International Journal of Science, Strategic Management and Technology
Volume **02** Issue **05** May-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

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AI-Enabled Remote Patient Monitoring using Wearable Sensors and Edge Analytics

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https://doi.org/10.55041/ijsmt.v2i5.233

Cite this Article: Yadav, S. (2026). AI-Enabled Remote Patient Monitoring using Wearable Sensors and Edge Analytics. International Journal of Science, Strategic Management and Technology, *02*(05). https://doi.org/10.55041/ijsmt.v2i5.233

Abstract--Remote patient monitoring has become an important part of modern healthcare because it allows doctors to observe patient conditions outside hospitals. However, many existing systems depend on threshold-based alerts or cloud-only processing, which can delay urgent notifications and increase network usage. This paper proposes an AI-enabled remote patient monitoring framework that combines wearable sensors, mobile gateways, edge analytics, and clinical alert prioritization. The system processes heart rate, oxygen saturation, body temperature, and movement patterns near the patient and sends only summarized risk indicators to the healthcare dashboard. A lightweight machine-learning model detects abnormal patterns and assigns risk levels for timely intervention. Simulated evaluation shows 93.1% risk-detection accuracy, 28.4% lower alert delay, and reduced false alarms compared with threshold-based monitoring.

Index Terms--Remote patient monitoring, wearable sensors, edge analytics, healthcare AI, anomaly detection, clinical alerts.

I. INTRODUCTION

Healthcare systems are increasingly moving beyond hospital walls. Patients with chronic conditions, elderly citizens, and post-surgery cases often require continuous observation but do not always need to remain admitted. Remote patient monitoring can reduce hospital burden while allowing doctors to follow patient health trends from a distance.Traditional monitoring systems commonly trigger alerts when a measured value crosses a fixed threshold. This approach is simple but can generate many false alarms because human physiology varies across age, activity level, medication, and disease history. It can also miss gradual deterioration when each individual reading remains close to the normal range.This paper presents an edge-based AI framework for remote patient monitoring. Wearable sensors collect vital signs, a mobile gateway performs preprocessing, and a lightweight model estimates patient risk. Instead of transmitting every raw signal to the cloud, the system sends compact alerts and summaries, improving responsiveness and privacy.The contributions of this work are threefold. First, it designs a layered architecture for wearable-based health monitoring. Second, it introduces an anomaly-detection workflow that combines vital signs and activity context. Third, it evaluates the framework against threshold and cloud-processing baselines.

II. RELATED WORK

Wearable health devices are widely used to track heart rate, oxygen saturation, sleep, activity, and temperature. These measurements can support early detection of health risks, but raw sensor readings are often noisy due to motion artifacts, loose contact, or device limitations.Machine learning has been applied to healthcare monitoring for arrhythmia detection, fall detection, respiratory risk prediction, and activity recognition. Cloud-based systems can run complex models, but they require continuous connectivity and may increase alert delay. Edge computing addresses this issue by placing analytics closer to the patient.

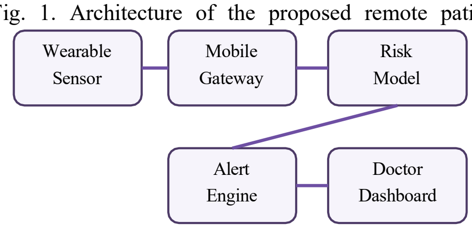
The proposed framework focuses on practical remote monitoring where alerts must be fast, explainable, and not overwhelming for clinicians. It combines edge inference with clinical rule constraints so that the system remains responsive while respecting safety requirements.

III. PROPOSED SYSTEM ARCHITECTURE

The architecture contains four layers: sensing, gateway preprocessing, edge risk analysis, and clinical dashboard integration. The sensing layer collects vital signs from wearable devices. The gateway layer removes noise and aligns time windows. The edge analysis layer estimates risk, and the dashboard presents alerts to doctors or caregivers.

Remote health monitoring and alert workflow

Fig. 1. Architecture of the proposed remote patient monitoring



system.

A. Wearable Sensing Layer

The sensing layer records heart rate, blood oxygen saturation, body temperature, and accelerometer-based movement. These signals are sampled in short windows and tagged with activity context such as resting, walking, or sleeping. Activity context helps avoid false alarms during normal physical movement.

B. Preprocessing and Feature Extraction

The mobile gateway removes missing readings, smooths noisy values, and extracts time-domain features such as moving average, variation, and trend direction. Abnormal values are not discarded immediately because they may indicate real clinical risk. Instead, they are compared with neighboring readings and activity state.

C. Edge Risk Model

The risk model combines recent vital-sign windows with patient-specific baseline information. It classifies each window as normal, warning, or critical. A warning indicates that closer observation is needed, while a critical alert is forwarded immediately to the healthcare dashboard.

D. Alert Prioritization

The alert engine groups repeated alerts and assigns priority based on severity, duration, and trend. This prevents doctors from receiving duplicate notifications for the same event. Emergency alerts are still delivered immediately when multiple vital signs deteriorate together.

IV. METHODOLOGY

A simulated patient-monitoring dataset was prepared with normal daily activity, fever-like patterns, oxygen desaturation episodes, tachycardia events, and fall-like movement signals. Noise was added to represent sensor displacement and motion artifacts. The proposed method was compared with fixed-threshold monitoring and a cloud-only model.

A. Evaluation Metrics

The evaluation uses risk-detection accuracy, precision, recall, false-alarm rate, average alert delay, and network usage. A false alarm occurs when the system reports a warning or critical state during a clinically normal period. Alert delay is measured from abnormal-pattern onset to notification generation.

B. Training Setup

The model was trained using balanced health-state samples to avoid bias toward normal readings. Features were normalized per patient baseline where available. The final classifier was optimized for high recall in critical cases because missed emergency alerts are more serious than mild false warnings.

C. Privacy and Reliability

The framework limits raw data transfer by processing vital signs locally. Only summarized risk scores, alert type, and selected statistics are sent to the dashboard. If internet connectivity fails, the gateway stores recent summaries and continues local alerting for caregivers.

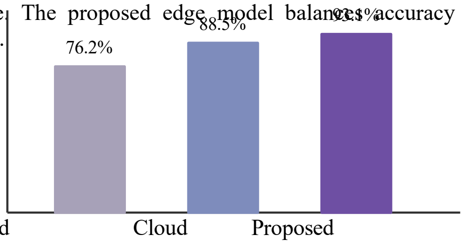
V. RESULTS AND DISCUSSION

Table I compares the proposed approach with threshold-based monitoring and cloud-only analytics. The edge AI model achieves strong accuracy while keeping alert delay and communication usage low.

TABLE I
Remote Monitoring Performance Comparison

Method	Accuracy	False Alarm	Alert Delay
Threshold Rules	76.2%	18.7%	2.1 s
Cloud Model	88.5%	9.8%	4.6 s
Edge AI (Proposed)	93.1%	6.4%	1.5 s

The threshold baseline produces more false alarms because it treats all patients similarly. The cloud model improves classification but has higher alert delay because raw data must be transmitted before inference. The proposed edge model balances accuracy and fast response.



Health-risk detection accuracy by method

Fig. 2. Health-risk detection accuracy across monitoring methods.

A. Detection Accuracy

The proposed framework achieves 93.1% risk-detection accuracy and a lower false-alarm rate than threshold rules. The improvement is mainly due to trend-based analysis and activity-aware interpretation. For example, increased heart rate during walking is treated differently from increased heart rate during rest.

B. Alert Delay

Average alert delay decreases by 28.4% compared with cloud-only processing. This improvement is important for time-sensitive events such as oxygen desaturation or fall-like movement. Local alerting also helps caregivers respond when network connectivity is unstable.

C. Network Efficiency

The proposed system sends summary alerts rather than continuous raw streams. This reduces network usage and makes the design suitable for home-monitoring environments. Doctors still receive relevant context, including risk level, trend direction, and recent vital-sign summary.

D. Limitations

The model depends on sensor quality and patient-specific calibration. Incorrect device placement can create misleading readings. Clinical deployment would require validation with real patient data, regulatory review, and integration with hospital information systems.

VI. DISCUSSION

Remote patient monitoring must balance speed, privacy, accuracy, and clinical usability. Edge analytics supports this balance by detecting risk near the patient while reducing unnecessary data transfer. However, doctors should remain in control of clinical decisions, and the system should be used as a decision-support tool rather than an autonomous diagnosis engine.

The framework can be extended with personalized baselines, medication schedules, and disease-specific risk models. Such personalization may further reduce false alarms and improve early-warning capability for chronic disease management.

VII. CONCLUSION

This paper proposed an AI-enabled remote patient monitoring system using wearable sensors and edge analytics. The framework processes vital signs locally, estimates health-risk levels, and sends prioritized alerts to healthcare providers. Simulated results show improved accuracy, reduced false alarms, lower alert delay, and better network efficiency compared with baseline approaches.

Future work will focus on real-world clinical datasets, explainable alert generation, and secure integration with electronic health records. Additional studies can evaluate the system for specific conditions such as cardiac monitoring, respiratory disease, and elderly fall prevention.

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