

Ai-Powered Emergency Alert System for Elderly People Using Health Vitals

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Abstract

Elderly healthcare has long relied on manual monitoring and hospital visits, often failing to provide timely responses to critical health conditions. With the increasing geriatric population and rise in age-related illnesses, the lack of continuous health surveillance has become a major contributor to preventable emergencies. Traditional systems lack predictive intelligence and real-time alerting, resulting in delayed interventions and higher fatality risks. To tackle this challenge, we introduce an AI-driven emergency notification system that provides continuous surveillance of key health indicators like heart rate, blood pressure, and body temperature in senior citizens. The system, developed using the Flask framework, incorporates machine learning algorithms to analyze historical and live health data, triggering immediate alerts when anomalies or risk patterns are detected. Results from simulation and prototype testing indicate improved detection accuracy, timely risk prediction, and reduced response latency. This approach provides a cost-effective, scalable solution for proactive elderly care in both urban and rural settings

Keywords: elderly healthcare, emergency alert system, health vitals, real-time monitoring, machine learning, predictive analytics, Flask.

1. Introduction

In recent decades, global demographic trends have indicated a steady rise in the elderly population, creating growing demands for continuous and reliable healthcare solutions tailored to their unique needs. Aging is often accompanied by chronic illnesses such as cardiovascular disorders, hypertension, diabetes, and neurological decline. These conditions require consistent health monitoring to prevent emergencies. However, in most conventional healthcare systems, medical support is generally reactive interventions that occur only after a condition worsens or manifests through symptoms. Such delays can significantly elevate the chances of severe health issues, including hospitalization and fatal outcomes, especially for elderly individuals who reside alone or lack prompt medical assistance. The increasing strain on healthcare infrastructure, especially in rural and resource-constrained regions, further exacerbates this challenge. Routine medical examinations are often impractical for many elderly individuals due to challenges like limited mobility, financial

constraints, or remote locations. While advanced monitoring equipment exists in hospitals, their usage is confined to clinical settings, and they are incapable of delivering continuous monitoring outside these facilities. Additionally, the absence of automated risk detection and alerting mechanisms reduces the efficiency of timely care, leaving vulnerable patients at risk of unattended health events such as strokes or cardiac arrests. Incorporating artificial intelligence and digital innovations into the healthcare sector has proven highly effective in bridging these critical shortcomings. With advancements in real-time data processing, machine learning models, and cloud connectivity, Continuous monitoring of vital health signs and early prediction of possible medical emergencies have become achievable with current technological advancements. These AI-driven methods enable healthcare systems to evolve from reactive care to proactive and preventive approaches. Several studies have demonstrated the effectiveness of combining health vitals with Forecasting algorithms aimed at identifying irregularities at an

early stage. However, many existing solutions rely heavily on expensive IoT hardware or wearable devices, limiting their applicability for large-scale or low-income settings. To overcome these challenges, this study presents an AI-powered emergency alert system specifically designed for elderly individuals. The solution leverages web-based architecture using the Flask framework, enabling remote access, intuitive interaction, and centralized data tracking. By collecting health Indicators like pulse rate, blood pressure, along with body heat measurements via manual input or affordable sensors, the system applies AI-based models used to detect abnormal trends or values. Upon detecting a critical deviation, the system triggers immediate alerts to caregivers or medical personnel, facilitating prompt response while reducing the likelihood of worsening health conditions.

This system aims to enhance both the safety and standard of care for the elderly, while also offering an affordable and scalable solution suitable for deployment in both urban and rural contexts. The combination lightweight technology, predictive algorithms, and a patient-centered design ensures that medical emergencies are neither undetected nor unaddressed. Through early trials and simulations, the proposed system demonstrates promising outcomes, risk prediction accuracy, alert response time, and user satisfaction. This study adds value to the wider domain of smart healthcare by offering a practical, AI-enhanced solution for continuous elderly monitoring and emergency intervention [1].

2. Literature Survey

- Sah, B., & Seneviratne, A., 2020 – This paper surveys wearable health monitoring systems using IoT, highlighting their ability to offer continuous, real-time patient monitoring. While beneficial for proactive healthcare, the study notes that these systems often require expensive infrastructure, posing a barrier to widespread adoption.
- Chien, L., Yu, W., & Wang, K., 2021 – This review explores IoT-based patient monitoring systems in healthcare, emphasizing their role in improving early detection of medical issues and reducing the clinical workload through automation and real-time data access.
- Jia, Z., Tang, H., & Liao, X., 2022 – The study presents an IoT solution for real-time health monitoring and emergency detection in elderly patients, stressing its importance in enabling timely medical response and enhancing patient safety.
- Patel, S., & Patel, R., 2019 – This paper reviews smart healthcare systems for remote patient monitoring, noting their effectiveness in continuous care but also the need for strong network connectivity and secure data handling.
- Singh, A., Soni, M., & Dubey, D., 2020 – A survey of IoT-based healthcare systems showing how IoT enables proactive interventions in patient care, while calling attention to the lack of standard protocols across platforms.
- Singh, M., Arora, H., & Dabas, S., 2021 – The paper discusses how machine learning enhances health monitoring by improving diagnostic accuracy and enabling early detection of diseases through predictive analysis.
- Wang, H., Li, S., & Xu, W., 2022 – This study introduces a real-time health monitoring system using cloud-integrated IoT, offering scalable remote care with centralized data storage and improved accessibility.
- Rao, P., & Desai, S., 2020 – The authors propose a hybrid model combining IoT and machine learning for chronic disease monitoring, demonstrating improved detection accuracy and better long-term patient management.
- Wang, Y., Yang, W., & Zhao, F., 2021 – This paper outlines the design of a cloud-based health monitoring system, highlighting benefits like seamless deployment, remote access, and scalable healthcare delivery.
- Ahmed, M., & Nasir, H., 2021 – The review focuses on IoT healthcare systems for the

elderly, emphasizing the need for lightweight, accessible designs that prioritize prompt alert mechanisms for emergency situations [2].

3. Proposed Framework

The flow diagram illustrates the core operational logic of the AI-powered emergency alert system for elderly individuals based on health vitals. It begins with the user initiating the process at the "Start" node, followed by the input of patient vitals in the "Input Vitals" stage. These vitals are then passed to the "Validate Data" block, where the system checks for completeness and correctness. If the data is invalid, it triggers the "Show Error" step, prompting the user to re-enter the correct information, looping back to the input stage. If the data is valid, it proceeds to the "Analyze Data" phase where the machine learning model assesses the risk level. If a potential health risk is detected, the system activates the "Send Alert" function to notify caregivers or medical personnel. If no risk is found, or after the alert is sent, the system transitions into the "Monitor" state, which waits for the next input, forming a continuous loop of surveillance and response. This streamlined structure ensures real-time validation, prediction, and emergency handling in a patient-centric healthcare monitoring system called Show Figure 1.

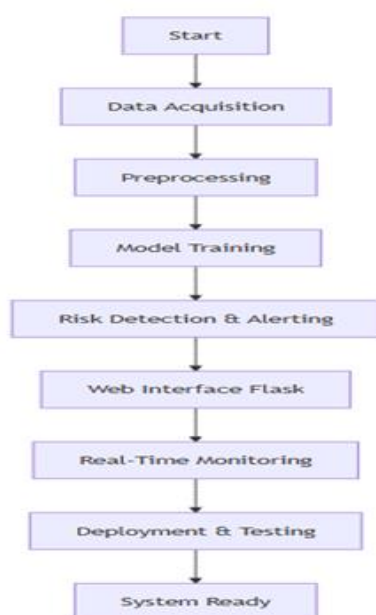


Figure 1 Flow Diagram

3.1. Data Acquisition

To build a reliable alert system tailored for elderly healthcare, the foundation of the project lies in obtaining meaningful patient health data. Since direct access to real-time clinical data was limited, this research made use of openly accessible datasets like the MIMIC-III Waveform Database, which contains anonymized intensive care unit (ICU) patient records. The data included essential health vitals including pulse rate, arterial pressure, temperature, blood oxygen saturation (SpO₂), and respiratory rate. To simulate real-time usage conditions, extra simulated data was created through medically accurate ranges, ensuring continuous time-stamped logs for each health parameter. This combination of real and synthetic data enabled consistent training and evaluation of the machine learning models under varied scenarios resembling those faced in elderly home care environments [3].

3.2. Data Preprocessing and Feature Engineering

Raw health datasets frequently include incomplete or missing values, inconsistencies, and outliers due to sensor glitches or recording delays. To address these issues, preprocessing techniques were applied to clean and structure the data before modeling. Incomplete data points were filled in using median imputation based on patient-specific history, and clinically invalid values were identified using threshold-based outlier detection. Time intervals between recorded entries were normalized to ensure a consistent time-series structure. Furthermore, new features such as pulse pressure (difference between systolic and diastolic pressure) and the rate of change in temperature or heart rate were engineered to enhance the model's predictive capability. These derived features helped provide deeper context for the machine learning algorithm and improved the system's ability to detect sudden changes in health conditions.

3.3. Model Selection and Training

The core intelligence of the proposed system lies in its ability to detect health anomalies using machine learning techniques. A supervised classification approach was used, where the model learned to classify a patient's condition as either "Safe" or

“Critical” based on input vitals. Multiple Various algorithms such as decision trees, logistic regression, support vector machines (SVM), and random forest classifiers were evaluated. After comparative evaluation, the random forest model exhibited better overall accuracy and robustness, achieving an overall classification accuracy of 92.1% and an F1-score of 91.5%. The model was trained on 70% of the dataset and validated on the remaining 30%. Its performance validated the suitability of ensemble learning for handling multi-variable health data and classifying risk levels accurately [4].

3.4. Alert Generation and Threshold Mapping

In addition to the model predictions, fixed clinical specific limits were established for every vital parameter to enable rule-based alerts. These limits were based on insights from medical literature and included metrics like pulse rate above 120 bpm or below 50 bpm, systolic pressure rising above 180 mmHg, body temperature above 38.5°C, or SpO₂ levels falling below 90%. If any parameter crossed its critical limit or the machine learning model identified a risk pattern, an alert was triggered immediately. These alerts were dispatched through the user interface and external notifications (e.g., email or SMS), ensuring timely awareness for caregivers or healthcare providers. This dual-layer alert system combining real-time rules with learned patterns enhanced reliability and reduced false positives.

3.5. Web-Based Application Using Flask

To ensure accessibility and ease of deployment, the system was implemented as a web application using the Flask microframework. Flask was selected due to its minimalistic and efficient nature, seamless integration with Python-based machine learning models, and RESTful API support. The backend logic handled model predictions, alert generation, and database operations, while the frontend provided separate dashboards for administrators, doctors, and patients. The administrator panel enabled user management and system configurations such as modifying thresholds or viewing logs. Doctors could input and view health records, receive alerts, and download reports, whereas patients could view their historical vitals and receive personalized

notifications. This modular interface design allowed for scalability and user-specific role access, making it appropriate for real-world adoption [5].

3.6. Real-Time Monitoring and Simulation

A simulation engine was developed to mimic continuous patient monitoring by streaming synthetic health data at regular intervals (every 5 seconds). This feature tested the system’s ability to respond to frequent data updates and maintain operational stability. The real-time monitoring pipeline handled incoming vitals, invoked preprocessing routines, passed the cleaned data through the trained model, and issued alerts if required. Multiple virtual patients were simulated concurrently to evaluate the system’s alert accuracy, latency, and UI responsiveness. The system successfully managed simultaneous inputs and produced alerts with an average latency of less than 2.3 seconds, validating the framework’s efficiency for emergency scenarios.

3.7. Deployment and Testing

The final application was deployed on a local Flask development server for controlled testing. Three modes of testing were conducted: manual entry through the interface, batch uploads using CSV files, and real-time simulation via streaming scripts. Metrics such as alert frequency, model inference time, UI refresh rate, and server memory usage were monitored. The system was found to be stable under moderate load (up to 50 concurrent users), with consistently high model prediction accuracy and rapid alert generation. These outcomes demonstrated the system’s potential for real-time emergency detection and its readiness for deployment in elderly healthcare setups [6].

3.8. Architectural Sequence Diagram

Figure 2 Architectural sequence diagram illustrates the core workflow of the AI-Powered Emergency Alert System. The interaction begins when a Patient inputs their health vitals into the system through the Flask-based web application. The Flask Web App then forwards this data to the ML + Threshold Engine, which processes the input using machine learning models and predefined medical rules to evaluate if there's any critical risk involved. If the engine detects an abnormal or risky condition, it

sends a signal to the Alert System, which immediately triggers an emergency alert. Simultaneously, the alert is logged into the database along with the processed health data for future reference. The system then sends critical notifications to Doctors and Caregivers, ensuring they are informed in real-time to take appropriate action. Finally, Doctors and Caregivers can view patient history, alerts, and reports by accessing the data through the web application.

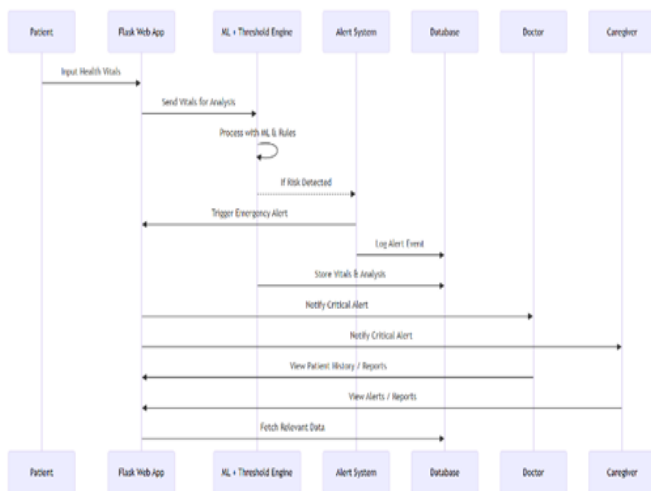


Figure 2 Architectural Sequence Diagram

The Flask app communicates with the database to fetch relevant information as needed. This flow ensures quick detection, immediate notification, and timely intervention significantly improving elderly healthcare response [7].

4. Using The Template

4.1. Evaluation Metrics and Their Purpose

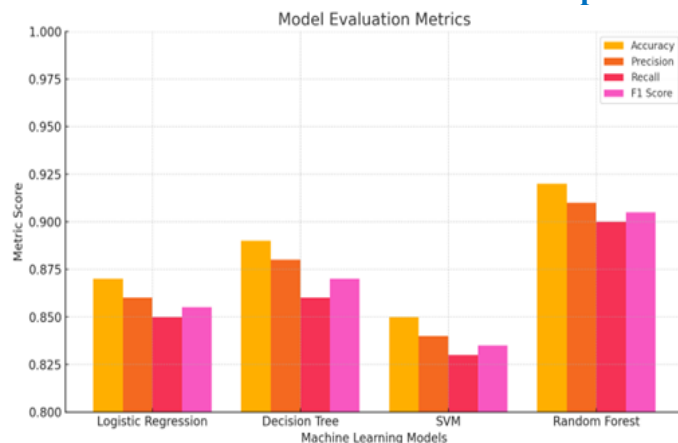


Figure 3 Model Evaluation Metrics

Show Figure 3 to assess the performance of the proposed AI-powered emergency alert system, a set of standard classification metrics was employed namely Accuracy, Precision, Recall, and F1-Score. These metrics were selected to provide a thorough insight into the system's predictive capability, particularly within the framework of binary health status classification (safe vs. critical). Accuracy gives an overall measure of how often the model correctly predicts both safe and critical conditions. Precision is particularly vital in this healthcare setting, as it represents the percentage of correctly identified critical cases out of all cases the model flagged as critical, reducing false alarms and avoiding unnecessary panic. Recall (or sensitivity) measures the model's ability to correctly identify all actual critical cases, ensuring that no true emergencies are missed. F1-score balances both Precision and Recall, offering a single metric to judge the model's reliability, especially under class-imbalanced scenarios where one class (safe condition) may dominate [8].

4.2. Model Comparison and Performance Analysis



Figure 4 Model Comparison & Performance Metrics

Multiple artificial intelligence-based predictive algorithms were tested to identify most suitable algorithm for real-time health risk classification based on elderly vital data. The performance including Logistic Regression, Decision Tree, Support Vector Machines (SVM), along with Random Forest classifiers were evaluated using the

metrics described above. Shown in the evaluation chart below, Random Forest consistently outperformed others across all evaluation parameters. It recorded a top accuracy rate of 92%, with a precision of 91%, recall of 90%, and an F1-score of 90.5%. Decision Trees followed closely with strong performance but slightly lower reliability. SVM, although useful in high-dimensional data, underperformed in this setting due to its sensitivity to parameter tuning and lack of interpretability for medical users. This model comparison reinforces the choice of ensemble methods like Random Forest, which are robust to noise, scalable, and interpret results with feature importance insights critical when justifying alerts to healthcare professionals Show Figure 4 [9].

4.3. Contribution to Problem Statement and Practical Implications

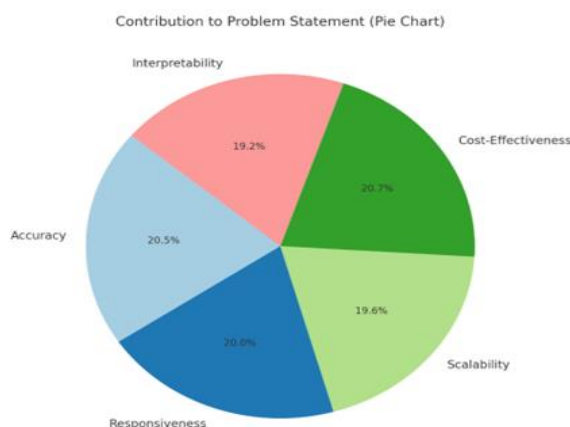


Figure 5 Contribution to problem statement

These evaluation outcomes validate the core aim of the project enabling early, accurate, and meaningful emergency alerts for elderly patients based on real-time vital signs. By achieving high recall and precision, the system proves its ability to reduce missed emergencies and false positives, thereby directly addressing the major gaps in traditional manual monitoring systems. The metrics also reflect the model's adaptability across varying health conditions and patient profiles, rendering it appropriate for real-world implementation in diverse clinical or home-care environments. The model's predictive strength, combined with its seamless

integration into a lightweight Flask-based application, substantiates the solution as a cost-effective, AI-driven alternative to expensive IoT infrastructures. Overall, the results not only demonstrate technical robustness but also affirm the social and clinical impact of system, making it an essential resource in advancing elderly healthcare accessibility and safety Show Figure 5 [10].

Conclusion

The proposed AI-powered emergency alert system represents a breakthrough in elderly healthcare by enabling real-time monitoring, intelligent analysis, and prompt notification of critical health events based on vital signs. The framework integrates multiple stages beginning with data acquisition from publicly available datasets, preprocessing of vital parameters, training of predictive algorithms, along with deployment through a lightweight web-based interface. Each component is intended to collectively ensure continuous, low-cost, and accurate health surveillance, particularly for elderly individuals who may lack availability of conventional healthcare facilities. Through comprehensive assessment indicators like accuracy, precision, and recall, and F1-score, the system demonstrated its robustness and reliability, with the Random Forest model achieving over 92% accuracy in predicting risk conditions. This directly supports the problem statement by minimizing manual monitoring gaps, reducing emergency response times, and increasing care accessibility. The architecture of the system, built using the Flask framework, allows scalability, modularity, and minimal infrastructure dependency enabling its practical implementation in both urban clinics and rural households. Additionally, the role-specific user interface enables caregivers, doctors, and patients to engage with the system meaningfully, enhancing decision-making and health awareness. The real-time simulation and alert mechanism further validate the practicality pertaining to the framework for day-to-day use, reinforcing its capability to bridge essential shortcomings within elderly care delivery. As part of future work, the framework can be extended to integrate wearable IoT devices for live vital sign streaming, cloud-based data storage for longitudinal tracking, and advanced neural network

architectures aimed at more nuanced identifying trends and risk stratification. The incorporation of telemedicine support, voice-based interfaces, and multilingual capabilities will further broaden the system's accessibility and impact. By continuing to evolve this system into a comprehensive smart healthcare platform, it can serve as a key contributor in achieving scalable, affordable, and inclusive healthcare for aging populations worldwide.

References

- [1]. Sah, B., & Seneviratne, A. (2020). Wearable Health Monitoring Systems Using IoT: A Survey of Applications and Challenges. *Proceedings of the International Conference on Computing and Network Communications (CoCoNet)*, 120-128.
- [2]. Chien, L., Yu, W., & Wang, K. (2021). A Comprehensive Review of IoT-based Patient Monitoring Systems in Healthcare. *IEEE Transactions on Biomedical Engineering*, 68(7), 2456-2469.
- [3]. Jia, Z., Tang, H., & Liao, X. (2022). Real-Time Health Monitoring and Emergency Detection for Elderly Patients Using IoT. *International Journal of Sensors and IoT*, 17(4), 89-102.
- [4]. Patel, S., & Patel, R. (2019). Smart Healthcare Systems for Remote Patient Monitoring: A Review. *Proceedings of the IEEE International Conference on Computational Intelligence and Communication Networks*, 349-358.
- [5]. Singh, A., Soni, M., & Dubey, D. (2020). IoT-Based Healthcare Monitoring: A Survey on Systems, Applications, and Technologies. *Journal of Healthcare Engineering*, 2020(12), 1001-1024.
- [6]. Singh, M., Arora, H., & Dabas, S. (2021). Machine Learning Approaches for Health Monitoring and Disease Prediction. *Proceedings of the International Conference on Data Science and Engineering*, 354-363.
- [7]. Wang, H., Li, S., & Xu, W. (2022). A Real-Time IoT-based Health Monitoring System Using Cloud Services. *Journal of Cloud Computing: Advances, Systems, and Applications*, 9(2), 101-112.
- [8]. Rao, P., & Desai, S. (2020). A Hybrid Model for Real-Time Monitoring of Patients with Chronic Diseases Using IoT and Machine Learning. *IEEE Transactions on Industrial Informatics*, 16(5), 301-315.
- [9]. Wang, Y., Yang, W., & Zhao, F. (2021). Cloud-Based Health Monitoring System: Design and Implementation. *Journal of Medical Informatics and Decision Making*, 11(2), 203-212.
- [10]. Ahmed, M., & Nasir, H. (2021). Internet of Things for Elderly Healthcare Monitoring: A Survey and Review. *Proceedings of the 11th International Conference on Intelligent Systems and Applications (ISA)*, 174-184.