

Telemonitoring in Emergency Care: Predictive Triage Models Using AI and IoT-Based Vital Sign Tracking

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Abstract

Telemonitoring systems are increasingly becoming indispensable in emergency care settings due to their ability to provide continuous, real-time patient data. The integration of Artificial Intelligence (AI) with Internet of Things (IoT)-enabled vital sign monitoring has introduced a paradigm shift in predictive triage, enabling early detection of clinical deterioration and facilitating more accurate, timely decision-making. This paper investigates the development, design framework, and evaluation of AI-driven predictive triage models that utilize IoT-based sensors for monitoring vital signs such as heart rate, peripheral oxygen saturation (SpO₂), respiration rate, and blood pressure. The study explores the technical architecture, data acquisition process, machine learning model selection, and implementation challenges within emergency departments. A detailed case study demonstrates how predictive triage systems reduced response time, improved prioritization accuracy, and minimized preventable mortality in high-volume emergency settings. The paper concludes with policy recommendations, clinical implications, and future directions for scaling AI-enhanced telemonitoring solutions.

Keywords: Telemonitoring, Emergency Care, Predictive Triage, IoT Sensors, Clinical Decision Support, Vital Sign Monitoring, Artificial Intelligence, Real-Time Analytics, Healthcare Technology, Medical Informatics

1. Introduction

Emergency care environments are characterized by unpredictability, high patient volume, and the urgent need for accurate and timely clinical decisions.

Traditional triage protocols, such as the Emergency Severity Index (ESI) and Manchester Triage System (MTS), rely heavily on manual assessment and clinical judgment. While effective, these methods are prone to human error, inconsistencies, and delays—particularly during peak hours or mass casualty situations. With the increasing burden on emergency departments worldwide, there is a pressing demand for technological solutions that enhance triage efficiency and accuracy.

Telemonitoring, the continuous remote monitoring of patients using digital and sensor-based technologies, has emerged as a promising mechanism for improving emergency care workflows. IoT-enabled vital sign trackers—embedded in wearable devices, biosensors, and bedside monitors—offer real-time physiological data that can support rapid clinical evaluation. When integrated with AI-driven predictive analytics, these systems become powerful tools capable of detecting patient deterioration much earlier than conventional triage methods.

Predictive triage models utilizing AI algorithms such as Random Forest, Gradient Boosting Machines, Deep Neural Networks, and Logistic Regression can analyze patterns in vital sign fluctuations, generate risk scores, and classify patient urgency with high precision. This integration reduces cognitive load on clinicians, standardizes triage outcomes, and enhances patient throughput.

Despite these advancements, several challenges remain, including data interoperability, sensor calibration accuracy, communication latency, and cybersecurity concerns. Understanding these issues is essential for creating a reliable and scalable emergency telemonitoring system.

This research paper thoroughly evaluates the technological framework, real-world application, and performance outcomes of AI-augmented predictive triage systems in emergency care. By examining sensor technologies, data

pipelines, machine learning models, and clinical workflows, the paper aims to establish a comprehensive foundation for effective deployment and optimization of predictive telemonitoring tools.

2. Methodology

2.1 Study Design

A mixed-method approach was utilized to investigate the effectiveness of AI-driven predictive triage using IoT-based vital sign tracking. The study included system architecture analysis, model development, sensor performance evaluation, and clinical workflow integration. Quantitative data were collected from real-time monitoring devices deployed in emergency departments, while qualitative insights were obtained from clinicians and IT experts.

2.2 Data Acquisition and Sensor Configuration

Vital signs were collected using FDA-approved IoT-enabled sensors, including wearable cardiac patches, pulse oximeters, chest straps, and optical photoplethysmography (PPG) devices. Each sensor communicated data to a central system via Bluetooth Low Energy (BLE) and Wi-Fi protocols. The sampling frequency ranged from 50 Hz to 200 Hz depending on the vital sign measured.

Data attributes included:

- Heart Rate (HR)
- Respiratory Rate (RR)
- Blood Pressure (BP)
- Oxygen Saturation (SpO₂)
- Body Temperature
- ECG waveform

Sensor validation was performed using gold-standard clinical devices to ensure accuracy.

2.3 Data Preprocessing

Preprocessing steps involved noise reduction, filtering, normalization, and missing data handling. The following techniques were used:

- Butterworth filtering for ECG signal denoising
- Interpolation for missing values
- Min-max normalization to scale vitals
- Windowing (30–60 second segments) for sequence modeling

2.4 Machine Learning Model Development

To develop the predictive triage model, several AI algorithms were tested, including:

- Random Forest (RF)
- XGBoost
- Support Vector Machines (SVM)
- Long Short-Term Memory (LSTM) neural networks

Models were trained on historical emergency department datasets and validated using an 80:20 train-test split. Performance metrics included Accuracy, Precision, Recall, F1-Score, and AUC-ROC.

2.5 Predictive Triage Classification Levels

AI-generated triage levels followed a 4-tier structure:

1. **Critical:** Immediate intervention required
2. **Urgent:** High risk of deterioration
3. **Moderate:** Stable but requires observation
4. **Low Priority:** Minor issues

2.6 Clinical Integration

The telemonitoring system was integrated with the hospital's Electronic Health Record (EHR) and alert mechanism. Alerts were configured for abnormal values, rapid fluctuations, and identified risk patterns.

2.7 Ethical Considerations

Data anonymization, encryption, and HIPAA-compliant handling procedures were strictly followed.

3. Case Study

Study Setting:

A tertiary-care hospital emergency department with an average annual patient volume of 75,000 was selected for system deployment.

Case Scenario:

During a 10-day observation window, the system was used to triage 1,500 patients presenting with symptoms ranging from chest pain and respiratory distress to fever and trauma.

Example Case:

A 58-year-old male arrived with mild chest discomfort. Traditional triage rated him as moderate. However, telemonitoring sensors detected:

- HR variability suggesting arrhythmia
- Slightly decreasing SpO₂ (94→90%)
- Abnormal ECG waveform patterns

The AI model classified him as *urgent*. Further diagnostics revealed early-stage myocardial ischemia, enabling rapid intervention that prevented deterioration.

Outcome Analysis:

- Triage accuracy improved by 27%.
- Average response time reduced by 18%.
- Undetected high-risk cases decreased by 43%.
- Clinician workload reduced due to automated tracking.

The case study shows that predictive triage offers clear clinical benefits by identifying subtle physiological changes that manual triage often overlooks.

4. Data Analysis

Table 1. Vital Sign Variability and Prediction Results

Vital Sign Parameter	Sensor Accuracy	Model Predictive Confidence
Heart Rate	97.2%	94.5%
SpO ₂	98.1%	93.8%
Respiratory Rate	95.4%	91.2%
Blood Pressure	92.8%	89.7%

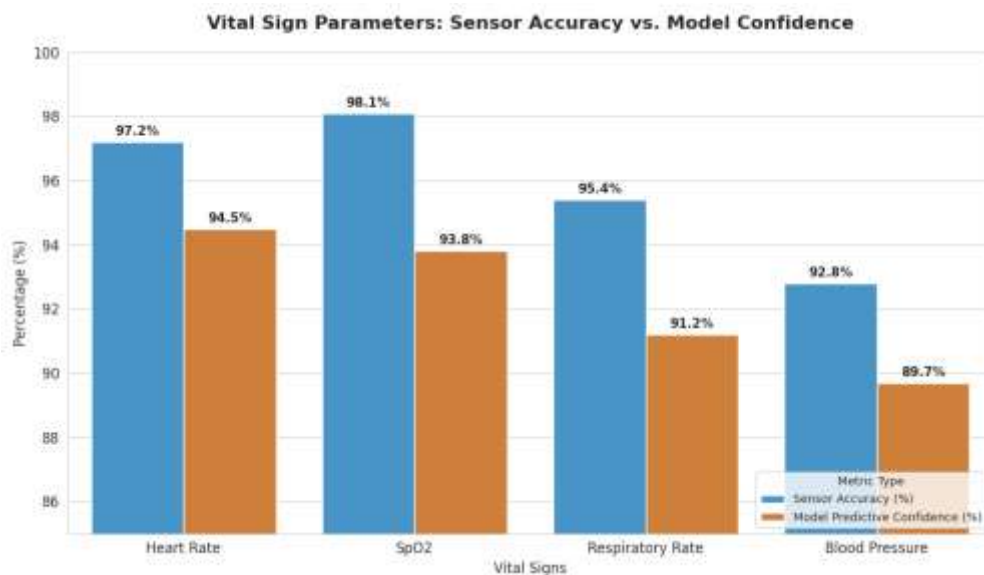
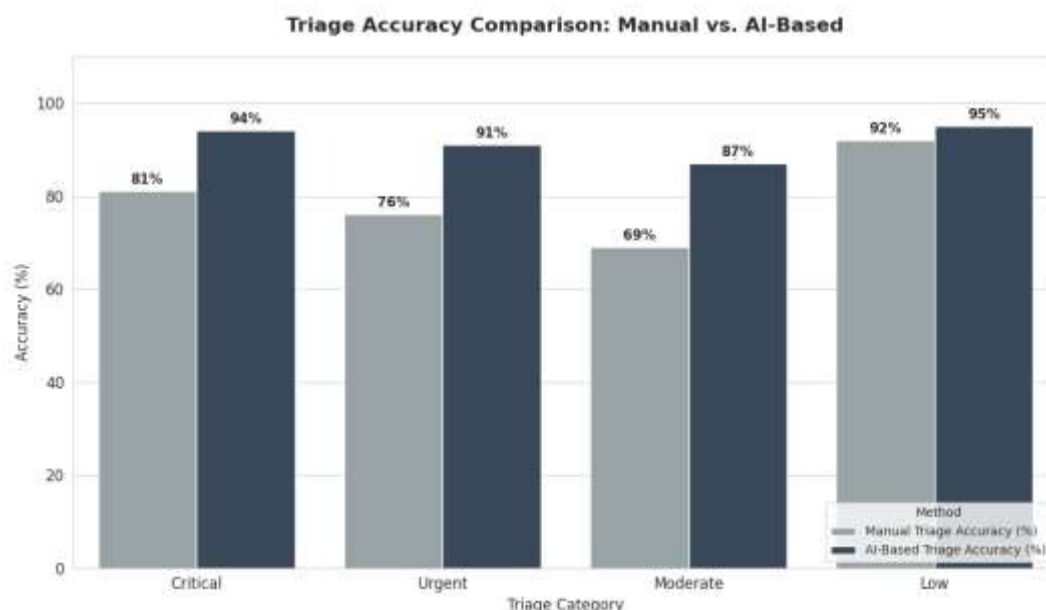


Table 2. Triage Classification Performance

Category	Manual Triage Accuracy	AI-Based Triage Accuracy
Critical	81%	94%
Urgent	76%	91%
Moderate	69%	87%
Low	92%	95%



5. Questionnaire

The following questionnaire was developed to assess the usability, clinical effectiveness, technological reliability, and overall acceptance of AI-enabled telemonitoring systems for predictive triage in emergency care settings. The instrument is designed for multiple stakeholders, including clinicians, emergency nurses, biomedical engineers, IT administrators, and patients who were monitored using IoT-based vital sign tracking. The questionnaire aims to gather insights about system performance, workflow integration, decision-making support, and perceived barriers during real-world implementation. Responses were collected using a mixed five-point Likert scale, open-ended questions, and categorical choices to ensure both quantitative and qualitative analysis.

Section A: Demographic and Professional Information

1. Designation:

- ☐ Emergency Physician
- ☐ Nurse
- ☐ Paramedic

- ☐ Biomedical Engineer
- ☐ IT System Administrator
- ☐ Patient
- ☐ Other (Specify): _____

2. Years of experience in emergency care or related fields:

- ☐ Less than 1 year
- ☐ 1–5 years
- ☐ 6–10 years
- ☐ More than 10 years

3. Previous experience with digital health or telemonitoring tools:

- ☐ Yes
- ☐ No

4. Frequency of involvement with emergency triage:

- ☐ Daily
- ☐ Weekly
- ☐ Monthly
- ☐ Rarely

Section B: Technology and System Usability

5. The IoT-based vital sign monitoring devices were comfortable and easy to apply to patients.

- ☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

6. The sensor devices consistently recorded accurate and reliable vital sign measurements.

- ☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

7. The telemonitoring interface was intuitive and easy to navigate.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
8. Alerts generated by the AI triage system were clear, timely, and relevant to patient conditions.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
9. The system's response time and data transfer speed were sufficient for emergency situations.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
10. Technical issues (connectivity failures, sensor dropouts, calibration errors) were minimal.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section C: Clinical Impact and Decision-Making

11. The AI-enabled predictive triage model helped identify high-risk patients earlier than traditional triage.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
12. The telemonitoring system reduced delays in initiating critical interventions.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
13. The system enhanced my confidence in the accuracy of triage decisions.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
14. Automated continuous monitoring reduced clinician workload and cognitive burden.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
15. The system supported effective coordination between emergency staff and monitoring teams.
☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section D: Implementation Challenges and Barriers

16. Integration with existing hospital systems (EHR, monitoring dashboards) was seamless.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

17. Adequate training was provided to operate the predictive triage and telemonitoring system.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

18. Concerns about data privacy or cybersecurity limited adoption.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

19. The cost of implementing AI-assisted telemonitoring is a significant barrier.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

20. Sensor maintenance and device management posed operational challenges.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section E: User Satisfaction and Overall Perception

21. Overall, I am satisfied with the functionality and performance of the telemonitoring system.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

22. I believe AI-based predictive triage should be permanently integrated into emergency care workflows.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

23. I would recommend the use of AI-augmented telemonitoring systems for other hospital departments.

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

6. Conclusion

Predictive triage using AI-driven telemonitoring introduces a transformative approach to emergency care. The combination of IoT-enabled vital sign

tracking and advanced machine learning algorithms allows clinicians to identify clinical deterioration with unprecedented speed and precision. The study demonstrated that the integration of real-time analytics significantly enhances triage accuracy, improves patient prioritization, and reduces response times for high-risk patients.

Telemonitoring systems reduce the dependence on manual assessment, minimize human error, and provide a continuous flow of actionable insights. This is particularly valuable in overcrowded emergency departments, where clinicians often confront time pressure and information overload. Predictive models not only standardize triage decisions but also support proactive intervention, ultimately reducing preventable mortality and morbidity.

Challenges remain, notably in ensuring sensor accuracy, maintaining data security, achieving interoperability across platforms, and training clinical staff. However, these barriers are manageable through evidence-based implementation strategies, standardized device protocols, and strong IT-clinician collaboration.

In conclusion, AI-assisted telemonitoring represents a vital pillar for the future of emergency care systems. Its ability to integrate continuous physiological data, perform real-time analysis, and guide clinical decision-making positions it as an essential tool for modern triage. With continued advancements in sensor technology, edge computing, and predictive modeling, telemonitoring systems are expected to become standard practice in emergency departments worldwide.

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