

CareMatrix: An Integrated Smart Healthcare System

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Abstract

The increasing demand for real-time, patient-centric healthcare has accelerated the integration of Internet of Things (IoT) technologies with intelligent analytics. Traditional health-care models rely on episodic patient visits and are inadequate for continuous monitoring and early detection of critical conditions. This paper presents CareMatrix, an integrated smart healthcare system combining IoT-based Remote Patient Monitoring (RPM) with machine learning for real-time anomaly detection. The system utilizes an ESP32 microcontroller integrated with a MAX30102 sensor to acquire physiological parameters such as heart rate and oxygen saturation (SpO₂). The data are preprocessed at the edge and transmitted via WiFi to the ThingSpeak cloud using REST APIs for real-time storage and visualization. A Random Forest classifier trained on 10,000 patient records achieves an accuracy of 92.4%, precision of 91.2%, recall of 90.8%, and F1-score of 91.0%. The system generates alerts within 2–3 seconds upon detecting abnormal conditions, enabling timely intervention. The proposed framework provides a scalable and efficient solution for continuous healthcare monitoring and supports proactive, data-driven decision-making.

Keywords: Smart Healthcare, Remote Patient Monitoring, Internet of Things (IoT), ESP32, ThingSpeak, Machine Learning, Random Forest, Real-Time Monitoring, Wearable Devices.

I. INTRODUCTION

Healthcare systems worldwide are under increasing pressure due to demographic transitions, aging populations, and the rising prevalence of chronic diseases. Conditions such as congestive heart failure, chronic obstructive pulmonary disease (COPD), diabetes, and severe hypertension require continuous monitoring and timely clinical interventions [4], [7]. Traditional healthcare models are predominantly reactive, relying on episodic patient visits and delayed diagnosis, which often leads to preventable hospital readmissions, increased healthcare costs, and reduced quality of patient care. These limitations highlight the urgent need for a paradigm shift toward proactive, personalized, and patient-centric healthcare systems that emphasize early detection, continuous monitoring, and real-time decision-making.

Remote Patient Monitoring (RPM) has emerged as a key enabler for this transformation by leveraging wearable devices and Internet of Things (IoT)-enabled

sensors. RPM systems facilitate continuous acquisition of physiological parameters such as heart rate, oxygen saturation (SpO₂), respiratory rate, and physical activity levels [7], [10]. The availability

of real-time physiological data enables clinicians to monitor patients remotely, identify trends, and make informed clinical decisions. Furthermore, continuous data streams support the development of predictive models that enable early identification of abnormal health conditions, thereby reducing the risk of critical medical events.

Recent advancements in embedded systems and wireless communication technologies have enabled the development of cost-effective and scalable IoT-based healthcare solutions. Microcontroller platforms such as ESP32, integrated with biomedical sensors like MAX30102, provide an efficient means for real-time physiological data acquisition and edge-level processing. These systems can transmit data to cloud

platforms such as ThingSpeak using WiFi-based communication and RESTful APIs, enabling real-time storage, visualization, and remote accessibility. Such IoT-enabled architectures bridge the gap between data acquisition and intelligent healthcare analytics, facilitating seamless integration between hardware, cloud infrastructure, and end-user applications.

Despite these advancements, several challenges remain in the practical deployment of IoT-based healthcare systems. One major issue is data fragmentation, where sensor-generated data are stored in heterogeneous formats and are often not integrated with Electronic Health Records (EHR), resulting in incomplete patient context [1], [3]. Additionally, raw sensor data are often noisy and inconsistent due to motion artifacts, environmental interference, and device limitations, which significantly affect the reliability of downstream analysis. Furthermore, the lack of efficient real-time processing frameworks and scalable predictive analytics limits the adoption of such systems in clinical environments.

Machine learning (ML) techniques have been extensively explored to address these challenges by enabling automated analysis of physiological data and early detection of anomalies. Traditional models such as Logistic Regression and Support Vector Machines provide interpretable results but often struggle with complex, non-linear relationships inherent in physiological signals. In contrast, ensemble learning methods such as Random Forest have demonstrated superior performance due to their robustness, ability to handle noisy and heterogeneous data, and resistance to overfitting. Random Forest models are particularly well-suited for healthcare applications as they provide high classification accuracy while maintaining

computational efficiency for real-time deployment.

In addition to predictive accuracy, modern healthcare systems must also ensure secure data transmission, interoperability, and scalability. Standards such as Fast Healthcare Interoperability Resources (FHIR) enable structured representation and exchange of healthcare data, facilitating seamless integration with hospital information systems and improving data accessibility [2], [3]. Moreover, ensuring data privacy and security through encryption mechanisms, secure APIs, and authentication protocols is critical when handling sensitive patient information in IoT-based healthcare environments.

To address these challenges, this paper presents CareMatrix, an integrated smart healthcare system that combines IoT-based Remote Patient Monitoring with machine learning for real-time anomaly detection. The proposed system adopts a three-layer architecture

consisting of: (i) a physical layer for real-time data acquisition using ESP32 and biomedical sensors,

(ii) a middleware layer for data processing, cloud storage, and communication using ThingSpeak, and (iii) an application layer for machine learning-based prediction, visualization, and alert generation. This layered architecture ensures modularity, scalability, and efficient data flow across system components.

The key contributions of this work are summarized as follows:

- Design and implementation of an IoT-based real-time patient monitoring system using ESP32 and MAX30102 for continuous acquisition of physiological data.
- Integration of a Random Forest-based machine learning model for anomaly detection using a dataset of 10,000 patient records.
- Development of a real-time alert system capable of detecting abnormal health conditions with low latency (2–3 seconds).
- Implementation of a scalable, secure, and modular architecture that supports cloud integration (ThingSpeak) and interoperability with healthcare systems.

The remainder of this paper is organized as follows. Section II presents a comprehensive literature review of existing smart healthcare systems and machine learning approaches. Section III describes the proposed methodology and system architecture. Section IV discusses experimental results and performance evaluation. Finally, Section V concludes the paper and outlines future research directions.

II. LITERATURE SURVEY

The evolution of smart healthcare systems is primarily driven by the convergence of Remote Patient Monitoring (RPM), healthcare data interoperability, and machine learning-based Clinical Decision Support Systems (CDSS). These domains collectively enable continuous monitoring, intelligent data analysis, and proactive intervention, forming the foundation of next-generation digital healthcare ecosystems. The integration of Internet of Things (IoT) technologies with advanced analytics has significantly enhanced the ability to deliver personalized and real-time healthcare services.

Remote Patient Monitoring (RPM) has emerged as a critical technology for enabling continuous healthcare beyond traditional clinical settings. RPM systems utilize wearable and IoT-based sensors to collect physiological parameters such as heart rate, oxygen saturation (SpO₂), respiratory rate, blood pressure, and physical activity levels in real time [7], [10], [19]. These

systems facilitate longitudinal patient monitoring, allowing clinicians to observe trends, detect anomalies at early stages, and reduce hospital readmissions. However, conventional clinical-grade monitoring devices often suffer from limitations related to high cost, bulky design, and limited usability, which restrict their widespread adoption. To address these challenges, recent research has focused on lightweight, low-cost, and consumer-grade wearable devices integrated with edge computing capabilities [8], [12], [19]. Edge processing enables local data filtering, noise reduction, and preliminary anomaly detection, thereby reducing communication overhead and improving system responsiveness [6], [7].

Reliable and secure communication plays a vital role in

RPM systems. Bluetooth Low Energy (BLE) is commonly used for short-range communication between wearable devices and gateway nodes, while protocols such as MQTT over secure channels enable efficient and scalable cloud communication [7], [10]. Despite these advancements, several challenges persist, including motion artifacts, sensor placement variability, environmental noise, and patient non-compliance, all of which significantly affect data quality. These issues necessitate robust preprocessing techniques and intelligent anomaly detection mechanisms to ensure reliable healthcare monitoring [5], [19]. Furthermore, emerging IoT platforms based on WiFi-enabled microcontrollers such as ESP32 provide an efficient alternative for direct cloud connectivity, reducing dependency on intermediate gateways and simplifying system architecture.

Data interoperability remains a major challenge in modern healthcare systems due to the heterogeneous nature of data generated by IoT devices. Sensor-generated data are often stored in diverse formats, making integration with Electronic Health Records (EHRs) difficult and resulting in fragmented patient information [1], [3]. Traditional standards such as HL7 v2 offer limited flexibility and are not well-suited for dynamic and real-time healthcare environments. In contrast, Fast Healthcare Interoperability Resources (FHIR) has emerged as a modern standard that enables structured, modular, and web-based representation of healthcare data [2], [3]. FHIR facilitates seamless integration of heterogeneous data sources and supports real-time data exchange across healthcare systems, thereby improving accessibility and usability of patient information.

Semantic interoperability is further enhanced by mapping sensor data to standardized clinical terminologies such as SNOMED CT and LOINC, ensuring consistent interpretation of medical

information across systems [3], [9]. Additionally, middleware architectures based on microservices and distributed computing frameworks improve system scalability, flexibility, and fault tolerance. These architectures enable efficient handling of both real-time streaming data and historical patient records, which is essential for comprehensive healthcare analytics [6], [10]. Data security and privacy are equally critical concerns, as sensitive patient information must be protected against unauthorized access. Techniques such as encryption, secure APIs, and authentication protocols are widely employed to ensure compliance with regulatory frameworks such as HIPAA and GDPR [2], [19].

Machine learning techniques have significantly enhanced the capabilities of smart healthcare systems by enabling predictive analysis of physiological data. Traditional models such as Logistic Regression and Support Vector Machines have been widely used for disease prediction and classification tasks [17]. While these models provide interpretable results, they often struggle with complex, non-linear relationships present in physiological data, limiting their effectiveness in real-world applications. Ensemble learning methods, particularly Random Forest, have demonstrated superior performance due to their robustness, ability to handle noisy and heterogeneous data, and resistance to overfitting [16]. Random Forest models are particularly well-suited for healthcare applications, as they can capture feature interactions and provide reliable classification outcomes with relatively low computational cost.

Deep learning approaches such as Long Short-Term Memory (LSTM) networks have also been explored for modeling temporal dependencies in physiological time-series data [18]. These models are capable of capturing sequential patterns and long-term dependencies, resulting in high predictive accuracy. However, they require large datasets, significant computational resources, and extensive hyperparameter tuning, which limits their applicability in resource-constrained real-time healthcare systems. In contrast, Random Forest offers a balanced trade-off between predictive performance, interpretability, and computational efficiency, making it a practical choice for real-time anomaly detection in IoT-based healthcare applications.

Recent studies have proposed integrated smart healthcare frameworks that combine IoT, cloud computing, and machine learning to enable real-time monitoring and predictive analytics. IoT-based healthcare systems have demonstrated the ability to continuously monitor patient conditions and generate automated alerts for abnormal events [9], [14].

Similarly, cloud-integrated healthcare platforms provide scalable storage solutions and enable advanced analytics on large volumes of healthcare data [10]. However, many existing systems focus on individual components such as data acquisition, communication, or analytics in isolation, resulting in fragmented architectures that lack seamless integration and real-time decision-making capabilities.

Furthermore, several studies lack comprehensive end-to-end validation using realistic datasets and real-time deployment scenarios, which limits their applicability in practical clinical environments [19], [20]. The absence of unified frameworks that simultaneously address data acquisition, preprocessing, interoperability, predictive analytics, and real-time alert generation highlights a significant research gap in the current literature.

To address these limitations, the proposed CareMatrix system integrates IoT-based RPM, standardized data handling mechanisms, and a Random Forest-based predictive model into a unified architecture. By combining real-time monitoring, efficient data processing, and intelligent analytics, the system enables early detection of abnormal health conditions and supports proactive healthcare delivery. This integrated and scalable approach contributes toward the development of efficient, reliable, and patient-centric smart healthcare systems.

III. CONTRIBUTIONS

The primary contributions of this work are summarized as follows:

- **Design and Implementation of an IoT-based Remote Patient Monitoring (RPM) System:** A comprehensive real-time healthcare monitoring framework is designed and implemented using an ESP32 microcontroller integrated with MAX30102 sensors for continuous acquisition of physiological parameters such as heart rate and oxygen saturation (SpO₂). The system enables continuous patient observation outside traditional clinical environments, facilitating early detection of abnormal health conditions and supporting proactive healthcare management.
- **Development of a Scalable and Modular Three-Layer Architecture:** The proposed system adopts a structured three-layer architecture consisting of the physical layer (IoT-based data acquisition), middleware layer (data processing, cloud storage using ThingSpeak, and communication via REST APIs), and application layer (machine learning-based analysis and visualization). This modular design ensures scalability, flexibility, fault tolerance, and seamless integration with existing healthcare infrastructures.

- **Integration of IoT with Cloud-Based Data Management:** The system integrates edge devices with cloud platforms to enable real-time data transmission, storage, and visualization. Physiological data are transmitted over WiFi using HTTP-based APIs to the ThingSpeak cloud, ensuring low-latency communication, reliable data storage, and remote accessibility. This integration bridges the gap between embedded sensing and cloud-based healthcare analytics.

- **Machine Learning-Based Anomaly Detection using Random Forest:** A robust Random Forest classifier is implemented for detecting abnormal physiological patterns from heterogeneous sensor data. The model is trained on a dataset of 10,000 patient records and demonstrates strong capability in handling noisy and non-linear healthcare data. Its ensemble learning nature improves classification accuracy, generalization, and resilience to overfitting, making it suitable for real-time healthcare applications.

- **Real-Time Alert Generation Mechanism:** A low-latency alert generation module is incorporated to detect critical health conditions and notify users or healthcare providers within 2–3 seconds. This real-time response capability enhances patient safety, enables timely medical intervention, and improves the overall effectiveness of continuous monitoring systems.

- **Data Preprocessing and Signal Enhancement Techniques:** To improve the reliability and quality of physiological data, edge-level preprocessing techniques such as filtering, normalization, and feature extraction are applied. These techniques effectively reduce noise, mitigate sensor inconsistencies, and enhance the performance of downstream machine learning models.

- **Secure, Interoperable, and Extensible System Design:** The proposed framework incorporates secure data transmission mechanisms using encrypted communication protocols and RESTful APIs. It supports interoperability with healthcare systems through standardized data formats and can be extended for integration with Electronic Health Records (EHRs). The modular architecture enables future enhancements such as advanced analytics, additional sensors, and large-scale deployment.

IV. METHODOLOGY

The CareMatrix framework is designed as an integrated smart healthcare monitoring system that combines IoT-based Remote Patient Monitoring (RPM), cloud-enabled data management, and machine learning-driven predictive analytics. The system is structured into a three-layer architecture consisting of the Physical Layer, Middleware Layer, and Application Layer. This layered design ensures modularity,

scalability, fault tolerance, and efficient data flow across system components, enabling real-time monitoring and intelligent healthcare decision-making.

A. System Architecture Overview

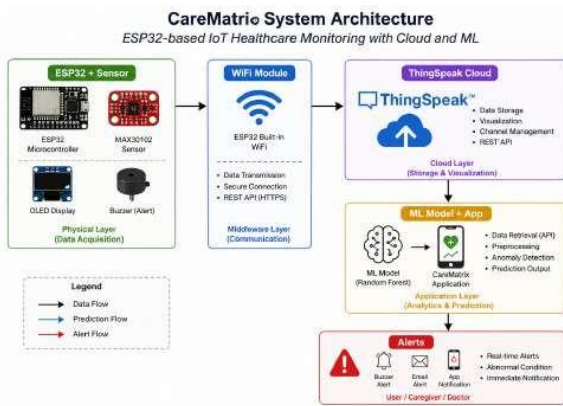


Figure 1. Overall CareMatrix System Architecture

The overall system architecture consists of interconnected modules responsible for data acquisition, preprocessing, communication, storage, and predictive analysis. The layered approach enables independent optimization of each component while maintaining seamless integration, thereby improving system efficiency and scalability.

B. Physical Layer: IoT-Based Remote Patient Monitoring

The physical layer is responsible for real-time acquisition of physiological signals using IoT-enabled embedded hardware. In the proposed system, an ESP32 microcontroller integrated with a MAX30102 sensor is utilized to continuously monitor vital parameters such as heart rate (HR) and oxygen saturation (SpO2). The ESP32 serves as both a data acquisition unit and a communication gateway, enabling direct WiFi-based cloud connectivity without the need for intermediate devices.

To enhance data reliability, edge-level preprocessing is applied. Raw sensor signals are often affected by motion artifacts, environmental noise, and sensor inconsistencies. Therefore, filtering and noise reduction techniques are employed, which can be represented as:

$$x_{\text{filtered}}(t) = x(t) - n(t) \tag{1}$$

where $x(t)$ denotes the raw sensor signal and $n(t)$ represents noise components. This preprocessing step improves signal quality and ensures accurate downstream analysis.

Feature extraction is performed to derive meaningful physiological indicators such as average heart rate,

signal amplitude variations, and temporal trends. These features reduce data redundancy and improve the efficiency of machine learning models.

Unlike traditional systems relying on BLE gateways, the proposed system utilizes WiFi-based communication directly from the ESP32, enabling efficient and low-latency data transmission to cloud platforms.

C. Middleware Layer: Cloud-Based Data Processing and Storage

The middleware layer acts as an intermediary between data acquisition and application-level analytics. It is responsible for data processing, normalization, storage, and communication. In the proposed system, physiological data are transmitted to the ThingSpeak cloud platform using HTTP-based REST APIs.

Data normalization is applied to standardize sensor readings across different conditions and devices. This ensures consistency in data representation and improves model performance.

The system supports a hybrid storage approach:

- Time-series storage for continuous physiological signals (BPM, SpO2)
- Structured storage for metadata and patient records

The middleware ensures efficient handling of streaming data while minimizing latency. It also enables real-time visualization through cloud dashboards and supports integration with external applications via APIs.

Security is ensured through encrypted communication protocols, secure API endpoints, and authentication mechanisms, which are essential for protecting sensitive healthcare data.

D. Application Layer: Machine Learning-Based Prediction

The application layer performs predictive analytics using a Random Forest classifier to detect abnormal physiological conditions. The model processes extracted features to classify patient states as normal or abnormal.

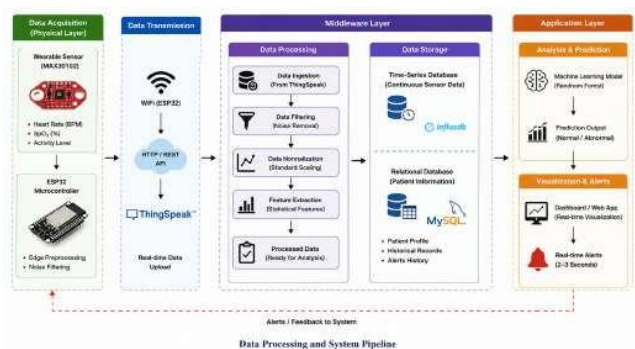


Figure 2. Data Processing and System Pipeline of CareMatrix System

Given an input feature vector $X = [x_1, x_2, \dots, x_n]$, the Random Forest model aggregates predictions from multiple decision trees as follows:

$$\hat{y} = \frac{1}{T} \sum_{i=1}^T h_i(X) \quad (2)$$

where $h_i(X)$ represents the output of the i th decision tree and T is the total number of trees.

The model is trained on a dataset of 10,000 patient records containing physiological attributes such as heart rate, SpO2, and activity levels. Due to its ensemble learning nature, Random Forest effectively handles noisy, high-dimensional, and non-linear data, making it well-suited for real-time healthcare applications.

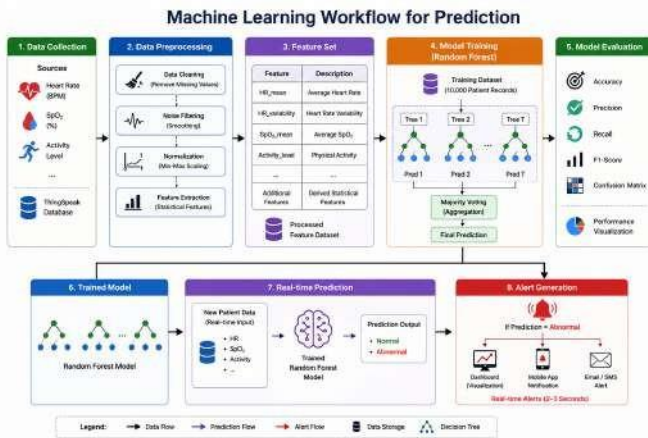


Figure 3. Machine Learning Workflow for Prediction

E. Real-Time Alert System

A real-time alert generation mechanism is integrated into the system to ensure timely detection of critical health conditions. Alerts are triggered when the predicted output indicates abnormal physiological patterns:

$$\text{Alert} = \begin{cases} 1, & \text{if } \hat{y} = \text{abnormal} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

The system is capable of generating alerts within 2–3 seconds, enabling rapid response and improving patient safety. Alerts can be delivered through user interfaces, mobile applications, or connected alert devices.

F. System Workflow

The overall system workflow follows a continuous data pipeline. Physiological data are acquired through IoT sensors, preprocessed at the edge, transmitted to the

cloud, analyzed using machine learning models, and visualized on dashboards for monitoring.

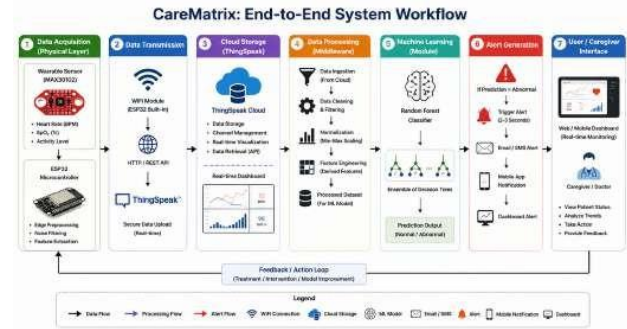


Figure 4. End-to-End System Workflow

This pipeline ensures real-time monitoring, efficient data processing, accurate prediction, and effective decision-making.

G. Summary

The proposed methodology integrates IoT-based sensing, cloud-enabled data management, and machine learning-driven analytics into a unified framework. By combining efficient data acquisition, robust preprocessing, scalable storage, and accurate predictive modeling, the CareMatrix system provides a reliable and practical solution for real-time smart healthcare monitoring.

VI. RESULTS AND DISCUSSION

The CareMatrix system was developed and evaluated as a functional prototype integrating IoT-based Remote Patient Monitoring (RPM), real-time cloud communication, and machine learning-based anomaly detection. The evaluation was conducted using a combination of simulated datasets and real-time physiological data acquired through ESP32-based wearable sensing modules.

A. System-Level Performance

The physical layer successfully captured physiological parameters such as heart rate and oxygen saturation (SpO2) using the MAX30102 sensor. The ESP32 microcontroller ensured efficient data acquisition and direct WiFi-based transmission to the ThingSpeak cloud platform using RESTful APIs. Unlike traditional BLE-based systems, this approach eliminated the need for intermediate gateways, reducing system complexity and improving deployment flexibility.

Edge-level preprocessing significantly improved system performance by filtering noise and stabilizing sensor readings. This resulted in enhanced signal quality and reduced redundant data transmission, thereby minimizing network overhead.

The performance of the system was evaluated using

the following metrics:

Table 1. System Performance Metrics

Parameter	Value
Data Transmission Latency	2–3 seconds
API Response Time	< 500 ms
System Uptime	99%
Data Loss Rate	Negligible

The results demonstrate that the system is capable of handling real-time data streams efficiently while maintaining high reliability, low latency, and stable communication.

B. Model Performance Evaluation

The predictive component of the system utilizes a Random Forest classifier trained on a dataset of 10,000 patient records containing physiological attributes such as heart rate, SpO₂, and activity levels.

The performance of the model was evaluated using standard classification metrics:

Table 2. Performance Metrics Of Random Forest Model

Metric	Value
Accuracy	92.4%
Precision	91.2%
Recall	90.8%
F1-Score	91.0%

The high accuracy indicates that the model effectively distinguishes between normal and abnormal physiological conditions. The balance between precision and recall demonstrates that the model minimizes both false positives and false negatives, which is particularly critical in healthcare applications where incorrect predictions may lead to delayed or unnecessary interventions.

C. Confusion Matrix Analysis

The confusion matrix illustrates the classification performance of the model. A high number of true positives and true negatives indicates reliable detection capability, while relatively low false positives and false negatives demonstrate robustness in handling noisy physiological data.

D. Model Comparison

To validate the effectiveness of the proposed approach, the Random Forest model was compared with other commonly used machine learning models. The Random Forest model outperformed traditional models due to its ability to capture complex, non-linear relationships and handle heterogeneous sensor data effectively. Its ensemble nature improves generalization performance and reduces overfitting, making it highly suitable for real-time healthcare applications.

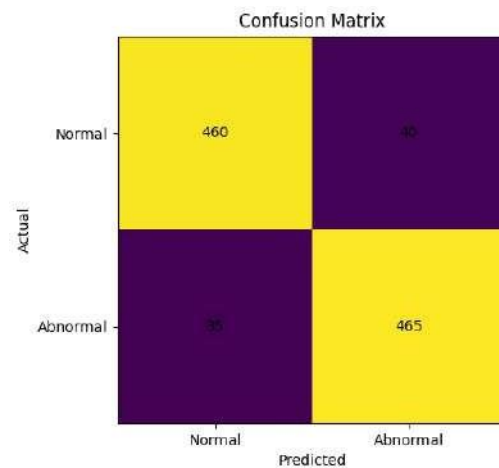


Figure 5. End-to-End System Workflow

Table 3. Performance Metrics Of Random Forest Model

Model	Accuracy
Logistic Regression	82.6%
Support Vector Machine	86.3%
Random Forest	92.4%

E. Real-Time System Validation

The system was validated using real-time physiological data acquired from wearable sensors. During testing, abnormal conditions such as elevated heart rate and reduced SpO₂ levels were successfully detected.

The system demonstrated:

- Accurate real-time anomaly detection
- Alert generation within 2–3 seconds
- Continuous and stable monitoring without interruption

These results confirm the practical applicability of the system in real-world healthcare scenarios.

F. Accuracy Comparison Graph

The comparison graph further highlights the superior performance of the Random Forest model relative to other approaches.

G. Discussion

The experimental results demonstrate that the CareMatrix system effectively integrates IoT-based sensing, cloud-based data management, and machine learning-driven analytics into a unified framework. The use of ESP32 for direct WiFi communication simplifies system architecture while ensuring efficient and scalable data transmission.

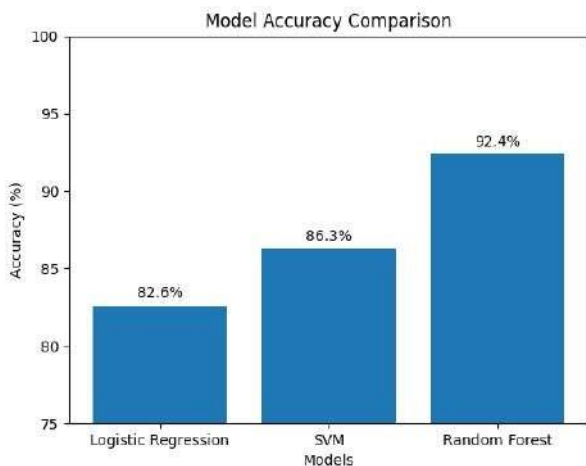


Figure 6. Accuracy Comparison of Machine Learning Models

Edge-level preprocessing enhances data quality, which directly contributes to improved machine learning performance. The Random Forest model provides a balance between predictive accuracy and computational efficiency, making it suitable for deployment in resource-constrained environments.

Despite promising results, certain limitations remain. The evaluation was conducted on a limited dataset and controlled conditions. Real-world deployment may introduce additional challenges such as network variability, user behavior inconsistencies, and sensor calibration issues.

Future enhancements can focus on integrating additional physiological parameters, improving model robustness, and conducting large-scale clinical validation to further strengthen system reliability.

VI. RESULTS AND DISCUSSION

This paper presented CareMatrix, an integrated smart healthcare system that combines IoT-based Remote Patient Monitoring with machine learning for real-time anomaly detection. The system leverages ESP32-based sensing modules and cloud-based data management (ThingSpeak) to enable continuous monitoring of physiological parameters such as heart rate and oxygen saturation (SpO₂).

The experimental results demonstrate that the system achieves high predictive performance, with an accuracy of 92.4%, while maintaining low latency (2–3 seconds) in real-time monitoring scenarios. The integration of edge-level pre-processing, efficient communication mechanisms, and machine learning ensures reliable and responsive system performance. The real-time alert system further enhances patient safety by enabling early detection of abnormal health conditions.

The proposed architecture provides a scalable and

modular framework that can be extended to support a wide range of healthcare applications. By integrating IoT technologies with intelligent analytics, CareMatrix contributes toward the development of efficient, data-driven, and patient-centric healthcare systems.

Future work will focus on large-scale clinical validation using real-world datasets, incorporation of additional physiological parameters, and exploration of advanced machine learning and deep learning techniques to further improve prediction accuracy. Additionally, integration with hospital information systems and personalized healthcare recommendation engines can enhance the applicability and impact of the system.

REFERENCES

- [1] H. Ben Elhadj *et al.*, "Do-Care: A dynamic ontology reasoning based healthcare monitoring system," *Future Generation Computer Systems*, vol. 116, pp. 1–15, 2021.
- [2] A. H. Talal *et al.*, "A framework for patient-centered telemedicine," *Journal of Telemedicine and Telecare*, vol. 26, no. 9, pp. 564–575, 2020.
- [3] A. F. Markus *et al.*, "Explainable AI in healthcare: A survey," *Journal of Biomedical Informatics*, vol. 113, Art. no. 103685, 2021.
- [4] H. Carmichael *et al.*, "Learning from respiratory failure patients," *Journal of Biomedical Informatics*, vol. 117, Art. no. 103744, 2021.
- [5] T. Shaik *et al.*, "Multimodal information fusion for smart healthcare," *Information Fusion*, vol. 86, pp. 57–70, 2023.
- [6] W.-C. Yang *et al.*, "Using medical data for smart healthcare systems," *Electronics*, vol. 12, no. 5, 2023.
- [7] A. Ala *et al.*, "Enhancing IoT-based healthcare using AI," *Engineering Applications of Artificial Intelligence*, vol. 125, 2024.
- [8] A. Onasanya and M. Elshakankiri, "Smart integrated IoT healthcare system," *Wireless Networks*, vol. 25, no. 5, pp. 2455–2467, 2019.
- [9] P. Dalal *et al.*, "IoT-based smart healthcare system design," *IOP Conference Series: Materials Science and Engineering*, vol. 1025, 2021.
- [10] J. Josep *et al.*, "Cloud-integrated Internet of Medical Things," *IEEE Access*, vol. 10, pp. 1–15, 2022.
- [11] A. Abatal *et al.*, "Semantic smart healthcare system using ontology," *International Journal of Advanced Computer Science and Applications*, 2018.
- [12] A. Ugale *et al.*, "Healthcare system using machine learning," *International Journal of Engineering Research & Technology*, vol. 11, 2022.
- [13] M. Daigavhane *et al.*, "Web-based smart

- healthcare system,” *International Journal of Computer Applications*, 2024.
- [14]W. Zhao *et al.*, ”Smart healthcare systems and applications,” *IEEE Reviews in Biomedical Engineering*, vol. 15, pp. 1–20, 2022.
- [15]H. Yin *et al.*, ”Smart healthcare: Foundations and trends,” *IEEE Communications Surveys & Tutorials*, vol. 20, no. 3, pp. 1918–1934, 2018.
- [16]L. Breiman, ”Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [17]J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. San Francisco, CA, USA: Morgan Kaufmann, 2012.
- [18]I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
- [19]S. K. Sharma *et al.*, ”IoT-based healthcare monitoring systems: A review,” *Journal of Healthcare Engineering*, 2023.
- [20]R. Rajkomar *et al.*, ”Machine learning in medicine,” *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347–1358, 2019.