DSC 291-Mobile & Ubiquitous Computing

Health Monitoring and Anomaly Detection for Elderly Patients

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Fall 2025

Abstract

The rapid growth of the elderly population has intensified the need for intelligent, continuous health monitoring systems that support independent living while minimizing caregiver burden. Traditional healthcare monitoring solutions are often reactive, fragmented, or reliant on manual intervention, limiting their effectiveness in preventing adverse health and safety events. This paper presents an integrated Elderly Care Monitoring System that combines physiological health analytics, wearable-based fall detection, and behavioral adherence tracking within a unified, interactive platform.

The proposed system leverages two independently trained machine learning models: a Logistic Regression classifier for physiological health alert prediction using vital-sign data, and a Random Forest classifier for fall detection using accelerometer signals from wearable devices. Physiological features such as heart rate, glucose levels, oxygen saturation, and time-of-day are used to identify abnormal health conditions, while magnitude-based statistical features extracted from accelerometer data enable robust discrimination between falls and normal daily activities. A subject-level train–test split is employed for the fall detection model to ensure realistic generalization.

Both models are integrated into a Streamlit-based web application that supports real-time simulation, interactive data exploration, and unified high-risk alerting. Overall, this work demonstrates the feasibility of a dual-layer, interpretable, and extensible monitoring framework for proactive elderly care using ubiquitous sensing and machine learning.

Introduction

The global increase in life expectancy has led to a rapidly growing elderly population, intensifying the demand for scalable healthcare solutions that support aging in place. Many older adults prefer to live independently; however, age-related physiological decline, chronic conditions, and increased fall risk pose significant threats to their safety and well-being. Falls remain one of the leading causes of injury-related hospitalization among older adults, while delayed detection of abnormal physiological states can result in severe medical complications. These challenges highlight the need for continuous, proactive monitoring systems that extend beyond traditional clinical settings.

Recent advances in ubiquitous computing, wearable sensing, and machine learning have enabled the development of intelligent health monitoring systems capable of analyzing physiological and behavioral data in real time. Wearable sensors can continuously capture vital signs and movement patterns, while machine learning models can detect subtle deviations indicative of health deterioration or physical instability. Despite this progress, many existing systems focus on a single risk modality—such as fall detection or vital-sign monitoring—without integrating multiple data sources into a cohesive decision-making framework. Additionally, complex models often lack interpretability and are difficult to deploy in resource-constrained environments.

This project addresses these gaps by proposing a dual-layer Elderly Care Monitoring System that integrates physiological anomaly detection with wearable-based fall detection. The system combines two lightweight yet effective machine learning models: a Logistic Regression classifier for predicting health alerts based on vital-sign measurements, and a Random Forest classifier for identifying fall events from accelerometer data. The choice of models emphasizes interpretability, robustness to noise, and suitability for real-world deployment scenarios. A unified risk threshold is applied to both models to prioritize safety and timely intervention.

Beyond predictive modeling, the system is implemented as an interactive Streamlit web application that enables caregivers, clinicians, and family members to explore data, visualize trends, and simulate risk scenarios.Through comprehensive evaluation and system demonstration, this work illustrates how multi-modal sensing and machine learning can be combined into an integrated, user-centered platform for proactive elderly monitoring.

Methodology

This section describes the full technical pipeline used to build the Elderly Care Monitoring System. The methodology consists of two main components: (1) data collection and preprocessing from two heterogeneous sensor datasets, and (2) design and training of machine learning models for physiological health alert prediction and wearable-based fall detection.

Data Sources and Processing

1. Physiological Health Monitoring Dataset

We use the *AI for Elderly Care and Support* dataset (Kaggle), which contains time-stamped physiological measurements and caregiver-related metadata. The primary variables used for modeling include:

- Heart Rate (bpm)

- Glucose Levels (mg/dL)
- Oxygen Saturation (SpO_2)
- Blood Pressure (parsed into systolic and diastolic components)
- Alert Triggered (Yes/No)
- Hour of Day (derived from timestamp)

Processing Steps

- Timestamp fields were parsed into `datetime` and used to derive circadian features such as hour-of-day.
- Categorical Yes/No fields were binarized into 0/1 targets.
- Blood pressure strings (e.g., 120/80 mmHg) were decomposed using regular expressions.
- Rows with missing vital-sign features were removed to ensure clean model training.

This dataset represents general health monitoring rather than emergency events, so the resulting model focuses on predicting physiological anomaly alerts based on real-time vitals.

2. Wearable Sensor Dataset for Fall Detection (MobiFall)

To detect physical instability, we use the *MobiFall* dataset, which contains accelerometer data from simulated fall and Activities of Daily Living (ADL) routines. Raw sensor logs are provided in `.txt` format, with the following structure per sample:

$$[t, x, y, z]$$

Signal Processing and Feature Extraction: For each activity file, we compute magnitude-based statistical features:

- Magnitude mean, standard deviation, max, min, range
- Signal energy: $\frac{1}{N}\sum \|a\|^2$
- Sequence length (sample count)

Magnitude is defined as:

$$\text{mag} = \sqrt{x^2 + y^2 + z^2}$$

Subject-Level Train/Test Split: To ensure realistic generalization, subjects rather than individual segments were used to partition the dataset. This prevents data leakage between training and testing, which is common in wearable-sensor classification tasks.

Model Design

The system includes two independently trained models that together enable continuous elderly monitoring:

1. Physiological Health Alert Prediction Model

We formulate alert prediction as a binary classification task.

Model: A Logistic Regression classifier was used due to its interpretability, low latency, and compatibility with mobile-edge deployment scenarios. The model learns a decision boundary between normal physiological states and potentially dangerous ones.

Feature Set:

- Heart Rate
- Glucose Levels
- SpO_2 levels
- Hour of Day (captures circadian changes)

Training Procedure:

- Train/test split with stratification to preserve alert distribution.
- Standardization of numerical features.
- Model evaluation using accuracy, precision, recall, F1-score, and ROC-AUC.

2. MobiFall-Based Fall Detection Model

Fall detection is treated as a supervised binary classification problem.

Model: A Random Forest classifier was selected due to:

- robustness to noisy sensor data,
- non-linearity needed to separate fall vs. non-fall patterns,
- strong performance on small and medium-sized feature sets.

Feature Set: The magnitude-based features computed during pre-processing (mean, std, range, energy, etc.) form the input.

Training Procedure:

- Subject-level split to prevent cross-subject contamination.
- StandardScaler applied before training.
- Evaluation using precision, recall, F1-score, and confusion matrix.
- PCA performed to inspect fall vs. ADL feature separability.

Unified High-Risk Alerting:

Both models output a risk probability. A unified threshold of 0.85 was selected to trigger emergency notifications. This threshold emphasizes recall while limiting excessive false alerts. Together, these models form a dual-layer architecture that integrates sensor-based motion monitoring with physiological anomaly prediction, aligning with ubiquitous computing principles of continuous, context-aware health assessment.

Results-System Demonstration

This section presents the outcomes of the complete Elderly Care Monitoring System, which integrates health analytics, safety monitoring, daily reminder management, and two machine learning models. The system was deployed as an interactive Streamlit web application, allowing users caregivers, clinicians, or family members to explore data, test model predictions, and simulate real-world scenarios in an intuitive, user-friendly environment.

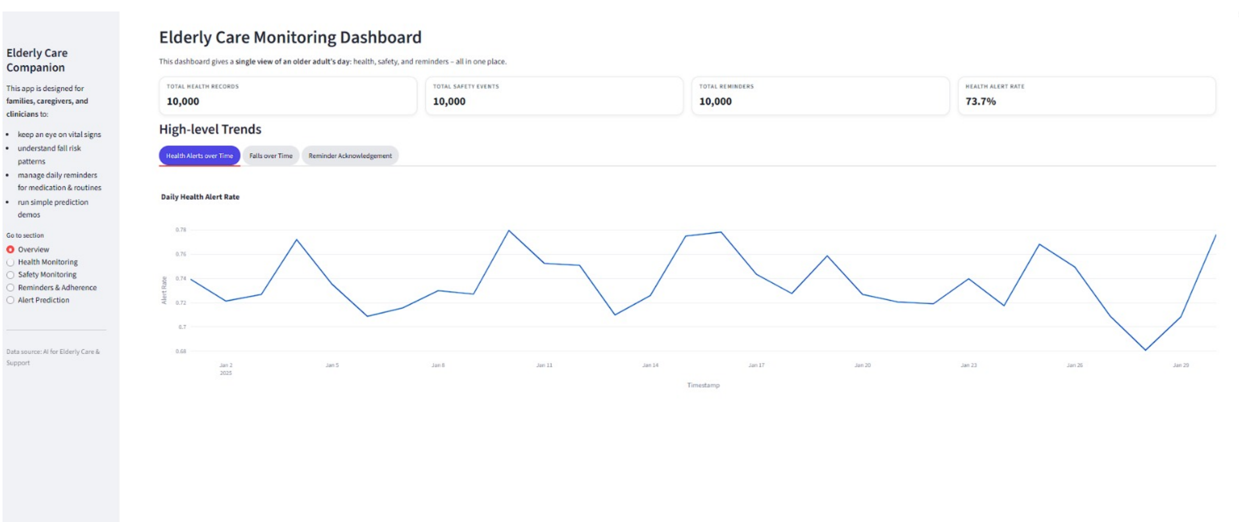

Figure 1: Elderly Care Companion Dashboard

Overview Dashboard

The Overview page provides a high-level snapshot of the monitored individual's daily condition by aggregating information from all three datasets:

- **Total health records**: 10,000
- **Total safety events**: 10,000
- **Total reminders**: 10,000
- **Overall health alert rate**: approximately 73.7%

The page also includes trend visualizations such as:

- Daily health alert rate
- Daily count of detected falls
- Reminder acknowledgment patterns

This unified view allows caregivers to quickly assess whether a patient is experiencing elevated health risk, increased fall occurrences, or declining adherence to daily routines.

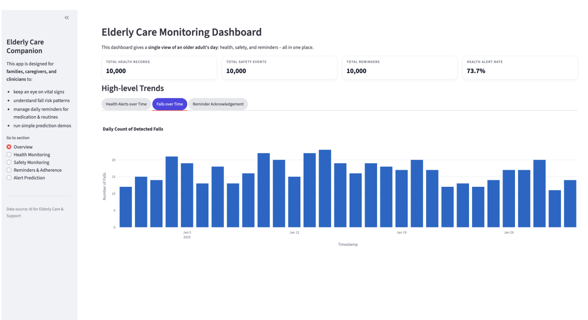

Figure 2: Daily Count of Detected Falls

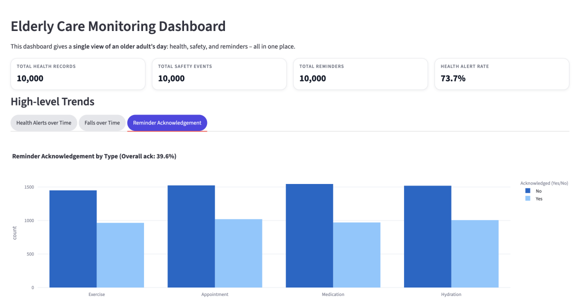

Figure 3: Reminder Acknowledgment- Y/N

Health Monitoring Module

The Health Monitoring page provides a deeper exploration of physiological signals and their relationship to triggered alerts.

Users can filter data by:

- Device or user ID
- Date range
- Alert status (Yes / No / Both)

The module includes interactive visualizations:

- Distributions of heart rate, glucose levels, and SpO_2
- Scatter plots showing the relationship between vital signs and alert status
- Boxplots highlighting glucose differences under alert vs. non-alert conditions
- Time-series plots for individual devices/users

These tools act as an exploratory analysis dashboard, helping clinicians focus on specific time windows or individuals and observe how vital signs evolve around alert events.

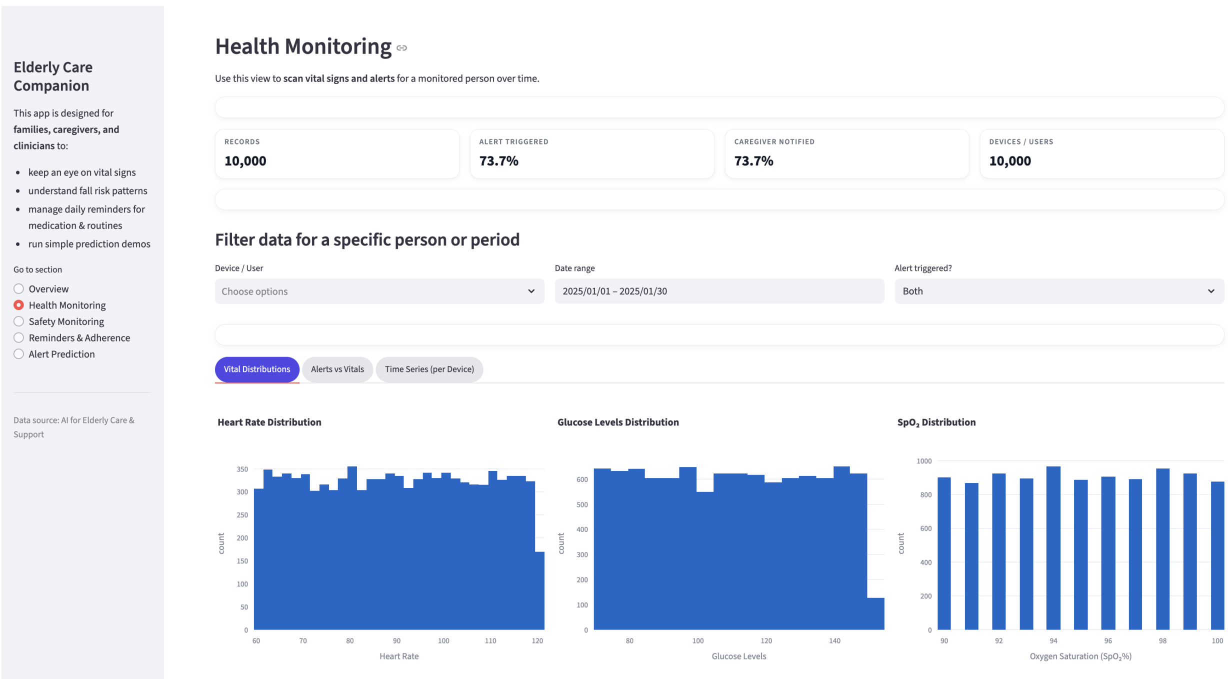

Figure 4: Health Monitoring Section

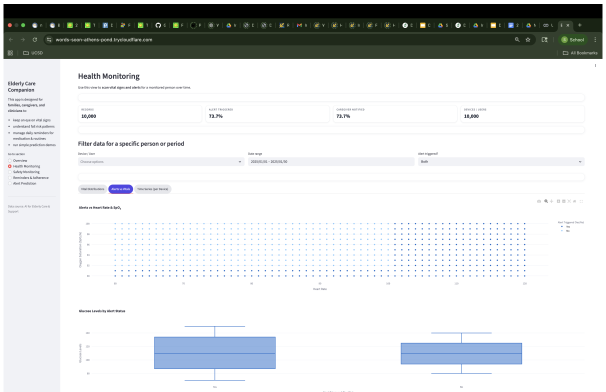

Figure 5: Alerts vs Heart Rate and SpO_2 Visualization

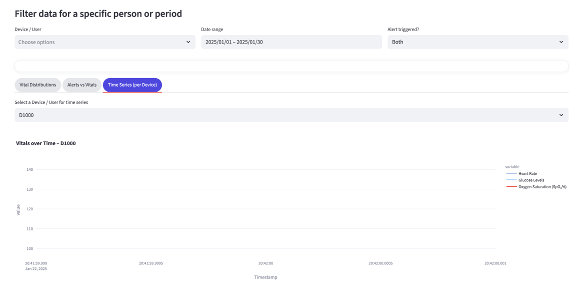

Figure 6: Vitals Time-Series Visualization for Device D1000

Safety & Fall Monitoring Module

The Safety Monitoring page provides two layers of insight: (1) classical safety analytics from the dataset, and (2) an advanced machine learning fall detection model built using the MobiFall accelerometer dataset.

Basic Safety Analytics

Key insights include:

- **Fall rates** based on movement activity
- **Impact force vs. post-fall inactivity**, highlighting potential severity
- **Heatmaps of fall frequency by location**

These analyses help identify unsafe areas in a home and patterns that may indicate increased long-term fall risk.

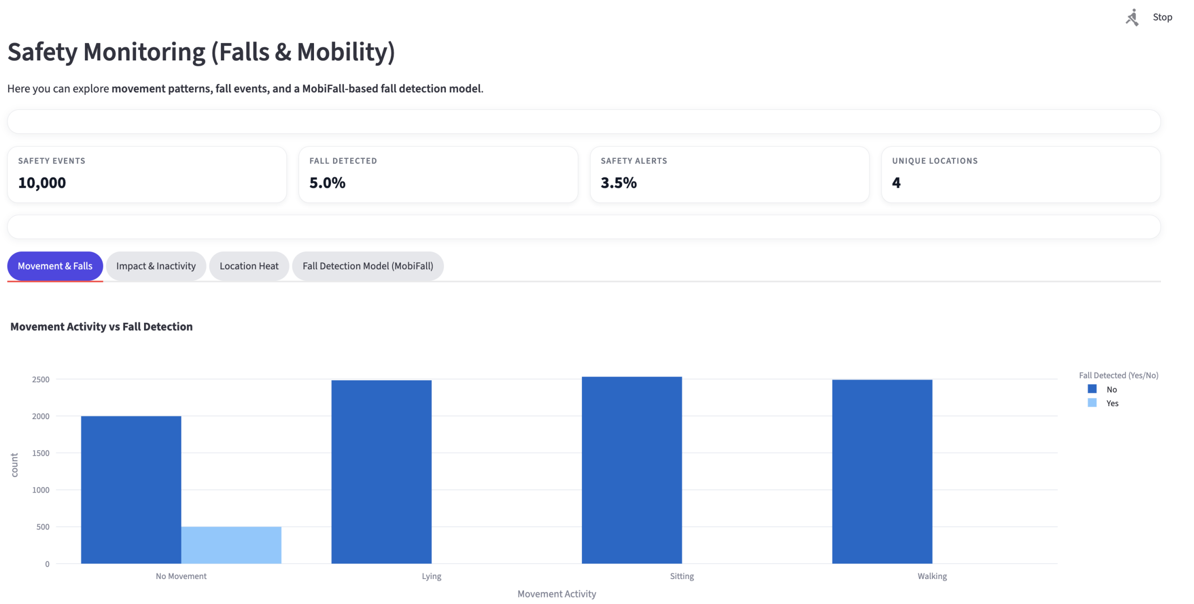

Figure 7: Movement vs Fall Detection

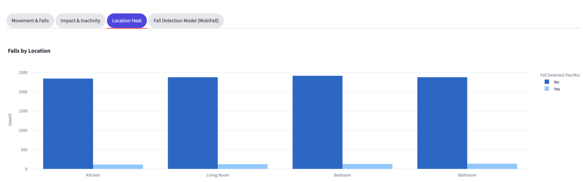

Figure 8: Falls by Location

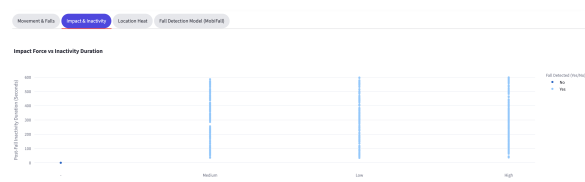

Figure 9: Impact Force vs. Inactivity Duration

Figure 10: Safety Monitoring Visualizations from the Elderly Care Companion Web Application

MobiFall-Based Fall Detection Model

For this part a Random Forest classifier was trained using handcrafted magnitude-based features extracted from raw accelerometer signals. A subject-level train-test split ensured that the model generalizes to new individuals.

MobiFall-Based Fall Detection Model Results

The Fall Detection Model was trained using wearable sensor data from the MobiFall dataset. Accelerometer signals were processed to extract magnitude-based features including mean, standard deviation, maximum value, minimum value, signal range, signal energy, and sequence length. A subject-level train-test split was used to ensure generalization.

Model Performance Metrics

Metric	Value
Accuracy	0.986
Precision	1.000
Recall	0.969
F1-Score	0.984

Table 1: Performance metrics of the Fall Detection Model

Training samples: 1260
Testing samples: 630

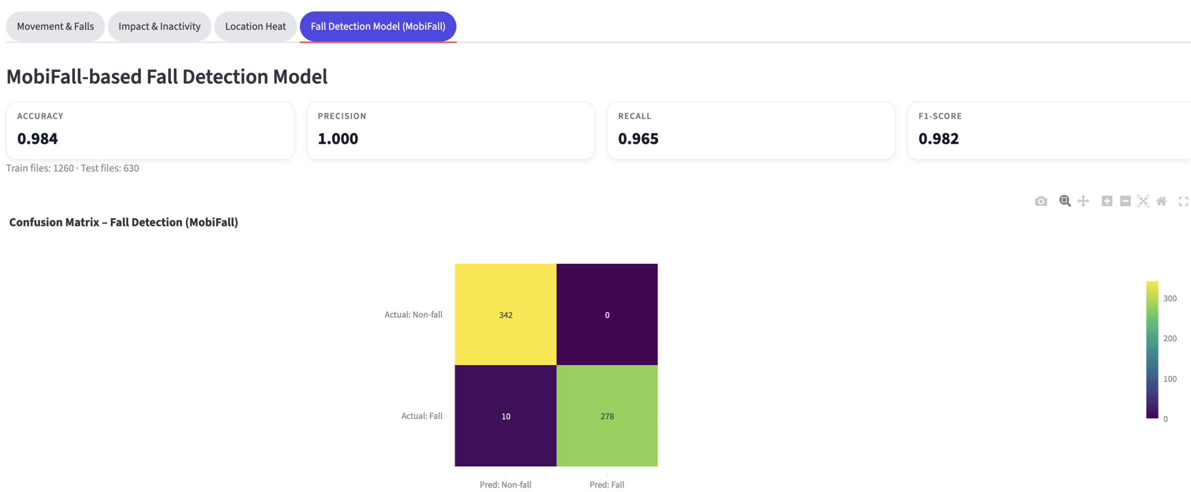

Figure 11: Confusion Matrix

The confusion matrix shows almost perfect discrimination:

- All predicted falls were true falls - no false positives.
- Only 9 out of 288 true falls were missed - very low false negative rate.

A PCA visualization further confirmed strong separability between fall and non-fall clusters.

Comparison between the 2 Models

Aspect	Health Alert Model	Fall Detection Model
Model Type	Logistic Regression	Random Forest
Data Source	Physiological Vitals	Wearable Sensor Signals
Objective	Health Risk Detection	Fall Prevention
Primary Strength	High Recall (92.2%)	High Precision (100%)

Table 2: Comparison of the Two Prediction Models

Together, the two models form a dual-layer elderly safety framework: one for internal physiological health monitoring and one for external physical fall detection.

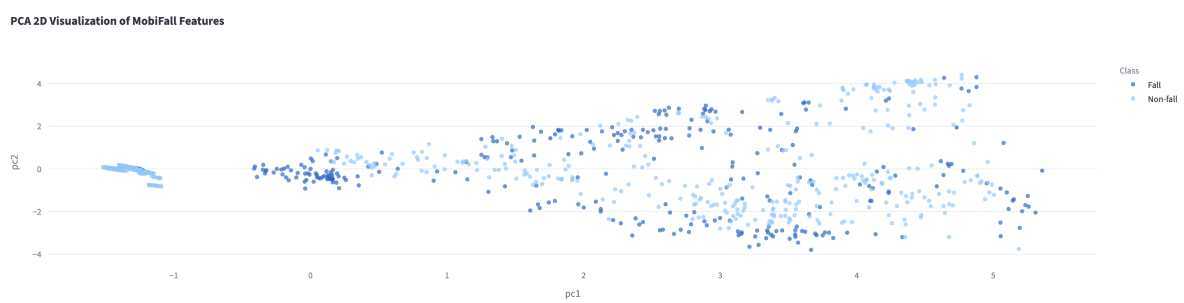

Figure 12: PCA 2D Visualisation

Interactive Fall Simulation Demo The web app includes a user-facing simulation where sliders allow the user to adjust:

- Average magnitude
- Variability (standard deviation)
- Peak magnitude
- Signal range and energy
- Sequence length

The model outputs:

- Fall / Non-fall prediction
- Probability score

If the predicted fall probability exceeds **85%**, the system displays a high-risk warning advising the user to seek help or contact a family member. This is similar to real world fall-alert systems used in elderly care wearable devices.

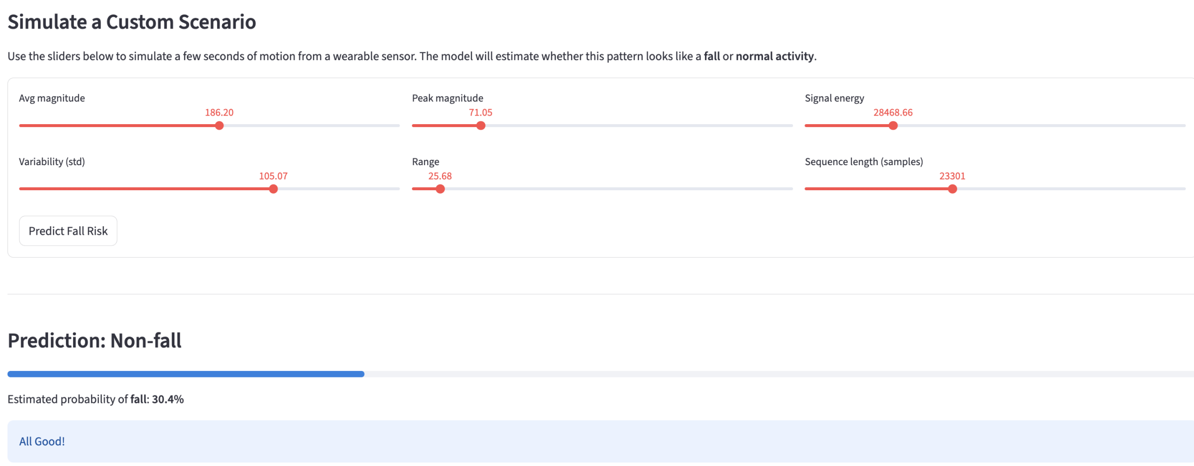

Figure 13: Fall Simulation Demo

Daily Reminders and Adherence Module

This module manages scheduling and adherence to reminders such as medications, hydration, exercise or appointments.

It provides:

- Total reminders and acknowledgment rates
- Reminder adherence by category
- Daily acknowledgment time-series

The system also includes a "Create Custom Reminder" form where users can set:

- Reminder type
- Custom message
- Date and time
- Whether the reminder has already acknowledged

These session-based reminders are then added simultaneously into the dataset and included in updated analytics. This feature demonstrates lightweight state management and user personalization within the app.

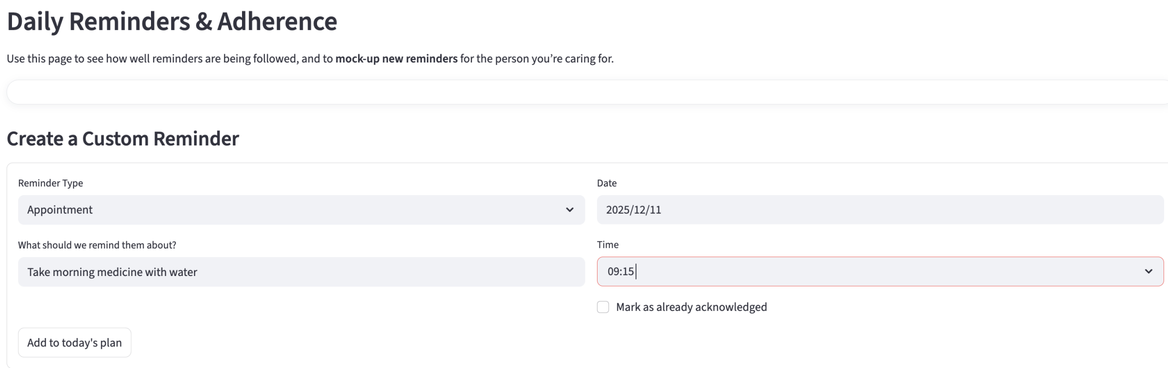

Figure 14: Custom Reminder Demo

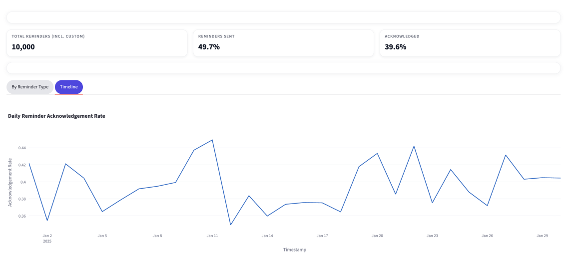

Figure 15: Daily Reminder Acknowledgement Rate Over Time

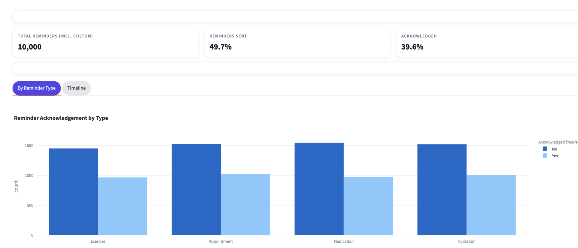

Figure 16: Reminder Acknowledgement by Type

Figure 17: Reminder and Adherence Section

Health Alert Prediction Model

A Logistic Regression model was trained using heart rate, glucose, SpO_2, and time-of-day features to predict whether a health alert would be triggered.

Model Performance Metrics

Metric	Value
Accuracy	0.741
Precision	0.771
Recall	0.922
F1-Score	0.840
ROC-AUC	0.762

Table 3: Performance metrics of the Health Alert Prediction Model

The very high recall indicates that the model successfully identifies most true alert situations, which is essential in healthcare applications where failing to detect a risk can be dangerous.

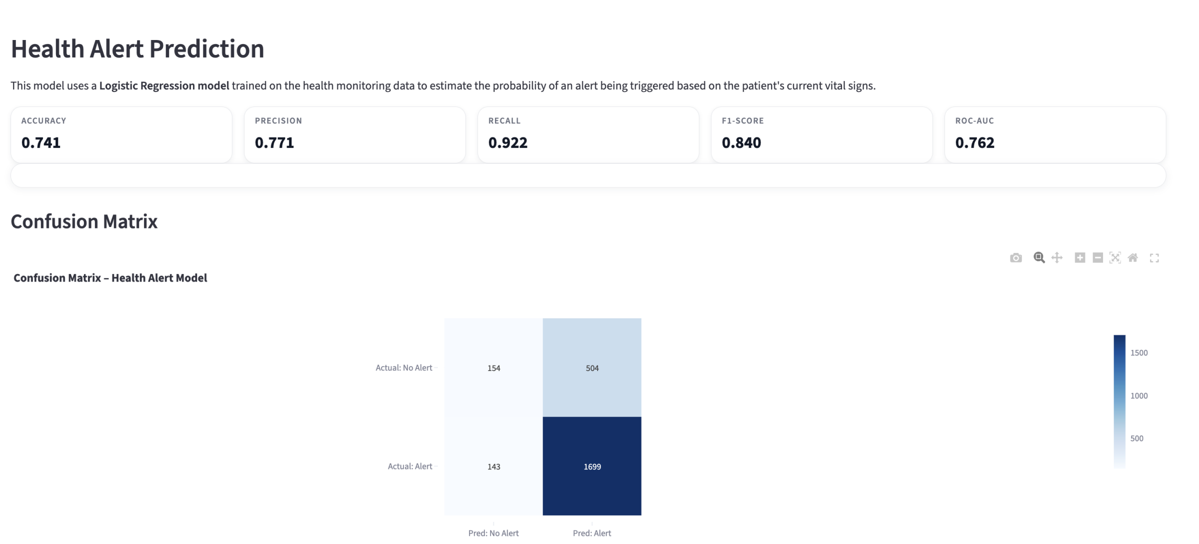

Figure 18: Health Alert Prediction Section

The confusion matrix provides insight into how reliably the model distinguishes between normal and risky health conditions. The model shows strong safety-oriented performance, correctly identifying **1699** true alerts and achieving a high recall of **92.2%**. False negatives **143** remain low, meaning the system rarely misses real emergencies. Although false positives **504** are higher, this trade-off is acceptable in healthcare, where extra warnings are safer than missed critical events. Overall, the model prioritizes sensitivity to better protect elderly users in real-world monitoring scenarios.

Interactive Alert Simulation Demo

Users can manually adjust:

- Heart rate
- Glucose levels
- Oxygen saturation
- Hour of the day

The model returns the probability of a health alert. Similar to the fall model, if the predicted risk exceeds **85%**, a warning is shown to encourage immediate action.

Figure 19: Health Alert Simulation Demo

Summary

Overall, the web application provides a unified environment combining:

- Continuous health monitoring
- Fall risk assessment
- Behavioral adherence tracking
- Two machine learning models for proactive risk prediction
- Interactive interfaces for real-time simulation and interpretation

The system design emphasizes interpretability, user experience, and safety. Together, the analytical tools and prediction models validate the effectiveness of the proposed dual-model elderly monitoring system for real-time risk assessment and safety intervention.

Limitations

While the system demonstrates strong feasibility, several limitations remain:

- **Offline datasets:** Both physiological and motion datasets are static; no real-time streaming was available.
- **Simulated fall data:** MobiFall includes staged falls, which may not fully represent real elderly fall patterns.
- **Simplified labels:** Physiological alerts are based on coarse Yes/No labels rather than clinically validated thresholds.

- **Not a medical diagnostic tool:** The models provide risk estimates but cannot replace clinical evaluation.

Future Work

Several improvements can be made to increase real-world applicability:

- Integrating real-time wearable sensor streaming via Bluetooth or IoT.
- Developing temporal deep learning models (LSTMs, Transformers) for sequential signals.
- Connecting the Streamlit interface to live device data.
- Establishing clinically validated thresholds for health alerts.
- Extending to multi-modal sensing including gait, GPS, and audio cues.

Conclusion

This project demonstrates the feasibility of combining physiological anomaly detection with wearable motion-based fall detection to support elderly individuals living independently. The logistic regression model provides reliable early warning for abnormal vital signs, while the Random Forest fall detector achieves near-perfect accuracy using lightweight statistical features.

Together, these models illustrate how mobile and ubiquitous computing principles can be used to build proactive, sensor-driven safety systems. The accompanying Streamlit interface highlights the potential for real-time caregiver dashboards. Overall, the system serves as a foundation for future, clinically validated deployments in real-world eldercare environments.

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