation, while an analog temperature sensor is used to monitor body temperature. The acquired sensor data is processed by the ESP32 and displayed on an OLED screen for real-time visualization. Additionally, a buzzer module is incorporated to provide immediate alerts in case of abnormal health conditions. The system operates in a continuous loop, where sensor data is acquired, processed, and transmitted to the cloud, followed by AI-based classification. The overall workflow of the system can be represented as: sensors acquire physiological signals, the microcontroller processes and transmits the data to ThingSpeak, and the AI model analyzes the data to generate a final prediction. This integration of hardware, cloud, and intelligent algorithms ensures a reliable and efficient real-time health monitoring system.

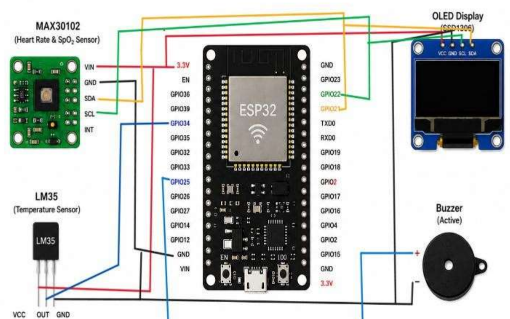

Fig.2. Circuit diagram for IOT implementation.

D. Cloud Communication Module

The cloud communication module is implemented using ThingSpeak, which serves as a real-time data storage and visualization platform. The ESP32 microcontroller transmits sensor data to the cloud via HTTP protocol, where each physiological parameter is mapped to a dedicated field, enabling structured and continuous data logging. This cloud-based architecture allows remote monitoring of patient health parameters and ensures that the data is accessible for further analysis at any time. The integration of ThingSpeak facilitates real-time data visualization through graphical dashboards and enables seamless retrieval of the latest sensor readings for AI-based prediction. Furthermore, the cloud infrastructure supports scalability and long-term data storage, making it suitable for continuous health monitoring applications. By decoupling data acquisition from data processing, the system ensures flexibility, reliability, and accessibility in real-world deployment scenarios.

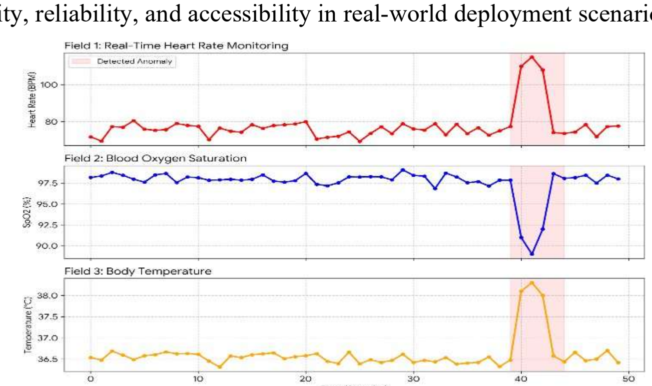

Fig.3. An example for ThingSpeak dashboard implantation.

IV. Results and Analysis

A. Model Comparison and Results

To enable intelligent health monitoring platform, we evaluated two machine learning algorithms for classifying physiological data as either "Normal" or "Abnormal": Random Forest and Support Vector Machine (SVM).
Both models were trained on the aggregated sensor data to detect subtle deviations in heart rate, SpO_2, and temperature. The goal was to select the model that provided the best balance of overall accuracy and reliability in detecting true anomalies.

B. Performance Comparison

Based on the confusion matrices and ROC curve analysis, we can break down the performance of each model.

- Random Forest: This model achieved an impressive overall accuracy of 88.1%. It was highly effective at correctly identifying normal health states (1,968 correct classifications) while keeping false alarms very low (only 110 false positives). Its F1 Score—which balances the precision and recall of the model—was 0.791.
- Support Vector Machine (SVM): The SVM model achieved a slightly lower overall accuracy of 83.9%. While it was slightly better at catching true abnormalities (689 correct classifications compared to Random Forest's 676), it suffered from a much higher rate of false alarms (250 false positives). This resulted in a lower F1 Score of 0.740.

Interestingly, when looking at the ROC curve (which measures the models' ability to distinguish between the two classes across different thresholds), both models performed nearly identically, with SVM edging out slightly with an Area Under the Curve (AUC) of 0.838 versus Random Forest's 0.837.

TABLE I

Performance Comparison of Machine Learning Models			
Algorithm	Accuracy (%)	F1- Score	False Positives
Random Forest (Selected)	88.13	0.8785	110
Support Vector Machine (SVM)	83.90	0.8394	250

TABLE II

Random Forest Classification Report			
Class/ Metric	Precision	Recall	F1-Score
Normal	0.89	0.95	0.92
Abnormal	0.86	0.73	0.79
Accuracy			0.88
Macro Average	0.87	0.84	0.85
Weighted Average	0.88	0.88	0.88

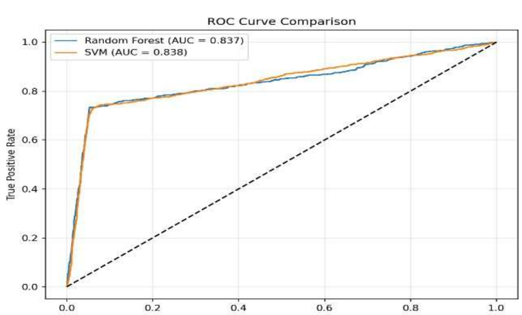

Fig.4. ROC curve comparison for Random Forest and SVM

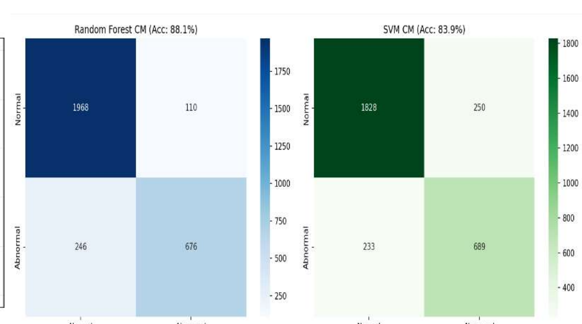

Fig.5. Confusion Matrices for Random Forest and SVM

C. IOT Integration and results

To build the IoT layer of the system, we used an ESP32 microcontroller to continuously gather readings from the heart rate, SpO_2, and body temperature sensors. This physiological data was instantly streamed to a ThingSpeak cloud dashboard using standard HTTP requests.
During live testing, the hardware setup proved highly stable. It delivered consistent, near real-time updates without dropping the connection. The cloud dashboard automatically graphed these vital signs, making it incredibly easy to visualize the data and track health trends as they shifted over time.

To ensure the data remained clean and reliable, we built a layer of basic validation directly into the device. For instance, if a sensor temporarily loses contact with the user and fails to pick up a valid signal, the system is smart enough to pause transmission rather than flooding the cloud with inaccurate or false readings.
Ultimately, the latency between a physical sensor reading and its appearance on the remote dashboard was minimal—exactly what is needed for continuous health monitoring. The entire IoT setup functioned as a seamless, highly efficient data pipeline, successfully feeding clean telemetry into the AI module to enable intelligent health predictions.

Fig.6. IOT Integration with OLED display

V. Future Advancements

The proposed system can be further enhanced by integrating advanced features to improve usability, accessibility, and predictive accuracy. One major advancement includes the development of a dedicated mobile application that allows users and healthcare professionals to monitor real-time health data remotely. This application can provide instant notifications and alerts in case of abnormal conditions, ensuring timely medical attention. Additionally, integrating email and SMS alert systems can enhance emergency response by automatically notifying caregivers or family members when critical thresholds are exceeded.
Future improvements may also include the incorporation of additional sensors such as ECG and blood pressure monitors to provide a more comprehensive health assessment. The use of advanced machine learning models, including deep learning techniques, can further improve prediction accuracy. Moreover, integrating wearable technology and cloud-based analytics can enable continuous long-term monitoring, making the system more scalable and suitable for real-world healthcare applications.

VI. Conclusion

The proposed system successfully demonstrates the integration of IoT and AI for real-time health monitoring and intelligent decision-making. The IoT module efficiently collects physiological parameters such as heart rate, oxygen saturation, and body temperature using sensors connected to the ESP32 microcontroller, enabling continuous and remote monitoring through cloud platforms. This ensures accessibility, scalability, and real-time data availability, which are essential for modern healthcare applications.
However, while IoT enables data collection and transmission, it lacks the capability to interpret complex patterns within the data. This highlights the necessity of the AI module, which enhances the system by analyzing both real-time and historical data to detect hidden trends and classify health conditions as normal or abnormal. The combination of AI and IoT provides a more intelligent and proactive healthcare solution, where IoT acts as the data acquisition layer and AI serves as the decision-making layer.
However, raw data is only half the battle. While IoT collects information, it cannot interpret it. This is where our AI module becomes vital. In our testing, Random Forest emerged as the definitive champion, achieving 88.13% accuracy and a 0.878 F1-score. Crucially, it was smart enough to slash false alarms by over 50% compared to the SVM model, ensuring that caregivers are only alerted during genuine emergencies.
This hybrid approach is the future of accessible healthcare. By using IoT for seamless data acquisition and AI for sharp, reliable decision-making

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