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Ai In Healthcare: A Review Of Smart Health Monitoring With Iot Wearables, Early Warning Scores And Predictive Deterioration Analytics

Thorat Pradnya Ajit[1]; Prof. S. S. Bhor[2]; Prof. M. C. Kolse[3]; Prof. S. K. Said[4]
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, India;

Abstract—Continuous monitoring of patient health is essential for early diagnosis and timely treatment, but conventional care depends on periodic manual checks that can miss critical changes between rounds. This paper reviews AI-based smart health monitoring for hospitals and home care. It examines IoT-enabled wearable sensors and medical devices that measure heart rate, temperature, blood oxygen saturation, blood pressure and activity; clinical early warning scores that convert vital signs into a risk score; and machine learning models that predict clinical deterioration more accurately than conventional regression, along with deep learning on electrocardiograms for arrhythmia detection, continuous prediction of acute kidney injury from electronic health records and large-scale smartwatch studies of atrial fibrillation. Public critical-care databases that enable model development are discussed. CNNs, random forests and SVMs for anomaly detection and classification of patient status as normal, warning or critical are compared using accuracy, precision and recall. A five-layer architecture comprising sensing, edge processing, secure communication, clinical analytics and care-team dashboard layers is proposed, together with research gaps, objectives, a comparison of monitoring approaches and challenges such as alarm fatigue, data quality, privacy, interoperability and clinical validation. The review concludes that AI-assisted monitoring can enable earlier intervention when designed to support clinicians.
Index Terms—Smart health monitoring, AI in healthcare, IoT wearables, early warning score, clinical deterioration, ECG, anomaly detection, remote patient monitoring

I. INTRODUCTION

On a busy hospital ward, nurses record vital signs every few hours. A patient may deteriorate between these checks, and subtle trends such as a slowly rising respiratory rate or falling oxygen saturation can be missed. At home, patients with chronic conditions are often monitored only at clinic visits.

Early warning scores such as the National Early Warning Score (NEWS) aggregate vital signs into a single number that triggers escalation. Smith *et al.* [1] showed that NEWS discriminates patients at risk of cardiac arrest, unplanned ICU admission and death.

AI can extend this idea by learning from continuous data and electronic health records to predict deterioration earlier and more accurately.

This paper reviews smart health monitoring technologies and AI methods and proposes a layered architecture for hospitals and home care.

II. BACKGROUND AND RELATED WORK

1. Monitored Parameters And Sensors

Fig. 1 groups monitored parameters into cardiovascular, respiratory, metabolic and activity signals, with typical sensors.



Fig. 1. Parameters and sensors in smart health monitoring.

2. Patient Status Levels

Systems classify patient condition into levels such as normal, warning and critical, each linked to an escalation protocol.

3. Review Of Related Studies

Early warning and deterioration. Smith *et al.* [1] validated NEWS as a predictor of adverse events. Churpek *et al.* [2] compared machine learning methods with logistic regression for predicting ward deterioration across multiple hospitals and found that

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random forests and gradient boosting were more accurate.

Deep learning on clinical data. Rajkomar *et al.* [3] predicted in-hospital mortality and readmission from raw electronic health records. Tomašev *et al.* [4] continuously predicted acute kidney injury up to 48 hours before it occurred. Hannun *et al.* [5] trained a deep network on single-lead ambulatory ECGs that classified arrhythmias with cardiologist-level performance.

Wearables. Perez *et al.* [6] studied more than 400,000 participants using a smartwatch to detect irregular pulse and found that notifications had a high positive predictive value for atrial fibrillation confirmed by ECG patch.

Data. MIMIC-III [7] is a freely accessible critical-care database widely used to develop monitoring models. Table I summarizes these works.

Ref.	Method	Key Findings	Limitations
[1]	NEWS validation	Predicts adverse events	Intermittent vitals
[2]	ML vs. regression on wards	ML more accurate	U.S. hospitals
[7]	MIMIC-III database	Open ICU data	Single centre
[3]	Deep learning on EHR	Accurate outcome prediction	Complex pipeline
[5]	ECG deep network	Cardiologist-level arrhythmia	Single-lead
[4]	Continuous AKI prediction	48-hour early warning	False positives
[6]	Smartwatch AF study	Large-scale screening	Low notification rate

TABLE I Summary of Literature Survey

III. RESEARCH GAP AND OBJECTIVES

1. Identified Research Gaps

- **G1:** Frequent false alarms cause alarm fatigue among staff.
- **G2:** Consumer wearables are less accurate than medical devices.
- **G3:** Models trained in one hospital may not generalize to others.
- **G4:** Few systems integrate home and hospital monitoring.
- **G5:** Privacy and security of continuous health data need strong protection.

2. Objectives Of The Review

- **O1:** To review IoT sensors and wearables for health monitoring.
- **O2:** To examine early warning scores and machine learning for deterioration prediction.
- **O3:** To compare classifiers for patient status classification.
- **O4:** To propose a five-layer smart health monitoring architecture.
- **O5:** To discuss challenges, privacy and clinical validation.

IV. DESIGN OF THE PROPOSED SYSTEM

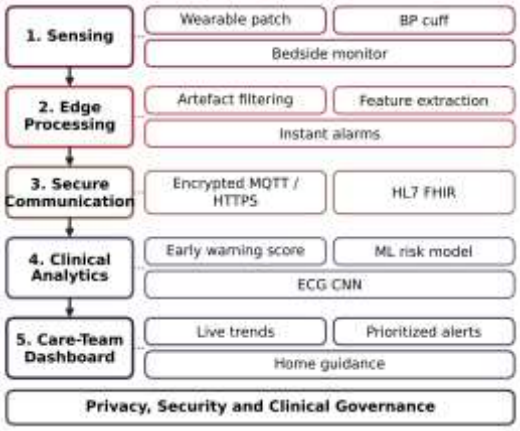


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI-based smart health monitoring architecture.

1. Sensing Layer

Wearable patches or bands measure heart rate, SpO_2, temperature and activity; cuff devices measure blood pressure; bedside monitors are connected in hospitals.

2. Edge Processing Layer

A gateway filters motion artefacts, computes features and runs a lightweight anomaly detector for immediate alarms.

3. Secure Communication Layer

Encrypted MQTT or HTTPS transmits data to the hospital system using interoperable formats such as HL7 FHIR.

4. Clinical Analytics Layer

Rule-based early warning scores and ML models (random forest, gradient boosting, CNN for ECG) classify status and predict deterioration risk.

5. Care-Team Dashboard Layer

Doctors and nurses see live trends, risk scores and alerts prioritized by severity; patients and caregivers receive guidance at home.

6. Methodology

Fig. 3 describes the workflow. An early warning score is computed as the sum of points for each vital sign,

$$EWS = \Sigma_v \, s_v(x_v) \quad (1)$$

where s_v maps vital sign v to points according to its deviation from normal. The ML model outputs a deterioration probability p, and the status is critical when p or EWS exceeds its threshold. Precision and recall are reported, with emphasis on recall for critical events.

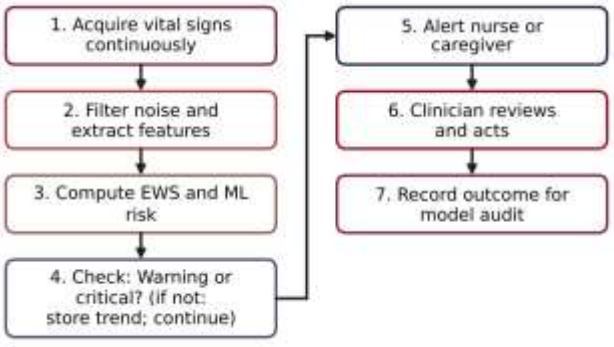


Fig. 3. Smart health monitoring and escalation workflow.

V. DISCUSSION AND COMPARISON

Table II compares monitoring approaches. Manual checks are reliable but infrequent, early warning scores are simple and validated, and ML models with continuous data are more accurate but need validation and integration.

Approach	Frequency	Accuracy	Effort
Manual vital checks	Every 4–8 h	Good per check	High staff effort
Early warning score	Per check	Validated	Low
Continuous wearable + rules	Continuous	Medium	Low
Continuous + ML model	Continuous	High	Needs validation

TABLE II Comparison of Health Monitoring Approaches

VI. CHALLENGES AND FUTURE DIRECTIONS

Table III summarizes challenges. Topol [8] cautioned that clinical AI must be validated prospectively before routine use, and the WHO guidance on AI for health [9] calls for transparency, accountability and protection of patient autonomy. In India, continuous health data must also be handled according to the Digital Personal Data Protection Act [10]. Future directions include cuffless blood pressure estimation, federated learning across hospitals, explainable risk scores and integration with India's digital health records.

Challenge	Mitigation
Alarm fatigue	Risk-ranked alerts; smart thresholds
Sensor accuracy	Medical-grade devices; artefact filters
Generalization	Local validation; recalibration
Interoperability	HL7 FHIR standards
Privacy	Encryption; DPDP-compliant consent

TABLE III Challenges and Mitigation

VII. CONCLUSIONS

AI-based smart health monitoring can detect deterioration earlier by combining continuous sensing

with predictive analytics. The reviewed literature shows that machine learning outperforms conventional scores, that deep learning can analyse ECGs and health records at expert level and that wearables can screen large populations. Reducing false alarms, ensuring privacy and validating models clinically are essential for safe adoption.

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