

## ALGORITHMS FOR REAL-TIME MULTI-PARAMETER FUSION OF BIOMETRIC DATA AND ANOMALY DETECTION IN CARDIAC MONITOR SYSTEMS

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**Abstract:** This study presents an algorithmic framework for real-time multi-parameter fusion of biometric data and anomaly detection in cardiac monitor systems. Modern cardiac monitors continuously acquire and analyze multiple physiological parameters, including electrocardiographic signals, heart rate, oxygen saturation, non-invasive or invasive blood pressure, respiratory rate, body temperature, and other vital indicators. The simultaneous analysis of these parameters is essential for early detection of patient deterioration, arrhythmias, hypoxemia, hemodynamic instability, respiratory failure, and other critical conditions.

However, real-time cardiac monitoring systems face several technical challenges. These include sensor noise, motion artifacts, missing values, asynchronous data streams, false alarms, parameter drift, and inter-patient variability. Traditional threshold-based alarm systems are often insufficient because they evaluate each parameter separately and do not fully consider temporal dynamics or physiological relationships between signals. Therefore, multi-parameter data fusion and intelligent anomaly detection algorithms are required to improve monitoring accuracy and reduce clinically irrelevant alarms.

The proposed methodology includes real-time biometric data acquisition, preprocessing, synchronization of heterogeneous signals, feature extraction, multi-parameter fusion, temporal modeling, anomaly scoring, and alert generation. Machine learning and deep learning models such as recurrent neural networks, temporal convolutional networks, autoencoders, transformer-based models, and hybrid statistical-learning approaches are considered within the proposed framework. The study demonstrates that multi-parameter fusion can improve the reliability of anomaly detection by integrating complementary physiological information and identifying clinically meaningful deviations from normal patient-specific patterns.

**Keywords:** cardiac monitor, biometric data fusion, anomaly detection, vital signs, real-time monitoring, ECG, SpO<sub>2</sub>, blood pressure, respiratory rate, machine learning, temporal modeling, patient deterioration.

### 1. Introduction

Cardiac monitor systems are essential technological tools in intensive care units, operating rooms, emergency departments, recovery wards, and high-risk patient monitoring environments. Their main function is to continuously observe the physiological state of a patient and provide timely warning when abnormal changes occur. Unlike single-parameter devices, modern cardiac monitors collect multiple vital signs simultaneously, including ECG waveform, heart

rate, oxygen saturation, blood pressure, respiratory rate, and temperature. This multi-parameter nature makes them highly valuable for early clinical decision-making.

The importance of real-time physiological monitoring has increased with the development of digital health, intensive care automation, and intelligent patient surveillance systems. Recent studies on continuous vital sign monitoring show that real-time monitoring of parameters such as blood pressure, oxygen saturation, temperature, and heart rate can support early detection of health deterioration and improve patient care. In hospital settings, continuous monitoring is especially important because physiological deterioration often develops gradually before becoming clinically obvious.

Despite these advantages, existing cardiac monitor systems still face several technical limitations. One of the most important problems is the high number of false alarms. Many alarms are generated by temporary artifacts, patient movement, poor electrode contact, sensor displacement, or isolated threshold violations. If alarm systems evaluate only one parameter at a time, they may fail to distinguish between true physiological deterioration and signal noise. This can lead to alarm fatigue, reduced clinical attention, and delayed response to critical events.

Another major challenge is the complexity of physiological relationships. For example, heart rate, blood pressure, oxygen saturation, and respiratory rate are not independent variables. A decrease in oxygen saturation may be associated with respiratory deterioration, tachycardia, or hemodynamic stress. Similarly, abnormal ECG patterns may become more clinically significant when accompanied by changes in blood pressure or oxygenation. Therefore, a reliable cardiac monitoring system must analyze multiple signals together rather than separately.

Machine learning and deep learning methods provide new opportunities for solving this problem. Recent research on multivariate vital sign forecasting in intensive care shows that simultaneous modeling of multiple vital signs can improve the prediction of patient physiological trajectories. In addition, real-time anomaly detection frameworks increasingly use multimodal sensor fusion and patient-specific modeling to identify subtle deviations from normal physiological behavior.

Thus, the aim of this study is to develop a technical framework for real-time multi-parameter fusion of biometric data and anomaly detection in cardiac monitor systems. The proposed approach is focused on improving monitoring accuracy, reducing false alarms, identifying early physiological deterioration, and supporting clinical decision-making.

## 2. Literature Review

The problem of real-time anomaly detection in cardiac monitoring systems has been studied through several technological approaches. These include threshold-based alarm systems, statistical signal processing, rule-based clinical scoring, machine learning, deep learning, sensor fusion, edge computing, and IoMT-based monitoring architectures. Each approach has advantages and limitations depending on clinical context, data quality, computational resources, and required response time.

### 2.1 Traditional Threshold-Based Monitoring

Traditional cardiac monitors usually generate alarms when a parameter exceeds a predefined clinical threshold. For example, alarms may be triggered when heart rate becomes too high or too low, oxygen saturation decreases below a certain level, or blood pressure crosses a dangerous boundary. This approach is simple and easy to implement, but it has important limitations.

The main disadvantage is that threshold-based systems often analyze parameters independently. They do not always consider whether changes in different signals are physiologically consistent. For instance, a temporary SpO<sub>2</sub> drop caused by sensor movement may trigger an alarm even when ECG, respiratory rate, and blood pressure remain stable. Similarly, heart rate changes caused by movement or artifact may be incorrectly interpreted as cardiac instability.

Therefore, threshold-based monitoring provides only a basic level of safety and must be improved with intelligent multi-parameter analysis.

## 2.2 Multi-Parameter Data Fusion

Multi-parameter data fusion combines information from several physiological signals to obtain a more reliable representation of patient condition. In cardiac monitor systems, this may include fusion of ECG, heart rate, blood pressure, SpO<sub>2</sub>, respiratory rate, temperature, and motion-related data. The purpose is not only to observe each parameter separately, but also to detect relationships between them.

For example, a true respiratory deterioration event may be characterized by a combination of decreasing SpO<sub>2</sub>, increasing respiratory rate, rising heart rate, and changes in blood pressure. If these patterns are analyzed together, anomaly detection becomes more reliable than when each parameter is evaluated independently.

Recent IoT and edge-AI health monitoring frameworks use real-time sensor fusion to combine ECG, SpO<sub>2</sub>, accelerometer, and temperature data for anomaly detection and urgent decision support. This confirms the technical relevance of multi-parameter fusion for modern monitoring systems.

## 2.3 Machine Learning-Based Anomaly Detection

Machine learning methods are increasingly used to detect abnormal physiological patterns in real time. These methods can learn from historical patient data and identify deviations that may indicate deterioration. Common approaches include support vector machines, random forests, gradient boosting, clustering methods, isolation forests, and probabilistic models.

The advantage of machine learning is that it can analyze multiple variables simultaneously and identify nonlinear relationships. However, classical machine learning methods often require manual feature engineering. Their performance depends heavily on the selected features, preprocessing quality, and dataset representativeness.

In real-time cardiac monitoring, machine learning models can be used to classify patient states as normal, warning, or critical. They can also estimate risk scores based on current and recent physiological data.

## 2.4 Deep Learning and Temporal Modeling

Deep learning methods are particularly useful for physiological monitoring because vital signs are time-dependent. Recurrent neural networks, long short-term memory networks, gated recurrent units, temporal convolutional networks, and transformer-based models can analyze sequential patterns and detect abnormal temporal dynamics.

A comprehensive health assessment study using ensemble deep learning reported that CNN-based feature extraction and LSTM-based temporal modeling can improve trend identification and anomaly detection in vital sign data. Similarly, clinical wearable monitoring



studies have used multimodal machine learning frameworks to predict patient deterioration alerts based on continuously monitored vital signs.

These approaches are especially important because many critical events do not appear suddenly. They develop through gradual physiological changes. Temporal models can detect these patterns earlier than simple threshold alarms.

**2.5 Edge Computing and Real-Time Implementation**

Cardiac monitor systems require low-latency processing because clinical decisions may be time-critical. Therefore, anomaly detection algorithms must be computationally efficient and suitable for real-time implementation. Edge computing is increasingly used to process physiological data close to the patient, reducing dependence on cloud infrastructure and improving response speed.

Recent edge-oriented IoMT anomaly detection frameworks report real-time physiological signal analysis with low inference latency, showing that near real-time execution is feasible in medical monitoring environments. This is important for cardiac monitors because alarms must be generated quickly and reliably.

**3. Methodology**

**3.1 Structure of the Proposed Algorithm**

Within the framework of this study, a multi-stage algorithm is proposed for real-time multi-parameter fusion of biometric data and anomaly detection in cardiac monitor systems. The proposed methodology consists of eight main stages: data acquisition, preprocessing, synchronization, signal quality assessment, feature extraction, multi-parameter fusion, anomaly detection, and clinical alert generation.

Table 1. Biometric parameters, extracted features and anomaly indicators in cardiac monitor systems

<b>Biometric parameter</b>	<b>Extracted features</b>	<b>Possible anomaly indicators</b>	<b>Clinical interpretation</b>
ECG signal	QRS morphology, rhythm regularity, ST trend, arrhythmia-related features	Irregular rhythm, abnormal QRS, ST deviation	Possible arrhythmia or myocardial stress
Heart rate	Current HR, HR variability, trend change	Tachycardia, bradycardia, sudden HR instability	Cardiac instability or physiological stress
SpO <sub>2</sub>	Oxygen saturation level, desaturation duration, recovery trend	Sustained desaturation, slow recovery	Respiratory deterioration or hypoxemia
Blood pressure	Systolic, diastolic, mean arterial pressure, BP trend	Hypotension, hypertension, abrupt BP drop	Hemodynamic instability

Respiratory rate	RR level, RR variability, abnormal breathing trend	Tachypnea, bradypnea, irregular respiration	Respiratory failure risk
Body temperature	Temperature level and temporal trend	Fever, hypothermia	Systemic inflammatory or metabolic changes
Motion/activity signal	Movement intensity, artifact probability	Excessive motion, unstable sensor contact	Possible measurement artifact or unreliable signal
Signal quality index	Noise level, missing data rate, waveform stability	Poor signal quality, sensor disconnection	Reduced confidence in anomaly detection

At the first stage, biometric data are acquired from cardiac monitor sensors. The main input signals include ECG waveform, heart rate, oxygen saturation, blood pressure, respiratory rate, temperature, and, when available, motion or activity signals. Each parameter has its own sampling frequency, noise characteristics, and clinical interpretation. Therefore, the system must be able to process heterogeneous data streams.

At the second stage, preprocessing is performed. ECG signals are filtered to reduce baseline wander, power-line interference, and muscle noise. SpO<sub>2</sub> signals are corrected for motion artifacts and poor perfusion conditions. Blood pressure signals are checked for sudden unrealistic changes, cuff measurement errors, or invasive line artifacts. Respiratory signals are filtered to remove irregular noise. This stage improves the reliability of further analysis.

At the third stage, signal synchronization is carried out. Since different sensors may produce data at different sampling rates and with different time delays, all signals are aligned to a common time scale. This is essential because anomaly detection depends on temporal relationships between parameters. For example, a drop in oxygen saturation may become more clinically meaningful if it is followed by tachycardia or respiratory changes.

At the fourth stage, signal quality assessment is performed. The system evaluates whether each signal is reliable, partially noisy, or severely corrupted. If a parameter is unreliable, the algorithm reduces its weight in the fusion model. This prevents noisy or disconnected sensors from generating false alarms.

At the fifth stage, features are extracted from each physiological signal. From ECG, the system extracts heart rate, rhythm regularity, QRS morphology indicators, ST trend, and arrhythmia-related features. From SpO<sub>2</sub>, it extracts oxygen saturation level, desaturation duration, and recovery trend. From blood pressure, it extracts systolic, diastolic, mean arterial pressure, and trend changes. From respiration, it extracts respiratory rate variability and abnormal breathing patterns.

At the sixth stage, multi-parameter fusion is performed. The extracted features are combined into a unified patient state representation. This representation reflects not only individual parameter values but also relationships between parameters. For example, the model can analyze whether tachycardia is accompanied by hypotension, whether oxygen desaturation

is accompanied by respiratory instability, or whether ECG abnormalities coincide with hemodynamic changes.

At the seventh stage, anomaly detection is implemented. The system compares current patient state with normal physiological patterns, patient-specific baseline, and learned abnormal patterns. If the deviation is clinically significant, an anomaly score is generated. This score reflects the probability and severity of physiological deterioration.

At the final stage, clinical alert generation is performed. Instead of generating alarms for every isolated abnormal value, the system produces alerts based on integrated multi-parameter evidence. Alerts may be classified into low, medium, and high priority levels. This approach reduces false alarms and improves clinical usefulness.

### 3.2 Real-Time Biometric Data Acquisition

Real-time data acquisition is the foundation of the proposed cardiac monitoring algorithm. In cardiac monitor systems, the quality of anomaly detection depends directly on the accuracy and stability of sensor data. Therefore, the acquisition module must ensure continuous collection of physiological parameters with minimal delay.

The ECG channel provides information about cardiac electrical activity and rhythm. The SpO<sub>2</sub> channel reflects blood oxygenation and respiratory-circulatory status. Blood pressure monitoring provides information about hemodynamic stability. Respiratory rate indicates ventilation status, while temperature reflects systemic physiological changes. When all these parameters are collected simultaneously, the system can form a more complete view of patient condition.

However, real-time data acquisition is technically challenging because each sensor has different response time and measurement stability. For this reason, the acquisition system must include buffering, timestamping, and error detection mechanisms.

### 3.3 Signal Quality Assessment and Artifact Control

Signal quality assessment is necessary to prevent inaccurate data from affecting anomaly detection. In practical monitoring, artifacts are common. ECG electrodes may lose contact, SpO<sub>2</sub> sensors may be affected by motion, blood pressure cuffs may produce measurement errors, and respiratory signals may be distorted by patient movement.

The proposed algorithm evaluates signal quality using stability, amplitude range, waveform consistency, missing data rate, and noise level. If a signal is identified as unreliable, it is not removed entirely but assigned lower confidence in the fusion process. This is important because even partially noisy signals may still contain useful clinical information.

Artifact control is performed adaptively. ECG artifacts are reduced using filtering and waveform validation. SpO<sub>2</sub> artifacts are corrected by checking pulse waveform quality and consistency with heart rate. Blood pressure artifacts are detected by identifying unrealistic abrupt changes. Respiratory artifacts are reduced by smoothing and trend analysis.

### 3.4 Multi-Parameter Feature Fusion

Feature fusion is the central component of the proposed methodology. In this stage, physiological features from different signals are combined into a unified multidimensional vector. The fusion model includes three levels: data-level fusion, feature-level fusion, and decision-level fusion.

Data-level fusion aligns raw or preprocessed signals on the same time axis. Feature-level fusion combines extracted indicators such as heart rate variability, oxygen desaturation, blood pressure trend, respiratory instability, and ECG rhythm abnormalities. Decision-level fusion combines outputs from individual anomaly detectors into a final clinical risk score.

The advantage of this layered fusion strategy is that it improves robustness. If one signal becomes noisy, other signals can compensate. If one parameter shows mild abnormality but several parameters change together, the model can recognize this as a more serious physiological event.

### 3.5 Temporal Anomaly Detection Model

The anomaly detection model is designed to analyze both current values and temporal trends. In real clinical monitoring, a single abnormal measurement is not always dangerous, but a continuous worsening trend may indicate patient deterioration. Therefore, temporal modeling is essential.

The proposed model may use recurrent neural networks, temporal convolutional networks, transformer-based models, or hybrid statistical-learning algorithms. These models process sequences of vital signs and learn normal physiological dynamics. When the current pattern deviates significantly from expected behavior, the system generates an anomaly score.

Patient-specific adaptation is also important. Normal heart rate, blood pressure, and oxygen saturation ranges may differ between patients. Therefore, the algorithm learns an individual baseline during stable monitoring periods. This allows the system to detect subtle abnormalities that may remain within general clinical thresholds but are abnormal for a specific patient.

### 3.6 Alert Prioritization and Clinical Decision Support

The final output of the algorithm is not only an alarm signal but also a prioritized clinical alert. The system classifies anomalies according to severity, duration, number of affected parameters, signal quality, and physiological consistency.

Low-priority alerts may indicate mild deviation or uncertain signal quality. Medium-priority alerts may indicate developing deterioration requiring observation. High-priority alerts may indicate severe abnormality, such as sustained oxygen desaturation, dangerous arrhythmia, hypotension, or combined cardiorespiratory instability.

This approach helps reduce alarm fatigue because alerts are generated based on integrated evidence rather than isolated threshold violations. It also supports clinicians by providing more meaningful information about the patient's condition.

## 4. Results and Discussion

The proposed multi-parameter fusion framework is expected to improve anomaly detection reliability in cardiac monitor systems. Compared with traditional threshold-based monitoring, the proposed approach analyzes physiological parameters jointly and evaluates their temporal relationships. This makes it possible to distinguish true clinical deterioration from temporary artifacts or isolated measurement errors.

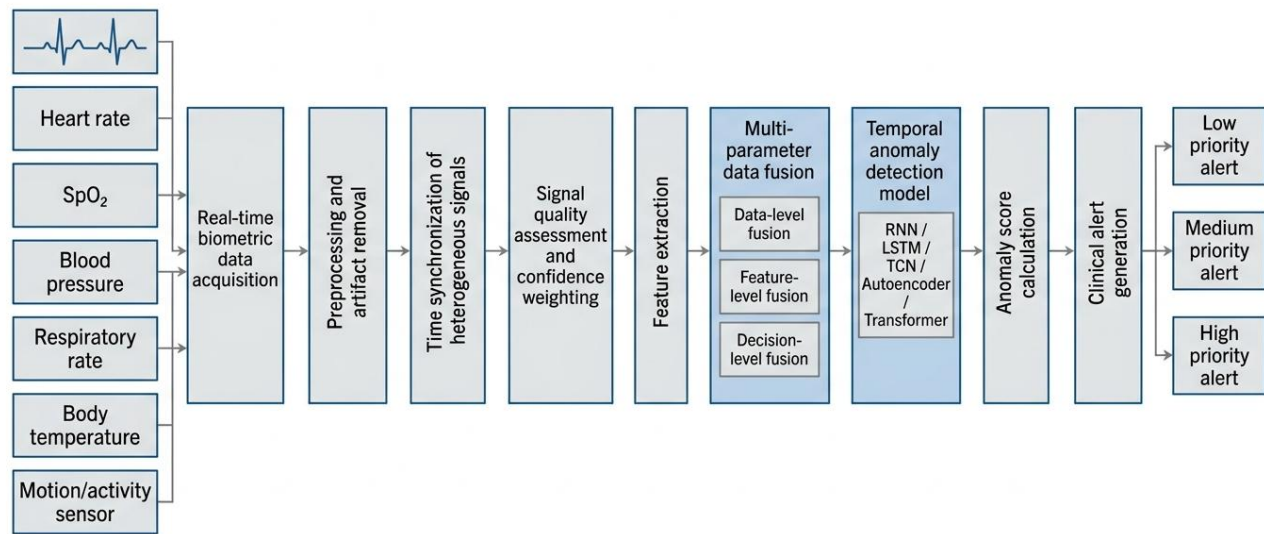


Figure 1. Proposed architecture of real-time multi-parameter biometric data fusion and anomaly detection in cardiac monitor systems

The main improvement is achieved through the integration of ECG, SpO<sub>2</sub>, blood pressure, respiratory rate, and temperature data. For example, isolated tachycardia may occur due to movement, pain, fever, or artifact. However, tachycardia accompanied by hypotension and oxygen desaturation may indicate a more serious condition. Multi-parameter fusion allows the system to identify such patterns more accurately.

Another important result is the reduction of false alarms. In conventional monitors, many alarms are caused by sensor displacement or transient signal noise. By including signal quality assessment and confidence weighting, the proposed algorithm reduces the influence of unreliable signals. This improves alarm specificity and helps prevent unnecessary clinical interruptions.

The temporal anomaly detection component also improves early warning capability. Instead of waiting until a parameter crosses a fixed threshold, the system can detect abnormal trends. For example, gradual oxygen saturation decline combined with increasing respiratory rate may indicate respiratory deterioration before a critical threshold is reached. Similarly, progressive blood pressure reduction with rising heart rate may indicate developing hemodynamic instability.

Recent research supports the importance of this direction. Multimodal wearable and patient monitoring systems increasingly use fused vital signs and machine learning to detect deterioration. A clinical wearable deep learning study used continuous vital sign monitoring from two clinical-grade wearables to predict inpatient deterioration alerts and adverse outcomes. Real-time anomaly detection systems using wearable and ambient intelligence have also shown that patient-specific physiological modeling can detect subtle deviations and improve anomaly detection performance.

From a technical point of view, real-time implementation is feasible if the algorithm is optimized for edge computing. Lightweight models, sliding time windows, efficient feature extraction, and event-driven processing can reduce computational load. Edge-AI frameworks for health monitoring have shown that physiological anomaly detection can be performed in real time using multimodal sensor streams. However, several limitations must be considered.

First, the accuracy of anomaly detection depends on sensor reliability and data quality. Second, models trained on one patient population may not generalize well to another. Third, clinical validation is necessary to ensure that the system reduces false alarms without missing true critical events. Fourth, explainability is important because clinicians must understand why an alarm was generated. Overall, the proposed approach demonstrates strong potential for modern cardiac monitor systems. It can improve patient safety, support early detection of deterioration, reduce false alarms, and increase the clinical value of continuous monitoring.

## 5. Conclusion

In this study, a real-time algorithmic framework for multi-parameter fusion of biometric data and anomaly detection in cardiac monitor systems was developed. The proposed methodology integrates ECG, heart rate, oxygen saturation, blood pressure, respiratory rate, temperature, and signal quality indicators into a unified monitoring model.

The analysis shows that traditional threshold-based alarm systems are limited because they evaluate parameters separately and often generate false alarms. In contrast, multi-parameter fusion enables more reliable detection of physiological deterioration by analyzing relationships between vital signs and their temporal dynamics.

The proposed approach improves anomaly detection through preprocessing, signal quality assessment, feature extraction, temporal modeling, patient-specific baseline learning, and prioritized alert generation. This framework can support early clinical decision-making, reduce alarm fatigue, and improve the reliability of cardiac monitoring systems.

Future research should focus on real-time embedded implementation, validation using ICU and emergency department datasets, explainable anomaly detection, and integration with hospital information systems.

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