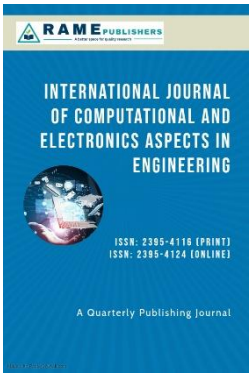
International Journal of Computational and Electronics Aspects in Engineering
Volume 7, Issue 5, November 2026, pp 616 - 631
https://doi.org/10.26706/ijceae.7.5.20261007

AI-Based Anomaly Detection in IoT-Enabled Patient Vital Sign Monitoring Systems

Marwa Riyadh Ahmed*

Northern Technical University, Technical Engineering College for Computer and AI, Mosul, Iraq

***Correspondence:** Marwa.riyadh@ntu.edu.iq



Abstract - Intelligent health monitoring technologies are being developed increasingly due to the limitations of traditional healthcare systems, which often rely on periodic measurements and fail to detect early physiological issues in real time. A significant challenge is accurately analyzing anomalies in continuous biometric data, as these measurements are generally unstable. Traditional statistical methods, such as the Z-score and threshold-based approaches, are quick and computationally simple but can result in a high number of false alarms. In contrast, unsupervised intelligent machine learning methods provide a deeper understanding of data patterns and do not depend on linear or batch learning techniques, which can be time-consuming and require substantial data storage. In this paper, we propose a hybrid health monitoring system based on the Internet of Things (IoT). This system includes real-time data collection using the ESP32 microcontroller, along with cloud storage through Firebase and advanced data analytics via Google Colab. We combine the Z-score statistical method with a dynamic threshold process and the Isolation Forest algorithm for monitoring abnormalities. This approach leverages the strengths of both statistical methods and machine learning to reduce false alarms effectively. We conducted tests that successfully detected various pathological patterns in real-time through a smartphone app implementation. We believe this system is feasible, flexible, and scalable enough to be widely used for patient monitoring, particularly in telehealth, elderly care, and preventive medicine.

Keywords: Anomaly detection; Isolation Forest; AI, IoT; vital signs.

Article – Peer Reviewed
Received: 30 August 2026
Accepted: 27 October 2026
Published: 10 November 2026

Copyright: © 2026 RAME Publishers
This is an open access article under the CC BY 4.0 International License.

https://creativecommons.org/licenses/by/4.0/

Cite this article: Marwa Riyadh Ahmed, "AI-Based Anomaly Detection in IoT-Enabled Patient Vital Sign Monitoring Systems", *International Journal of Computational and Electronics Aspects in Engineering*, RAME Publishers, vol. 7, issue 5, pp. 616-631, 2026.
https://doi.org/10.26706/ijceae.7.5.20261007

1. Introduction

The concept of integrating observation, visualization, and control has expanded significantly in the age of the Internet of Things (IoT), encompassing various domains. For example, modern smartphones enable direct access to extensive networks and facilitate real-time data streaming. Machine learning methods are now employed to develop models that can predict potential dangers in various situations. In the healthcare industry, artificial intelligence (AI) and machine learning technologies have revolutionized medical systems. Applications focused on disease prediction are becoming essential for maintaining healthcare and promoting global well-being. While robotic systems cannot completely replace medical personnel, they significantly contribute to preventing potential harm to patients by providing accurate predictions.[3, 4, 5].

Optimal health is an integrated solution that encompasses physical, mental, and social aspects, all of which need to be maintained through preventive check-ups, healthy lifestyle habits, exercise, and the treatment and monitoring of chronic diseases. Preserving health also involves raising awareness and promoting both therapy and prevention. Together, these elements help improve health outcomes, enhance access to medical care, and support personalized interventions tailored to the specific conditions of individual patients [7, 8]. Health is not solely a matter of physical well-being; mental health plays a crucial role in a holistic approach to health. With the advancement of sensing techniques, large-scale data collection is now possible across various settings, even with a limited number of sensors placed in different parts of the human body for improved tracking and analysis accuracy [9].

As medicine evolves, algorithms must be continually updated in a centralized manner, which means they can quickly become outdated as new knowledge and technology emerge. This situation leads to future challenges, including the possibility that users may increasingly turn to paid supplements for these systems. [5].

Machine learning, artificial intelligence, and blockchain technology are effective tools for enhancing the security of Internet of Medical Things (IoMT) systems. These approaches can improve system performance and address challenges such as denial-of-service attacks and single points of failure. Additionally, machine learning techniques can reduce errors in physical layer authentication by 64 percent compared to traditional authentication methods. Overall, IoMT systems can gain significant advantages from the integration of machine learning, artificial intelligence, and blockchain technology.[10]

Combining the Internet of Things (IoT) and artificial intelligence (AI) can create a ubiquitous smart healthcare ecosystem. This integration involves using AI in coordination with IoT "smart" devices, enabling advanced data processing and actionable insights for improved decision-making. Ultimately, this leads to better patient outcomes. For instance, AI algorithms can analyze telemetry data from connected medical devices to identify variances and make recommendations for preventative measures before a disease progresses, thereby reducing the risk of emergency situations and enhancing patient safety. [11]

Combining the Internet of Things (IoT) with artificial intelligence (AI) can create a pervasive smart healthcare ecosystem. This integration involves using AI in conjunction with IoT-enabled devices, facilitating advanced data processing and providing actionable insights for improved decision-making, ultimately leading to better patient outcomes. For instance, AI algorithms can analyze data from connected medical devices to identify variances and make preventive recommendations before a disease progresses. This approach not only reduces the risk of emergency events but also enhances patient safety. [13].

In this project, we are developing an IoT-assisted health monitoring system that combines real-time biometric data for intelligent analysis and decision-making. We begin by retrieving physiological signals from sensors and saving them to a Firebase real-time database. After that, we process and analyze this data using Google Colab to identify any abnormalities, employing advanced machine learning algorithms such as statistical baselines and the Isolation Forest algorithm. The activity data is then displayed via a mobile application, allowing for long-term monitoring of both individual patients and clinical team responses as soon as any unusual patterns in biometrics are detected. Additionally, our system architecture facilitates performance measurement and visualization of results through graphical dashboards, which help validate the model's trustworthiness and influence decision-making. Our goal is to establish an effective methodology and analytical framework to detect any abnormalities in vital signs early through non-intrusive sensory monitoring of patients. This approach will serve as a foundation for the future of smart healthcare services, shifting the focus from reactive to preventive care.

2. Related Work

Recent developments in Artificial Intelligence (AI) and the Internet of Things (IoT) within the healthcare industry have led researchers, including Mandip R et al., to focus significantly on smart, continuous patient monitoring systems. Recently, techniques such as anomaly detection and physiological biomarker analysis have been increasingly utilized in healthcare to enable early diagnosis for patients and healthcare teams, allowing for quicker interventions. Several studies have emphasized the adoption of machine learning algorithms, which can greatly enhance accuracy for real-time monitoring by leveraging patterns derived from a continuous flow of biometric data, such as heart rate, ECG, respiration, temperature, and SpO2.[14] The findings indicate that a high-performance anomaly detection (AD) framework typically comprises three stages: data preprocessing, feature extraction, and machine learning-based classification or anomaly score generation. These techniques have demonstrated potential for saving time in anomaly detection and improving clinical awareness, particularly in fast-paced environments like emergency rooms and post-operative settings.

Improvements in anomaly detection have been achieved through the use of IoT-based health monitoring platforms that facilitate remote sensing, low-latency communication, and distributed computing. In [15], researchers proposed an intelligent IoT architecture that incorporates unsupervised anomaly detection models such as Isolation Forest and LSTM directly at the edge. This approach minimizes cloud usage and reduces data transmission load. The findings indicated that the Isolation Forest algorithm is particularly well-suited for real-time systems, as it is computationally efficient and does not rely on labeled data—a common challenge in the medical field due to the high costs associated with producing accurate labeled datasets. In a related study, several researchers have deployed deep learning techniques to analyze temporal anomalies in biometric measurements, demonstrating that LSTM/GRU networks improve sensitivity to gradual changes and health decline [16]. However, these techniques tend to be computationally intensive and require periodic retraining, making them less suitable for resource-constrained IoT devices.

Furthermore, in addition to model selection, methods have been developed to enhance the reliability and robustness of health monitoring by addressing noise and low-quality signals from wearable sensors.[17] For instance, unsupervised algorithms such as Isolation Forest have proven effective in detecting anomalies and physiological artifacts prior to clinical inspection of the signals. This significantly improves system reliability, especially in suboptimal environments like home monitoring for elderly care.[18] Additionally, personalization techniques have been proposed to reduce the number of false alarms caused by individual variations in signals. By creating patient-specific models for PPG signal anomaly detection, we can compare these models to generalized ones by learning the average individualized thresholds based on each patient. As a result, PPG signal anomaly detection becomes more efficient and accurate for long-term monitoring. Using similar personalization methods, our approach aims to minimize false alarms arising from signal differences among individuals. [19,20]

Despite significant progress, there are still three major gaps that require attention.[21] First, most studies have focused on only one or two signals, whereas patient deterioration is clearly indicated by the simultaneous changes in multiple biomarkers. Second, the majority of previous research has concentrated on algorithm performance without providing a comprehensive alerting system that is integrated with healthcare providers or systems. Third, many studies have been conducted in controlled laboratory settings rather than in real-world situations, which are affected by factors such as network delays, the frequency of false alarms, and necessary preventive actions.

This study proposes a general system for anomaly detection in AIoT-based monitoring of body vital signs, specifically heart rate and oxygen saturation (SpO_2). The process incorporates statistical methods, such as normalized scores, learning of abnormal regions, and moving models, along with unsupervised techniques using Isolation Forest for detection. This framework is designed for real-time detection of unusual events that may pose risks in the healthcare system's warning process. It also considers multi-signal analysis, employs a lightweight algorithm, and includes integrated alerting capabilities. These advancements aim to enhance health monitoring for the elderly, making it applicable in real-time field settings.

This approach has been explored previously, but in light of recent research, we are able to refine our strategy by comparing our system to effective anomaly detection systems in health and healthcare. Initially, many of these studies focused on purely statistical methods, using techniques such as Z-scores and thresholds to identify physiological events, as well as machine learning methods like Support Vector Machines (SVMs) and deep learning algorithms. However, most of these methods rely on offline data analysis and do not accommodate real-time data collection, storage, or continuous monitoring from the cloud. They also fail to address the immediate challenges faced by patients and the clinical data at the point of care. Our proposed system addresses these issues by integrating real-time IoT-based data gathering with ESP32 sensors and cloud storage (Firebase), while employing both statistical and unsupervised learning techniques for anomaly detection.

Conventional statistical methods are efficient and quick; however, they often produce a high number of false alarms due to their inability to effectively process noise responses. In contrast, machine learning applications such as Isolation Forest offer a more reliable way to identify anomalies in time series data. These methods perform particularly well in both time series and multivariate analyses. There is substantial evidence that utilizing machine learning and clustering techniques enhances reliability and detection performance. Additionally, while many existing systems prioritize algorithm performance, our system focuses on practical applications. It includes a mobile app and a cloud-based monitoring system, making it more suited for real-world healthcare scenarios, including remote patient monitoring and elderly care. Table 1 presents a comparison between our proposed system and related previous systems.

Table 1. Comparison between the proposed system and previous related systems

Feature	Traditional Systems	ML-based Systems	Proposed System
Real-time Data	Limited	Mostly offline	Yes
IoT Integration	-	Partial	Yes
Cloud Storage	-	Optional	Firebase
Methods Used	Statistical only	ML only	Hybrid
False Alarm Handling	Weak	Moderate	Improved
Mobile Monitoring	-	-	Yes
Scalability	Limited	Moderate	High

3. Methodology

The dataset used in this study consists of actual physiological data collected from humans using wearable devices. It was obtained from an external source and contains physiological monitoring records of patients who utilized these sensor devices. This dataset features time-series signals such as heart rate (HR), blood oxygen saturation (SpO2), temperature, and respiration rate, which were recorded using medical or wearable devices for the purposes of this research and analysis. Prior to using the dataset in the anomaly detection framework, it underwent preprocessing, which included noise removal, normalization, and addressing missing values. Importantly, the dataset does not contain any personal information and is considered anonymous. It was utilized in this research while fully adhering to ethical standards for dataset usage.

3.1 System Implementation

The proposed system is designed and implemented as a smart health monitoring system that utilizes the ESP32 as the main processor and communication module. This choice is due to the ESP32's low power consumption and its built-in capability for wireless communication using Wi-Fi. A group of biosensors is connected to the microcontroller to measure the patient's basic physiological values, including heart rate, SpO_2, body temperature, and respiration (Figure 1). These sensors provide real-time readings of various parameters and produce analog signals, which are then sent to the microcontroller for processing.

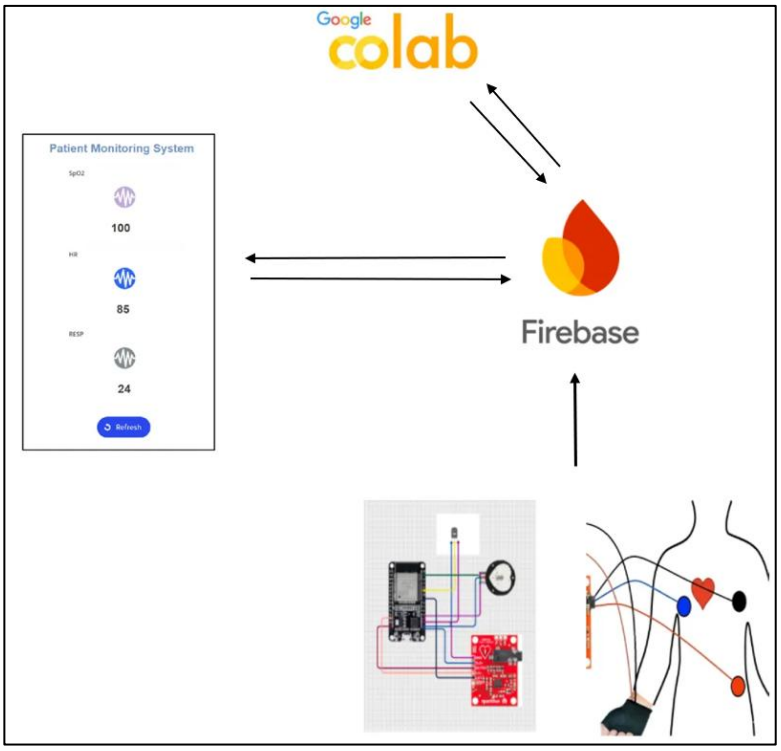


Figure 1. Hardware architecture of the system

The ESP32 gathers biometric data and organizes it into a time-series format before transmitting it wirelessly to a Firebase cloud database. Firebase serves as a real-time database solution, providing persistent and secure storage while allowing other analytics tools to access the data. Meanwhile, real-time measurement results are displayed in a dedicated mobile application, enabling caregivers and end users to monitor vital signs through an interactive graphical dashboard. In addition to the real-time display, a parallel system has been established to forward this information to the Google Colab analytics environment, where it can be processed using abnormal detection algorithms, including the Tauchtan algorithm, dynamic thresholding, z-score, and Isolation Forest. This integration of hardware and algorithmic analysis creates a comprehensive solution that transforms raw data accumulation into actionable insights, paving the way for artificial intelligence and machine learning applications. This approach aims to enhance preventive healthcare and provide early warnings for critical health events. Overall, our product offers a practical solution that combines field biosensing with cloud storage and enables data analysis and visualization. This integration is intended to support the development of IoT applications in smart health and medical scenarios. The prototype's flowchart is illustrated in Figure 2.

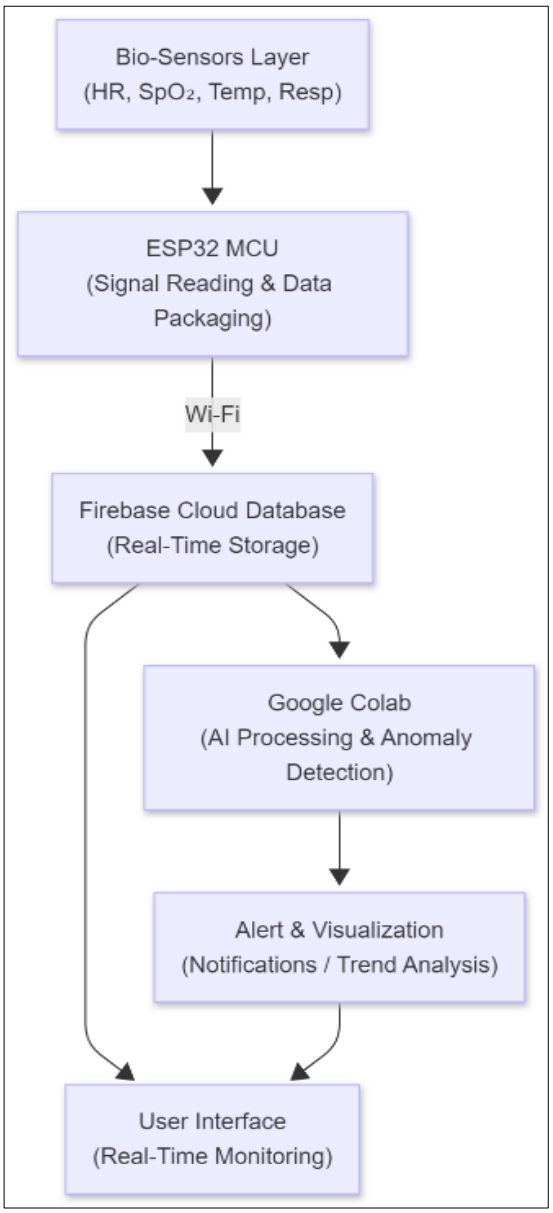


Figure 2. Flowchart of the prototype

3.2 System Architecture

The system components include multiple sensors that communicate with a microcontroller or other IoT devices (e.g., heart rate and respiratory monitors). These sensors continuously monitor the patient's health.

Figure 3 presents an overview flowchart of the IoT and AI-based health monitoring system, outlining the process from biometric data acquisition to decision-making, data storage, and analysis.

In the first layer, known as the Sensor Layer, basic bio-statistical information is gathered, including heart rate (HR), respiration (RESP), blood oxygen saturation (SpO_2), and temperature. This information is transmitted through the Communication Layer using low-power wireless communication protocols (such as Wi-Fi) to ensure a consistent stream of data updates to the processing platform. Once the data is received, it undergoes processing through a pre-processing layer, which involves noise reduction, signal de-noising, and normalization, to enhance and prepare the data for further analysis.

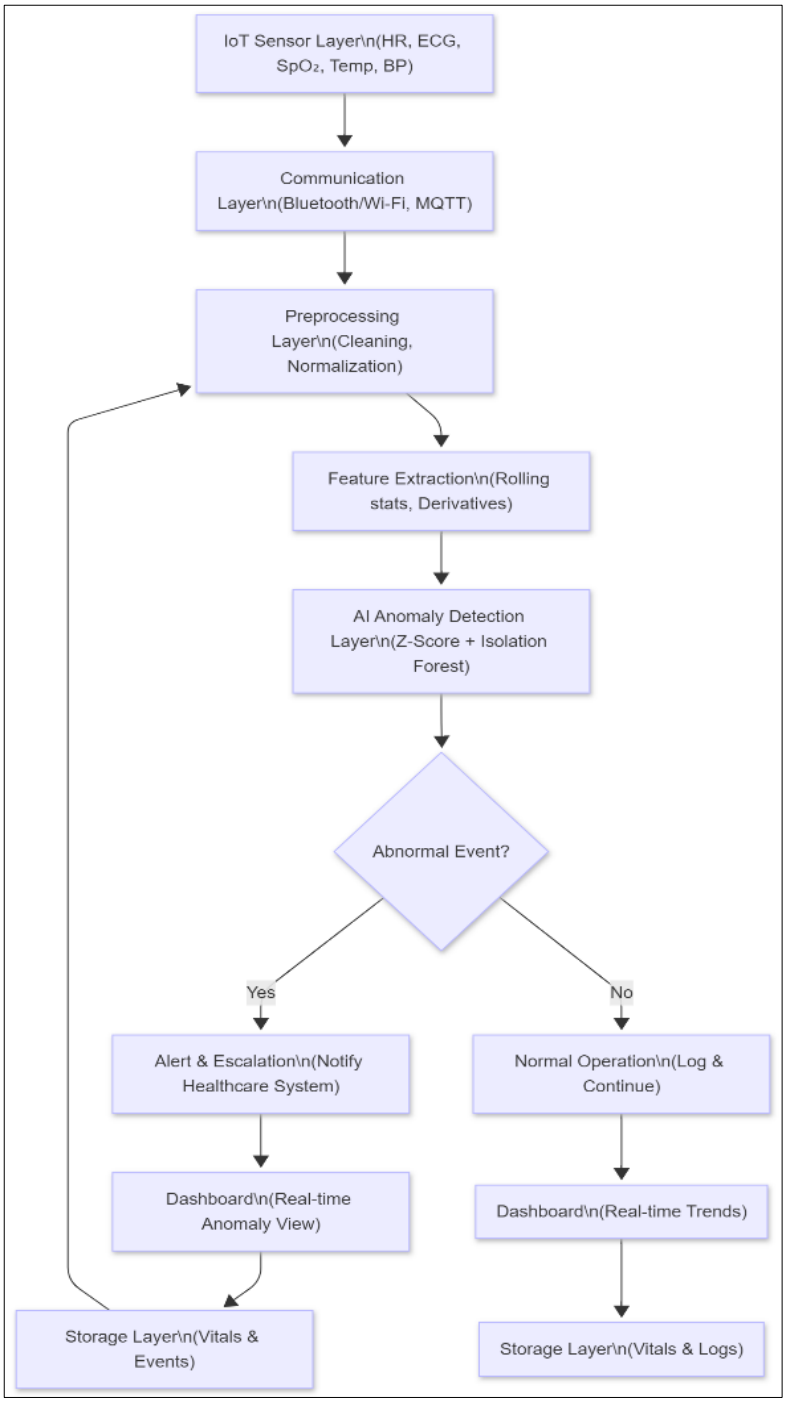


Figure 3. Flowchart of proposed implementation

The Feature Extraction Layer processes temporal data to extract valuable analytical features, such as signal derivatives and kinetic changes. These features are essential for explicitly identifying a patient's physiological behavior. Once the features are extracted, the data is sent to the AI Anomaly Detection Layer, where anomaly detection occurs using Z-Score and Isolation Forest algorithms. This detection is based on comparing current measurements against established historical patterns. When an anomaly is detected, the system activates the alerting pipeline, which triggers a process to alert and escalate the situation. Immediate alerts are sent to both the healthcare system and the monitoring platform. The event is displayed in real-time on a dashboard and stored as a critical event in the storage layer. If no anomalies are observed, the information is stored as usual, allowing key trends to be identified without generating any alerts or escalations. In both scenarios, the data is ultimately saved to the storage layer for future analysis and for training predictive models aimed at proactive healthcare. The system enhances preventive healthcare by reducing clinical risks through early treatment of potential critical cases and improves the quality of healthcare monitoring using IoT (Internet of Things) and AI (Artificial Intelligence).

4. User Interface & System Integration

The application dashboard is used to create a real-time health monitoring interface. The real-time sensor data, including HR, SpO2 values, and RESP, are displayed on the dashboard (Figure 4).

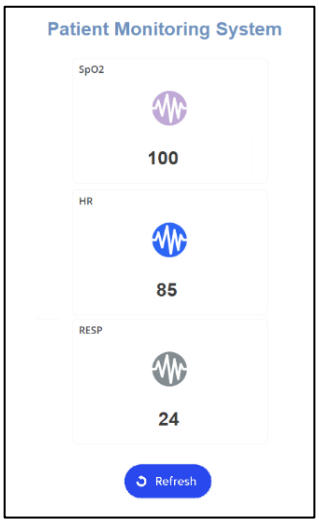


Figure 4. Application dashboard

The system allows users to request more detailed health data. The application is compatible with various RESP, HR, and SpO2 levels, as shown in Figure 4. The connection between the dashboard, application, and data processing module is established through APIs and data synchronization mechanisms.

4.1 Database

This study employs Firebase to deliver real-time cloud storage, as illustrated in Figure 5. It can immediately store critical data collected from sensors and facilitates real-time processing and anomaly detection algorithms (as shown in Figure 5) for effective analysis and error correction. Firebase maintains an open communication line with the application device, enabling the monitoring of patient conditions and providing early alerts. This continuous tracking helps understand the current situation and the patient's feelings, allowing it to be used as a case study.



Figure 5. Firebase real time database

4.2 Mathematical Formulation of Anomaly Detection Methods

This article expands and clarifies the procedure to ensure that the methodology is explicit and organized throughout the data collection and analysis process. We define the data collection process using an ESP32 microcontroller, which can interface with biomedical sensors to measure heart rate, blood oxygen saturation, temperature, and respiratory rate. The data collected via Wi-Fi is stored in a Firebase database in real-time, using a timestamped format for easy retrieval. This ensures that the data are traceable and reusable for future studies and analyses. Before utilizing the collected information, data preparation must be performed. This includes addressing missing values through front and back imputation, reducing noise, and normalizing the data. If you plan to conduct analysis from scratch, it is essential to outline these steps clearly, as the approach taken for data preparation can be applied in future studies as well. To detect outliers, we employ both statistical and machine learning methods.

The Z-score method utilizes a fixed threshold value, while the dynamic threshold method operates over a sliding time window to account for changes in the situation. The Isolation Forest algorithm is also implemented, but it does not have a specific contamination parameter, resulting in the detection of only a limited number of outliers. The Z-score method can be applied to compare each vital sign value against the average. The main objective is to identify the minimum and maximum outlier values within the data. If a value is close to the mean, it is considered normal; if it is far from the mean, it is classified as an anomaly.

$$Z = \frac{x - \mu}{\sigma}$$

Where:
x: the current value of the vital sign
μ: the arithmetic mean of the data
σ: the standard deviation

The deviation referred to here is the standard deviation. When there is a significant difference in a value represented by the Z-score, whether positive or negative, the likelihood of encountering an abnormal value increases.

This method is straightforward and quick, but it can be influenced by short-term fluctuations or noise within the data itself. Unlike the Z-score, which is based on the overall mean, this approach relies on the data being observed or measured over a moving time frame. In other words, it examines only a set of values that are temporally close to the current moment.

$$\mu_t = \frac{i}{N} \sum_{i=t=N}^{t} x_i$$

$$Threshold = \mu t \pm k \cdot \sigma t$$

Where:
N: Time
μt: Local mean
σt: Local standard deviation
k: Coefficient

We first calculate the local mean and local standard deviation from a given cycle, which allows us to develop dynamic thresholds that adjust over time. This approach enables us to better account for the natural variation in vital signs, such as a gradual increase in heart rate or a decrease in respiration rate. Additionally, it helps to reduce false alarms caused by temporary fluctuations. When we refer to the isolation forest, we emphasize that we do not rely on averages or statistical distributions to differentiate between values in random trees.

In essence, outlier values that deviate from the norm are rare and can be isolated with greater accuracy.

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}}$$

Where:
$E(h(x))$: Average path length to isolate the point
c(n): a normalization factor based on the number of data points
s(x,n): the degree of outlier
Note if:
s(x,n)≈1 → Strong outlier
s(x,n)<0.5 → Normal

In simpler terms, abnormal data points typically follow fewer steps in a decision tree. The level of abnormality detected for any given point is determined by its size. This approach is particularly effective for complex, multivariate data and is suitable for unsupervised learning scenarios. To understand the relationship between two variables, such as heart rate (HR) and pulse (PULSE), we use the correlation coefficient. This coefficient measures how closely the two variables are related. When both variables are analyzed together, the correlation can also indicate a relationship with the overall signal, which may involve two or more points. If there is no relationship between the variables, the correlation coefficient will be close to zero.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2} \cdot \sqrt{\sum(y_i - \bar{y})^2}}$$

Measures the relationship between two variables (such as HR and PULSE)

r=1 → Strong positive correlation
r=0 → No correlation
r=−1 → Inverse correlation

This also helps in the recognition and understanding of which vital signs are interacting with one another, which is very important in most healthcare systems since some changes are physiologically connected to each other. These equations were used to construct the analysis of vital signs data, where the Z score is so fast to get data that can tell you what the changes are, and dynamic threshold allows you to rapidly change with times and the Isolation Forest algorithm is also to analyze it from different backgrounds. Correlation analysis is also used to determine the relationships between different biosignals and improve the interpretation and decision-making efficiency.

4.3 Performance Evaluation & Validation Quantitative

To more rigorously evaluate the proposed anomaly detection framework, we design a quantitative evaluation with standard classification metrics, including Precision, Recall, and F1-score. These metrics are used to measure the performance of detection algorithms in detecting abnormal physiological patterns and reducing false alarms and missed detections. The evaluation compares three approaches, Z-score, dynamic thresholding and Isolation Forest on the same physiological test data. For a fair and consistent evaluation, the predicted anomaly labels are compared to independently established ground-truth annotations.

true positives, true negatives, false positives and false negatives. The reason for the emphasis on recall is that missed abnormal events can have serious consequences in healthcare monitoring. Precision is also considered important since too many false alarms might diminish the practical utility of ongoing monitoring systems. The resulting metrics give a quantitative basis for comparing the detection methods. Where sufficient labelled data are available, confidence intervals and other statistical analyses are used to evaluate the robustness of the observed differences. The aim of this assessment is to determine if the proposed hybrid framework provides measurable improvements over single anomaly detection methods.

To put it plainly, understanding the future of the proposed system involves considering its scalability impact on the healthcare system, particularly in hospitals today. This system's structure allows for immediate scalability, which is essential for managing a growing number of patients. By utilizing cloud-based systems like Firebase, we can effectively handle the high-speed influx of real-time data from patient monitoring systems. In large-scale applications using ESP32 devices, multiple ESP32 units can be connected to various patients, continuously transmitting physiological data to a centralized database. This setup enables healthcare providers to monitor multiple patients on a single screen, facilitating remote monitoring without the need to physically attend to each patient individually. This approach optimizes resources across the entire healthcare system.

From an operational perspective, the system can be deployed in hospitals for monitoring both patients and their conditions, as well as in aging care centers for remote management of such patients and in home healthcare systems. The anomaly detection feature aids medical practitioners in identifying patients' medical needs at critical moments, allowing for timely notifications. The system is adaptable to various clinical settings because it operates on both traditional hardware and cloud-based platforms (such as ESP32 devices), which offer low network costs. Utilizing this system can enhance healthcare infrastructure and provides an affordable, effective, and efficient technology-based healthcare solution.

5. Results and Discussion

We conduct comprehensive sampling and preprocessing of biometric data from an advanced monitoring system that leverages Internet of Things (IoT) technologies and artificial intelligence (AI). Our aim is to rigorously evaluate the effectiveness of an anomaly detection model for physiological signals, contrasting it with traditional statistical methods to highlight its superior capabilities. By collecting fundamental biometric data—such as heart rate (HR), pulse, oxygen saturation (SpO_2), and respiration (RESP)—measured simultaneously over an extended continuous period, we simulate real-world health monitoring scenarios. Following this, we execute an in-depth descriptive analysis of the data's distributions and characteristics. We also investigate the intricate interrelations among biometric indices to uncover their dynamic performance and the physiological dependencies that exist between them. In the final part of the chapter, we delve into Z-scores, dynamic thresholds, and an Isolation Forest-based statistical model for anomaly detection, carefully assessing their sensitivity in differentiating normal measurement patterns from anomalies. Our findings underscore the efficacy of this innovative methodology in refining the identification of critical health cases while significantly minimizing false alarms. This approach paves the way for developing a robust deep learning-based intelligent system that enhances active healthcare support and empowers real-time clinical decision-making.

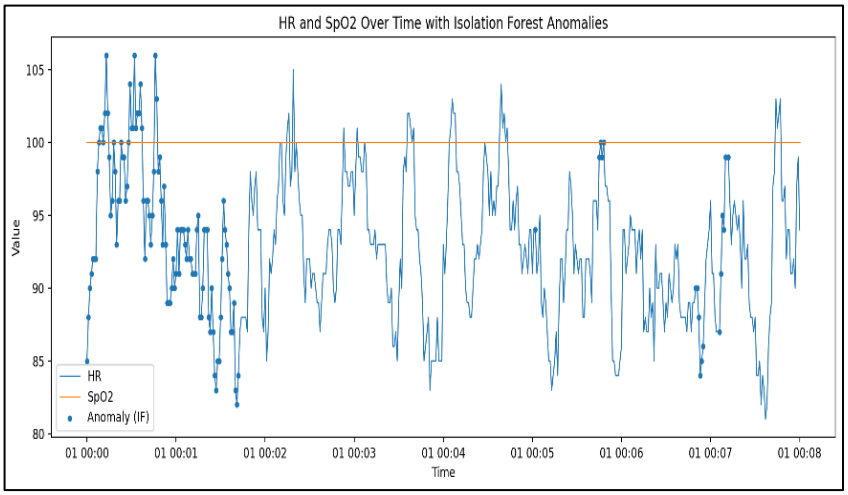


Figure 6. Heart rate and SpO2 with anomalies distribution over time

Figure 6 illustrates the heart rate (HR) and blood oxygen saturation (SpO_2) over time, highlighting the anomalies identified by the Isolation Forest model. The HR is represented by the blue curve, which shows significant fluctuations compared to the SpO_2, depicted in orange, which remains relatively stable. The dark blue points on the HR line indicate instances where the system detected abnormal changes relative to the general trend of the signal. From the figure, it is evident that HR experiences rapid peaks and valleys, making it more sensitive to instantaneous changes than SpO_2, especially in individuals experiencing stress, fatigue, or sudden physiological activity. Some of these extreme HR values were classified as anomalies by the Isolation Forest model, suggesting the effectiveness of our method in detecting abnormal response patterns during normal variations in biological signals. These findings highlight the importance of integrating multiple biomarkers when assessing health status. For example, an increase in HR without a corresponding decrease in SpO_2 may indicate a temporary, benign physiological variation. In contrast, significant abnormalities in both HR and a drop in SpO_2 are more concerning and suggest a severe condition. Consequently, anomaly detection methods play a crucial role in enabling smart monitoring systems, allowing for timely notifications to experts or care providers about drastic changes, thus reducing the reliance on manual assessments or continuous monitoring.

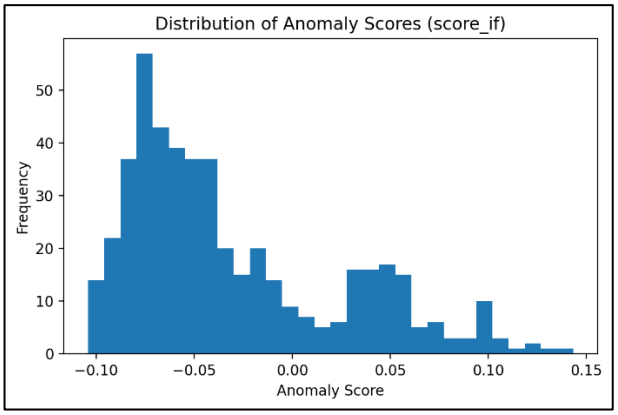


Figure 7. Anomaly scores distribution

Figure 7 illustrates the distribution of scores for both normal and abnormal behavior, with normal data represented in blue and abnormal data in red. The graph shows how values are concentrated around the central range, which the Isolation Forest algorithm identifies as indicative of true, or normal, behavior. Most scores are found on the negative side of the horizontal axis, primarily between -0.10 and -0.03, indicating that the majority of processed biometric readings can be categorized as normal, without abnormalities. This trend arises from the fact that the main biometric signals tend to be stable over time. Only a few values show a shift towards the positive range, which the algorithm subsequently considers as outliers. The distribution forms a unimodal curve, allowing normal data that deviates from the typical pattern to be easily recognized and differentiated from outliers, which are dispersed at the edges. This aligns with common observations in healthcare systems, where pathological or critical conditions occur less frequently than normal measurements. Consequently, the graph demonstrates the model's effectiveness in distinguishing between normal patterns and abnormal cases, highlighting the advantage of using unsupervised models for continuous vital sign monitoring in smart healthcare technologies.

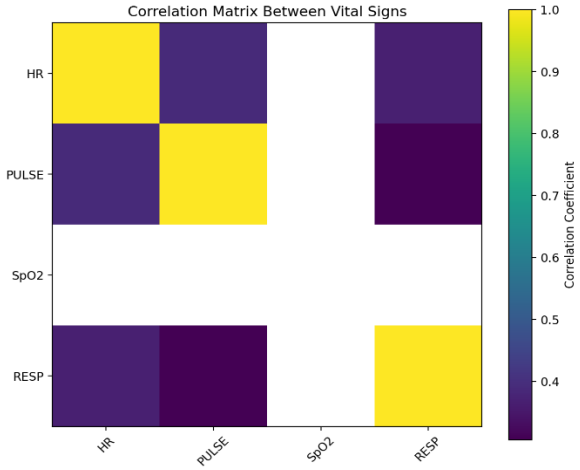


Figure 8. Feature Correlation Matrix

Figure 8 shows the relationship among HR, PULSE, SpO2, and RESP.** A correlation matrix is presented in the figure, indicating the significance of heart rate (HR), pulse rate (PULSE), blood oxygen saturation (SpO2), and respiratory rate (RESP). The data demonstrates strong statistical support for these relationships. Specifically, the correlation between heart rate and pulse rate is very high, typically greater than 0.9, often reflected in bright yellow cells that indicate a correlation coefficient close to unity (1.0). This alignment is expected, as pulse is a direct reflection of heart activity, meaning both metrics will generally move in the same direction with high correlation. Conversely, a weaker correlation between HR and RESP, as well as between PULSE and RESP, is indicated by darker shades closer to purple in the matrix. This suggests that respiratory rate is not directly influenced in a linear fashion by heart rate or pulse rate during normal breathing. However, the relationship between breathing and heart activity is synchronous and continuous under certain conditions, such as stress or hypoxia, especially when combined with respiratory and cardiac diseases. The lack of correlation observed in SpO_2 levels is surprising. This could be due to insufficient data or missing values that prevent a precise correlation coefficient from being calculated within this sample. Alternatively, it may indicate that the relationship between SpO_2 and other variables recorded during this time is not directly linear with any of the other indicators. Blood oxygenation typically shows a differential nature compared to other indexes, as it is influenced by several factors, such as lung efficiency, perfusion, and blood oxygen levels. These factors are not necessarily synchronized with heart rate or respiratory rhythm over short time frames. This may explain why the matrix reflects an anticipated physiological reality. While some biomarkers clearly coordinate with one another, as they represent similar physiological responses, others may act relatively independently. This emphasizes the importance of including multiple biomarkers in future research to gain a more comprehensive understanding of a patient's health. Additionally, these findings highlight the necessity of implementing sophisticated and validated analytical models, such as multivariate anomaly detection algorithms, rather than relying solely on univariate measures in clinical practice or early warning systems.

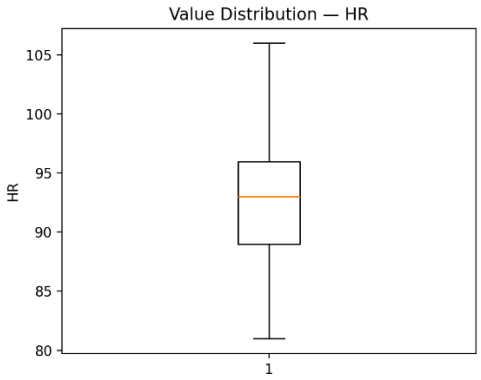


Figure 9. HR value distribution

Figure 9 presents a visual representation of the distribution of heart rate counts. Most of the measurements cluster around a narrow range centered on the mean, with some natural variation at the upper and lower ends of the box. The long upper and lower bands indicate that there is minimal variation in heart rate (HR) during the monitoring period. No significant outliers were observed outside the plot, suggesting that the majority of measurements fall within the physiologically normal range.

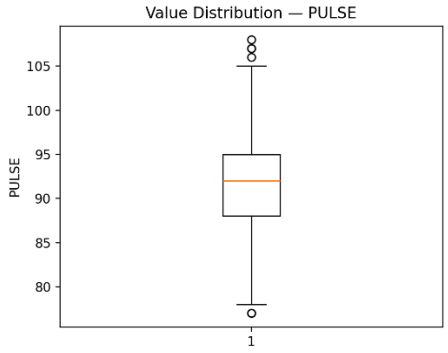


Figure 10. Pulse value distribution

Figure 10 displays the distribution of pulse values, which closely resembles the heart rate (HR) trend. However, there are some outliers at the upper end of the plot. These outliers correspond to spikes in heart rate variability (HRV) compared to the other measurements. This phenomenon may arise from non-stationary conditions, such as being in motion, experiencing emotional distress, or changing physical workload. Despite the presence of these large values, the distribution remains concentrated around a typical range for each individual, further supporting the strong correlation between HR and pulse, as highlighted in the previous paragraph discussing the correlation matrix.

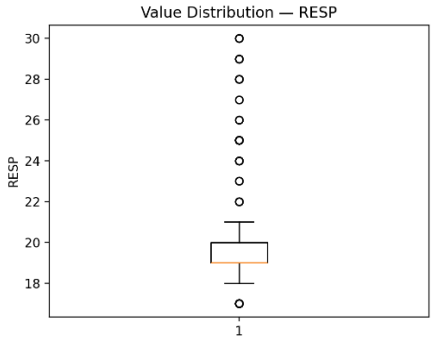


Figure 11. RESP value distribution

Figure 11 shows that the baseline values of respiratory rate (RESP) are closely distributed, indicating that breathing patterns were regular and within expected norms. However, if there are a significant number of extreme points above the upper boundary, this suggests spikes in some records. These spikes could be due to changes in respiration patterns caused by sudden movements, deep breaths, changes in body position, or even sensor errors. This indicates that the respiration signal is more sensitive to motion artifacts compared to other signals..

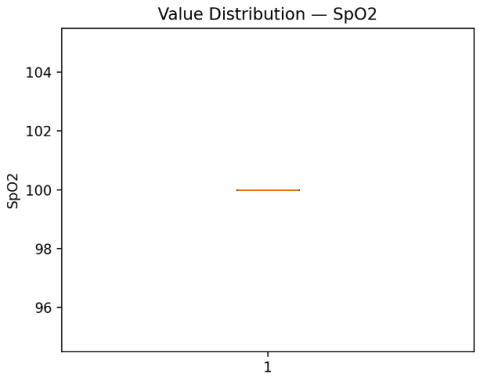


Figure 12. SpO_2 value distribution

Figure 12 shows that the final response demonstrates good stability of SpO_2 levels. The overall mean value remained unchanged, with no significant variations, indicating a normal level of oxygen saturation throughout the observation period. The absence of extreme values and large fluctuations confirms that SpO_2 is less volatile than other biomarkers, remaining stable in terms of respiratory efficiency at rest, unless an acute pathological process occurs. The average SpO_2 did not change during the measurement period, meaning that oxygen saturation stayed within the normal range throughout the entire

experiment. Without extreme values or large fluctuations, SpO_2 is indeed a more stable biomarker compared to others for assessing anomalies in this study. In contrast, heart rate and pulse exhibit similar distributions, with extreme events in pulse showing the same level of occurrence. However, the respiratory rate after a stroke demonstrates significant variation due to fluctuations in pulse, and changes in other biomarkers can occur within just one minute. These results highlight the natural variability in individual biomarker dynamics, emphasizing the importance of considering this variability when implementing intelligent anomaly detection, rather than relying on a static threshold-based approach.

Table.2. Anomalies detection by using dynamic threshold and Z-Score

vital	z3_count	dyn_count
HR	0	1
PULSE	0	0
SpO2	0	0
RESP	17	4

The comparison of the number of anomalies detected in various vital signs and their features using two different algorithms: Dynamic Threshold and Z-score. The vital signs measured include heart rate (HR), pulse, oxygen saturation (SpO_2), and respiratory rate (RESP), as shown in Table 2. The findings reveal that the Dynamic Threshold method identified one anomaly in heart rate and four anomalies in respiratory rate, but no anomalies in pulse or SpO_2. This suggests that the Dynamic Threshold method is more conservative. It is designed to minimize unnecessary alerts by only signaling an issue when a substantial and sustained anomaly is detected.

contrast, the Z-score method is more sensitive and responds quickly to changes. It detected 17 anomalies in respiratory rate but none in heart rate, pulse, or SpO_2. This increased sensitivity arises from its reliance on standard deviations from the mean, which allows it to react swiftly to sudden fluctuations, even if these are brief or merely noise. This characteristic explains the higher number of detected anomalies in respiratory rate compared to other parameters. In conclusion, the comparison indicates that while the Z-score method is more sensitive, it is also less reliable and tends to generate more false alarms. Conversely, the Dynamic Threshold method, while less sensitive, offers greater stability, only triggering alerts when significant deviations persist over time. Therefore, the combination of both approaches—using Dynamic Threshold to filter out noise and leveraging the sensitivity of Z-score—could prove beneficial to ensure that significant cases are not overlooked.

Table.3. Dynamic threshold and Z-Score for Anomalies detection

vital	z_in_IF	dyn_in_IF
HR	0	1
PULSE	0	0
SpO2	0	0
RESP	17	0

Table 3 compares the number of outliers detected using two methods—dynamic thresholding and Z-Score—against a common reference: the results obtained by the Isolation Forest model. As shown in Table She01, both traditional methods align with the smart model's detections for four key vital signs: heart rate (HR), pulse (PULSE), blood oxygen saturation (SpO_2), and respiration (RESP). The findings indicate that the dynamic thresholding method detected only one outlier for HR, with no other consistent results across the other vital signs compared to the Isolation Forest model. In contrast, the Z-Score method showed a strong alignment with the RESP model results, identifying 17 anomalies that matched the abnormal scores indicated by the Isolation Forest.

These findings confirm that the Z-Score method is more effective for outlier detection according to the smart model, particularly for rapidly changing biomarkers like respiration. Meanwhile, dynamic thresholding demonstrates a more conservative performance, which does not consistently match the smart model's detections but helps prevent unnecessary alarms in relatively stable signals such as HR and SpO_2. Overall, Z-Score is found to be effective in capturing frequent and short-term anomalies and shows high consistency with Isolation Forest results. On the other hand, dynamic thresholding is more suitable for stable signals but is less consistent in detecting subtle anomalies.

This comparison highlights the importance of utilizing both approaches: applying dynamic thresholds to reduce noise and false alarms while leveraging the sensitivity of Z-Score for early detection of anomalies in vulnerable biomarkers, all within an intelligent framework informed by the Isolation Forest for decision-making.

An exploratory benchmark was performed using 735 records from the PhysioNet/Computing in Cardiology Challenge 2015 dataset. The reference labels distinguish true arrhythmia alarms (n = 294) from false alarms (n = 441). The analyzed input consisted of ECG-derived features extracted from the 270–300 s pre-alarm window. The evaluation used five-fold cross-validation with out-of-fold predictions, comparing Z-Score, Isolation Forest, Logistic Regression, and a preliminary hybrid classifier.

The preliminary hybrid classifier combined supervised ECG features with Z-Score and Isolation Forest-derived scores. It should not be described as a validated dynamic-threshold or ECG–PLETH fusion system. PLETH feature integration was investigated separately and is not reflected in the performance results below.

Table 4. Overall out-of-fold classification performance on 735 records.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Z-Score	16.33	2.72	4.66	55.51
Isolation Forest	10.53	2.72	4.32	51.84
Logistic Regression	55.00	71.09	62.02	65.17
Hybrid Model	54.93	70.07	61.58	65.03

Logistic Regression achieved the highest overall F1-score (62.02%) and accuracy (65.17%). The preliminary hybrid model achieved an F1-score of 61.58% and accuracy of 65.03%, indicating no improvement over Logistic Regression in this experiment. The unsupervised Z-Score and Isolation Forest baselines exhibited very low recall (2.72%), highlighting their limited effectiveness for the evaluated alarm-verification task under the selected configurations.

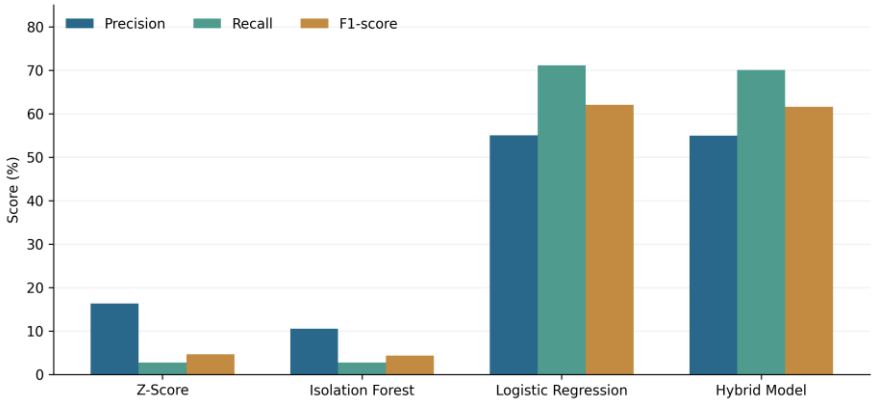


Figure 13. Precision, recall, and F1-score of the four evaluated models.

The hybrid classifier correctly classified 206 true alarms and 272 false alarms. It generated 169 false-positive classifications and missed 88 true alarms (false negatives).

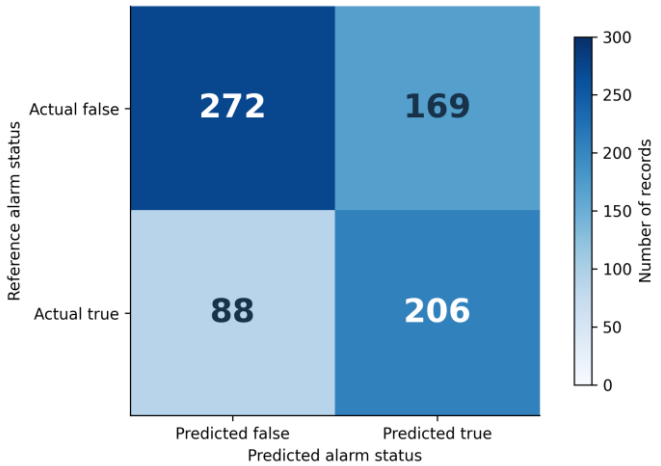


Figure 14. Out-of-fold confusion matrix for the preliminary hybrid model (n = 735).

Thus, although the model detected approximately 70% of true alarms, its false-positive burden remained substantial.

6. Conclusion

When using two statistical baselines—Z-score and dynamic thresholding—an unsupervised anomaly detection model, specifically the Isolation Forest, was applied to biometric time series data. Significant differences in performance were observed in the detection process. For instance, the static Z-score method produced a much higher number of alerts. The more noise or transient variations present in the signals, the more confidently the model could recognize them, making the noise-differentiated parameters more successful. In contrast, the adaptive local signal-agreeing threshold method reduced the number of alerts by utilizing local signal pattern analysis, effectively suppressing short-term anomalies while maintaining stability. On the other hand, the Isolation Forest model is more versatile, as it can identify various types of anomalies effectively. However, it can be challenging to differentiate true anomalies from false positives, particularly in cases where we observe increased heart rate alongside decreased SpO_2. The analysis of the time-series plot reveals a strong correlation between positive and negative relationships of vital signs. This indicates a high probability of significant correlations among different vital signs. The results demonstrate the advantages of AI-assisted models in IoT-based biometric monitoring, particularly regarding improved accuracy in anomaly detection and reduced false alarms compared to traditional statistical methods. Our findings suggest that the Isolation Forest algorithm can serve as a reliable monitoring and preventive service for IoT health data. This data can aid in fine-tuning the dynamic threshold window, which should be set approximately between 30 to 120 seconds, to achieve a balance between sensitivity and false alerts. Furthermore, it allows for the determination of contamination parameters based on the proportion of recognized anomalies during the calibration of the Isolation Forest model. Additionally, when labeled clinical events are available, it's essential to compare the performance of these AI-assisted methods with traditional statistical techniques. Metrics such as Precision, Recall, and F1-Score should be incorporated for a quantitative evaluation and to ensure that the model demonstrates superiority over baseline statistics-based approaches.

References

[1] K. Qi, "Advancing hospital healthcare: achieving IoT-based secure health monitoring through multilayer machine learning," *J. Big Data*, vol. 12, no. 1, Art. no. 1, 2025.

[2] Rehman, S. Abbas, M. A. Khan, T. M. Ghazal, K. M. Adnan, and A. Mosavi, "A secure healthcare 5.0 system based on blockchain technology entangled with federated learning technique," *Comput. Biol. Med.*, vol. 150, Art. no. 106019, 2022.

[3] U. Sadar, P. Agarwal, S. Parveen, S. Jain, and A. J. Obaid, "Heart disease prediction using machine learning techniques," in *Int. Conf. Data Sci., Mach. Learn. Appl.*, Singapore: Springer Nature Singapore, Dec. 2023, pp. 551–560.

[4] E. C. P. Neto, S. Dadkhah, S. Sadeghi, H. Molyneaux, and A. A. Ghorbani, "A review of machine learning (ML)-Based IoT security in healthcare: A dataset perspective," *Comput. Commun.*, vol. 213, pp. 61–77, 2024.

[5] Li, J. Wang, S. Wang, and Y. Zhang, "A review of IoT applications in healthcare," *Neurocomputing*, vol. 565, Art. no. 127017, 2024.

[6] R. Vasanth, M. Paranthaman, and P. Sivaprakash, "ML and IoT coupled biomedical applications in healthcare: Smart growth and upcoming challenges," in *Internet of Things Enabled Machine Learning for Biomedical Applications*, CRC Press, 2025, pp. 1–22.

[7] Das, U. Ghosh, S. Shetty, and S. Mohanty, "Machine learning-enabled IoT applications for smart healthcare monitoring systems," *Adv. Comput.*, vol. 137, pp. 175–218, 2025.

[8] Y. Asiri, H. T. Halawani, A. D. Algarni, and A. A. Alanazi, "IoT enabled healthcare environment using intelligent deep learning enabled skin lesion diagnosis model," *Alex. Eng. J.*, vol. 78, pp. 35–44, 2023.

[9] P. Roman-Naranjo, A. M. Parra-Perez, and J. A. Lopez-Escamez, "A systematic review on machine learning approaches in the diagnosis and prognosis of rare genetic diseases," *J. Biomed. Inform.*, vol. 143, Art. no. 104429, 2023.

[10] J. Singh, N. P. Singh, D. S. Hasan, N. A. Shelke, A. Namdev, and N. Girdhar, "An integrated machine learning and IoT based approach for enhanced healthcare efficiency and personalized treatment," in *Int. Conf. Intell. Syst. Design Appl.*, Cham: Springer Nature Switzerland, Dec. 2023, pp. 143–153.

[11] H. Hu, J. Xu, M. Liu, and M. K. Lim, "Vaccine supply chain management: An intelligent system utilizing blockchain, IoT and machine learning," *J. Bus. Res.*, vol. 156, Art. no. 113480, 2023.

[12] S. A. Siddiqui, A. Ahmad, and N. Fatima, "IoT-based disease prediction using machine learning," *Comput. Electr. Eng.*, vol. 108, Art. no. 108675, 2023.

[13] A. Ghubaish, T. Salman, M. Zolanvari, D. Unal, A. K. Al-Ali, and R. Jain, "Recent advances in the Internet of Medical Things (IoMT) systems security," *IEEE Internet Things J.*, vol. 8, no. 1, pp. 299–318, 2021, doi: 10.1109/JIOT.2020.3045653.

[14] A. Malibari, "An efficient IoT-Artificial intelligence-based disease prediction using lightweight CNN in healthcare system," *Measurement: Sensors*, vol. 26, Art. no. 100695, 2023.

[15] G. Rajkumar, T. G. Devi, and A. Srinivasan, "Heart disease prediction using IoT based framework and improved deep learning approach: Medical application," *Med. Eng. Phys.*, vol. 111, Art. no. 103937, 2023.

[16] K. K. Baseer, K. Sivakumar, D. Veeraiah, *et al.*, "Healthcare diagnostics with an adaptive deep learning model integrated with the internet of medical things (IoMT) for predicting heart disease," *Biomed. Signal Process. Control*, vol. 92, Art. no. 105988, 2024.

[17] R. Ghorbani, M. J. T. Reinders, and D. M. J. Tax, "Personalized anomaly detection in PPG data using representation learning and biometric identification," *Biomed. Signal Process. Control*, vol. 94, Art. no. 106216, 2024, doi: 10.1016/j.bspc.2024.106216.

[18] R. Xu *et al.*, "Assessing electrocardiogram and respiratory signal quality using an unsupervised isolation forest model," *mHealth*, vol. 9, Art. no. e25415, Aug. 2021, doi: 10.2196/25415.

[19] P. H. Charlton *et al.*, "The 2023 wearable photoplethysmography roadmap," *Physiol. Meas.*, vol. 44, no. 11, Art. no. 111001, 2023, doi: 10.1088/1361-6579/acdaeb.

[20] M. J. Rodrigues *et al.*, "Physiological and behavior monitoring systems for smart environments," *Sensors*, vol. 20, no. 8, Art. no. 2186, Apr. 2020, doi: 10.3390/s20082186.

[21] S. Sundrani *et al.*, "Predicting patient decompensation from continuous numeric and waveform vital sign monitoring in the emergency department," *NPJ Digit. Med.*, vol. 6, Art. no. 57, 2023, doi: 10.1038/s41746-023-00803-0.

[22] M. F. Mahdi, "Enhancing cloud security through artificial intelligence: Detecting advanced cyber attacks and analyzing anomalous patterns," *Int. J. Comput. Electron. Aspects Eng.*, vol. 6, no. 3, pp. 108–120, 2025.

[23] S. Q. Ameen, R. G. S. Alsultan, Z. S. Hussain, and Z. T. Abdul-Rahmman, "A hybrid RSA–ElGamal framework for secure end-to-end communications in resource-constrained IoT networks," *Int. J. Comput. Electron. Aspects Eng.*, vol. 7, no. 2, pp. 140–153, 2026.

[24] M. K. Yousif, "Enhanced diabetic retinopathy classification using hybrid EfficientNetB0 with CBAM," *Int. J. Comput. Electron. Aspects Eng.*, vol. 7, no. 2, pp. 176–188, 2026.

[25] L. H. Albak, "ANFIS-based intelligent framework for predicting health risk levels associated with diabetes and blood pressure abnormalities," *Int. J. Comput. Electron. Aspects Eng.*, vol. 7, no. 2, pp. 305–315, 2026.

[26] R. Abdulhammed, "A secure AI-based thalassemia diagnosis framework," *Int. J. Comput. Electron. Aspects Eng.*, vol. 7, no. 4, pp. 389–398, 2026.