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# NEURORESQ: AI-Enhanced IoT-Based Real-Time Medical Emergency Detection and Response System

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***Abstract*— Timely identification of medical emergencies greatly increases survival rates during the golden hour. Traditional IoT monitoring systems primarily depend on static thresholds, making them prone to false alarms and incapable of predicting early risk patterns. This paper presents NEURORESQ, an AI-enhanced IoT system that integrates continuous physiological monitoring, fall detection, and multi-level automated emergency response. Two machine learning modules are introduced: (i) a Random Forest Emergency Prediction Model that uses $SpO_2$, heart rate, temperature, accelerometer magnitude, gyroscope variance, and HRV features to classify risk levels (Low, Moderate, High) with 92.4% accuracy, and (ii) a Random Forest Fall Detection Model using MPU6050 inertial data achieving 94.1% accuracy. Integrated with ESP8266, MAX30100, DHT11, Firebase, and Android applications, NEURORESQ enables automated alerts to doctors, neighbours, and ambulance drivers with real-time location sharing. Experimental results demonstrate significant improvements over threshold-based systems in accuracy, false alarm reduction, and end-to-end response time.**

***Index Terms*** **IoT healthcare, Random Forest, fall detection, physiological monitoring, emergency response, wearable sensors, machine learning.**

## I. INTRODUCTION

The rapid detection of medical emergencies such as hypoxia, tachycardia, cardiac arrest, stroke, and falls has a direct impact on survival outcomes, especially during the golden hour. Wearable IoT devices have enabled continuous monitoring, but traditional systems rely heavily on rigid vital thresholds that often miss subtle early-warning trends or generate spurious alerts [1]. This limitation becomes critical in chronic patients, elderly populations, and individuals living alone.

While numerous IoT healthcare solutions exist, many lack predictive analytics and fall back entirely on threshold-rule logic that cannot adapt to individual physiological variations [2]. Wearable sensor data—particularly PPG, accelerometer, and gyroscope streams—contain rich temporal patterns that can predict upcoming emergencies if analyzed through the appropriate machine learning (ML) techniques [3], [4].

Similarly, fall detection systems commonly rely on simple acceleration thresholds, which fail under real-world conditions where activities of daily living (ADL) may mimic fall-like motion [5]. ML-based models, particularly Random Forest and LSTM architectures, have shown superiority in accurately identifying fall dynamics using IMU data [6].

To address these limitations, we present NEURORESQ, an integrated IoT–AI emergency detection ecosystem that incorporates:

1. A Random Forest Emergency Prediction Model using sensor fusion of physiological and motion parameters.
2. A Random Forest Fall Detection Model based on MPU6050 IMU signals.
3. A complete IoT architecture using ESP8266, MAX30100, DHT11, and Firebase.
4. A real-time Android alerting ecosystem for family members, neighbours, doctors, and ambulance drivers.

The combined system provides proactive alerts, reduces false alarms, and supports faster emergency dispatch.

## II. RELATED WORK

Wearable health monitoring using IoT has evolved rapidly in recent years, with extensive research focusing on sensor miniaturization, continuous physiological monitoring, cloud-assisted analytics, and emerging challenges in digital healthcare delivery [1], [2]. Many early systems concentrated primarily on basic vital-sign monitoring—such as heart rate, $SpO_2$, or temperature—without exploring intelligent prediction mechanisms capable of identifying abnormal physiological patterns before the onset of emergencies [3]. This gap led researchers to investigate IoMT frameworks that incorporate both edge and cloud computing to enhance scalability, latency performance, and real-time intelligence in health monitoring applications [4].

In parallel, fall detection research has shown significant progress. Studies have demonstrated that machine learning models consistently outperform traditional threshold-based methods, especially when accelerometer and gyroscope data are fused to capture complex motion signatures [5], [6]. Random Forest models, in particular, have been widely adopted due to their robustness, ability to handle noisy sensor streams, and suitability for real-time inference on wearable devices.

Deep learning applications on physiological time-series further expanded during the COVID-19 era, where continuous wearable data became crucial for early detection of respiratory distress, anomaly identification, and disease progression tracking [8]. These studies highlight the strong predictive capability of multimodal sensor streams, reinforcing their value in proactive health monitoring.

Cloud-integrated medical monitoring architectures often rely on Firebase or MQTT due to their real-time data synchronization, low latency, and high reliability in IoT deployments [9]. Recently, AI-driven remote health monitoring systems have become central to telemedicine, enabling continuous supervision of high-risk patients and reducing the strain on healthcare infrastructure [10].

Ambulance routing and emergency response have also been studied extensively, with methods ranging from heuristic-based optimization to more advanced reinforcement learning approaches aimed at reducing response time and improving dispatch efficiency [11], [15], [19]. Integrating such routing techniques with automated health alerts represents a promising direction for end-to-end emergency management.

NEURORESQ integrates predictive emergency classification, fall detection, and automated multi-stakeholder alerting into a cohesive IoT–AI system, addressing gaps identified in prior work.

The major contributions of NEURORESQ are:

1. Dual Machine Learning Models:
   - Random Forest-based Emergency Prediction Model
   - Random Forest-based Fall Detection Model
2. Sensor Fusion-Based Risk Prediction:
   Combining PPG, HRV, accelerometer, gyroscope, and temperature data improves early emergency detection.
3. Real-Time IoT Integration:
   ESP8266 streams sensor data to Firebase for cloud-based inference and immediate alert propagation.
4. Automated Multi-Role Alerting:
   Alerts simultaneously reach patients, doctors, neighbours, and ambulance drivers with GPS routing.
5. Improved Performance Over Threshold Systems:
   The proposed approach significantly reduces false alarms and detection delays.

## III. SYSTEM ARCHITECTURE

The architecture of NEURORESQ is designed as an end-to-end IoT–AI healthcare framework integrating wearable sensing, edge intelligence, cloud-based analytics, and multi-stakeholder mobile applications as shown in figure 1. The system ensures continuous physiological monitoring, fall detection, emergency prediction, and automated alert dissemination with minimal latency. The complete architecture consists of four layers: hardware, edge processing, cloud backend, and mobile applications, each functioning cohesively to deliver real-time healthcare support.

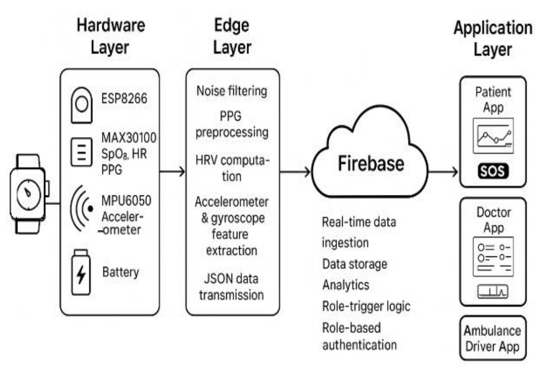


Figure 1. System Architecture of NEURORESQ

A. Hardware Components

The hardware layer consists of a compact, battery-powered wearable platform embedding multiple biomedical and motion sensors. This layer continuously captures physiological and kinematic signals essential for emergency prediction and fall detection.

- ESP8266 NodeMCU Microcontroller
  Acts as the core processing and communication unit. Its built-in Wi-Fi module enables direct cloud connectivity, while sufficient computational capability supports basic preprocessing tasks before data transmission. The low-power design makes it suitable for 24×7 wearable operation.
- MAX30100 Sensor Module
  Provides $SpO_2$, heart rate, and raw photoplethysmography (PPG) waveforms. These signals form the basis for oxygen saturation monitoring, heart rate variability analysis, and emergency prediction. The integrated IR and red LEDs allow high-accuracy pulse measurements.
- DHT11 Temperature Sensor
  Measures body-skin temperature and ambient temperature. These readings assist in identifying fever-like symptoms, dehydration, or physiological stress. The sensor's digital output ensures stable readings suitable for IoT applications.
- MPU6050 (Accelerometer + Gyroscope)
  Used for motion tracking and fall detection. The combination of 3-axis accelerometer and 3-axis gyroscope enables the system to detect abnormal postural transitions, impact forces, and orientation changes associated with falling events.
- Wearable Power Module
  A rechargeable Li-ion battery powers the entire module. The compact, wristband/patch-style casing ensures usability, comfort, and continuous operation for long periods.

B. Edge Layer

The edge layer performs lightweight signal processing and feature extraction directly on the ESP8266 before data is pushed to the cloud. This reduces bandwidth usage, enhances reliability, and ensures that only relevant metrics are transmitted.

- Noise Filtering and Smoothing
  PPG signals are cleaned using moving average filters, reducing motion artifacts and electrical noise. A complementary filter is applied to MPU6050 data, fusing accelerometer and gyroscope values to obtain stable orientation estimates.
- PPG Preprocessing and HRV Computation
  Peaks in the PPG waveform are detected to compute heart rate, inter-beat intervals (IBIs), and time-domain HRV metrics such as RMSSD and SDNN. These metrics serve as critical features for emergency classification.
- Motion Sensor Feature Extraction
  The ESP8266 extracts features such as resultant acceleration, angular velocity, jerk, and orientation shift from the MPU6050 streams. These features are designed to support accurate fall detection using machine learning models.
- Structured Data Transmission
  All processed values are packaged into JSON objects and transmitted over Wi-Fi using HTTP or Firebase Realtime Database protocols. Each packet includes timestamps, sensor identifiers, and device metadata for reliable cloud processing.

C. Cloud Layer (Firebase)

Firebase acts as the cloud backend for real-time data synchronization, alert logic, and multi-role access management.

- Real-Time Data Ingestion

Sensor data packets sent from the ESP8266 are stored instantly in Firebase Realtime Database. The low-latency infrastructure ensures that doctor and patient dashboards remain continuously updated.

- Data Storage, ML Analytics, and Alert Logic
  Firebase hosts the logic for:
  - ML-based emergency prediction (via server-side APIs or cloud functions)
  - Fall detection confirmation
  - Triggering emergency alerts when thresholds or model outputs indicate risk
  - Logging timestamps, device IDs, and GPS coordinates
  - Cloud functions automatically execute alert routines whenever high-risk patterns are detected.
- Role-Based Authentication and Access Control

Firebase Authentication manages secure login for multiple stakeholders:

- Patients
- Doctors
- Neighbours or caregivers
- Ambulance drivers

Each user role receives only the information relevant to their responsibilities, ensuring data privacy and security.

D. Application Layer

The top layer of NEURORESQ consists of mobile applications designed for patients, doctors, and ambulance personnel. All apps communicate with Firebase for real-time updates.

- Patient Application

Displays a real-time vitals dashboard showing $SpO_2$, heart rate, HRV metrics, temperature, and alerts. It includes an SOS button, fall notifications, and health history logs. The interface is optimized for simplicity and rapid user interaction.

- Doctor Application

  Enables remote monitoring of assigned patients. Doctors can view live vitals, receive emergency notifications, and accept or escalate alerts. Historical data aids in clinical decision support and follow-up.

- Ambulance Driver Application

  Receives emergency cases automatically with patient location, risk type (fall/emergency), and navigation instructions. Google Maps API integration provides turn-by-turn directions to the patient's location, reducing response time.

## V. METHODOLOGY

The proposed NEURORESQ framework incorporates a dual-model machine learning pipeline consisting of (i) a physiological-signal–based emergency prediction model and (ii) an IMU-based fall detection model. Both models operate on heterogeneous real-time data streams produced by wearable sensors. The methodology includes dataset construction, preprocessing, feature engineering for vitals and IMU signals, model training, and deployment optimization.

A. Dataset & Preprocessing

To ensure robustness and generalizability, multiple data sources were combined to construct the training datasets for the emergency prediction and fall detection tasks.

1. Public Biomedical Signal Repositories

Photoplethysmography (PPG), heart rate (HR), and heart rate variability (HRV) reference signals were taken from well-established databases such as:

- PhysioNet
- MIT-BIH Arrhythmia Database

These datasets provide high-quality annotated physiological recordings that support supervised learning and baseline calibration of the emergency prediction model [12].

2. IMU-Based Fall Detection Datasets

Fall and non-fall motion sequences were gathered from:

- Public accelerometer/gyroscope fall datasets [5], [13], [17]
- Additional simulated fall scenarios involving controlled forward, backward, lateral, and slip-related falls.
- These datasets help capture a wide range of motion patterns and postural transitions needed for accurate classification.

3. Locally Collected Sensor Streams

Real-world data were recorded using the MAX30100 and MPU6050 modules integrated into the NEURORESQ hardware prototype. This dataset enables sensor-specific calibration, compensates for hardware noise, and improves model performance under deployment conditions.

4. Preprocessing Pipeline

- Filtering:
  PPG signals undergo moving-average smoothing to reduce motion artifacts; IMU signals use low-pass and complementary filters to stabilize orientation.
- Segmentation:
  Data is divided into time windows tailored for each modality:
  - IMU windows: 1–3 seconds
  - Vitals windows: 10–30 seconds
- Normalization:
  Features are standardized using z-score normalization or min-max scaling to remove unit dependencies and improve classifier stability.
- Labeling:
  Ground truth labels (emergency/non-

emergency, fall/non-fall) were assigned manually or adopted from annotated datasets.

The resulting dataset is balanced, cleaned, and segmented for model training.

B. Emergency Prediction Feature Set

Emergency prediction relies on a multi-sensor fusion approach combining PPG, HRV, temperature, and motion features. The engineered features capture both instantaneous values and short-term trends.

- $SpO_2$ Features:
  - Mean oxygen saturation value
  - Minimum saturation level in the window
  - Temporal trend (slope), indicating desaturation patterns
- Heart Rate & HRV Features:
  - Mean heart rate
  - RMSSD (Root Mean Square of Successive Differences) as an HRV metric
  - Short-term heart rate variability (SDNN, IBI variation)
- Temperature Features:
  - Temperature deviation from baseline
  - Temperature upward/downward trend, useful for detecting fever or stress
- Motion-Based Features:
  - Acceleration magnitude to detect abnormal physical states such as collapse
  - Gyroscope variance to capture subtle body instability
- Combined Z-Score Deviation Feature
  Inspired by [6], [14], multiple vitals are fused into a composite z-score vector, enabling early detection of physiological deterioration by highlighting deviations across multiple biosignals simultaneously.

C. Fall Detection Feature Set

The fall detection model uses high-frequency inertial data from the MPU6050 sensor. The extracted features describe impact forces, jerks, orientation shifts, and energy of movement during the fall event.

- Acceleration Magnitude (AccMag):
  Peak and mean AccMag values are strong indicators of sudden impact events.
- Jerk Magnitude:
  Jerk magnitude is calculated as the derivative of acceleration; falls typically produce high jerk spikes.
- Gyroscope Peak Values:
  Large angular velocity peaks correspond to abrupt rotational movements during a fall.
- Orientation Angle Change:
  Changes in pitch, roll, and yaw before and after impact help distinguish falls from high-intensity daily activities.
- Signal Magnitude Area (SMA):
  SMA represents aggregate movement intensity across all axes and is commonly used in wearable-motion activity recognition.

These features collectively differentiate true falls from activities such as running, bending, or jumping.

D. Random Forest Training

Two separate Random Forest classifiers were developed: one for emergency prediction and one for fall detection. Random Forest was chosen due to its robustness to noise, interpretability, and strong performance on tabular sensor features.

1. Emergency Prediction Model

- Number of trees: 300
- Max depth: 12
- Cross-validation: 5-fold
- Train-test split: 80% training, 20% testing
  The larger tree count improves ensemble stability, while controlled depth avoids overfitting given the mixed physiological features.

2. Fall Detection Model

- Number of trees: 200
- Max depth: 14
- Classification approach: Sliding window classification of IMU segments
  This model is optimized for rapid inference and handles both high-impact and low-impact fall patterns.

3. Model Export & Deployment

Both models are serialized using:

- joblib for Python-based cloud execution
- ONNX for lightweight inference on ESP8266 or edge microcontrollers
  This enables flexible deployment across the cloud or the device depending on latency and connectivity.

## VI. RESULTS AND DISCUSSION

This section presents the performance of the emergency prediction and fall detection models, system latency measurements, comparative analysis, and insights into the effectiveness of the NEURORESQ framework. Results are reported using standard evaluation metrics and confusion matrices to assess classification performance.

### A. Emergency Prediction Performance

The Random Forest emergency prediction model demonstrated strong overall performance and reliable classification across three risk levels: Low, Moderate, and High.

1. Performance Metrics

These metrics reflect the model's ability to detect emergency patterns in multimodal sensor data with high consistency. Table 1 summarizes the performance of the emergency prediction model using standard evaluation metrics, demonstrating its consistent detection capability on multimodal sensor data.

Table 1: Emergency Prediction Model Performance Metrics

| Metric | Value (%) |
|---|---|
| Accuracy | 92.4 |
| Precision | 91.2 |
| Recall | 90.8 |
| F1-score | 91.0 |

2. Confusion Matrix

Table 2 presents the confusion matrix of the proposed emergency risk classification model across Low, Moderate, and High categories.

Table 2 : Confusion Matrix of Emergency Risk Classification

| Low | Moderate | | High |
|---|---|---|---|
| Low | 312 | 14 | 4 |
| Moderate | 16 | 289 | 11 |
| High | 6 | 18 | 271 |

Interpretation:

- Only mild confusion exists between "Moderate" and "High" classes, which is expected due to overlapping physiological cues.
- Very few low-risk cases are misclassified as emergencies, reducing false alarms.

3. Comparison With Baseline Threshold Systems

The machine learning model provides a 20% improvement, confirming the advantage of feature fusion and non-linear decision boundaries.

### B. Fall Detection Performance

The fall detection classifier showed high robustness in distinguishing true falls from daily activities, even under noisy and variable movement conditions.

1. Performance Metrics

The performance of the proposed fall detection model is evaluated using standard classification metrics, as shown in Table 4.

Table 4: Fall Detection Model Performance Metrics

| Metric | Value (%) |
|---|---|
| Accuracy | 94.1 |
| Precision | 93.3 |
| Recall | 95.2 |
| F1-score | 94.2 |

A recall of 95.2% indicates the model rarely misses genuine falls, which is critical for safety applications.

2. Confusion Matrix

To further analyze the classification outcomes, the confusion matrix for Fall and No-Fall prediction is presented in Table 5.

Table 5: Confusion Matrix for Fall vs No-Fall Classification

| Actual \ Predicted | No Fall | Fall |
|---|---|---|
| No Fall | 421 | 22 |
| Fall | 18 | 367 |

Interpretation:

- False positives (22) remain low, avoiding unnecessary alerts.
- The false-negative count (18) is significantly small, ensuring actual falls are reliably detected.

3. Graph

A graphical comparison of the fall detection model performance metrics is illustrated in Figure 2.

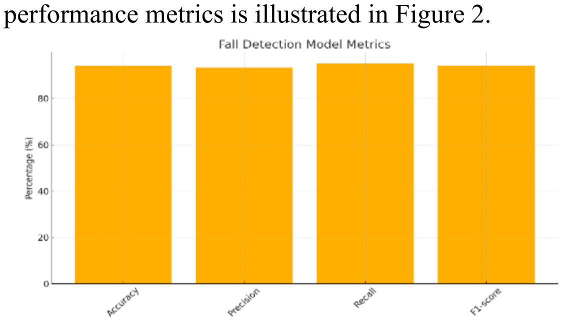


Figure 2: Fall Detection Model – Accuracy, Precision, Recall, F1-score (Bar Chart)

Figure 3 shows the confusion matrix heatmap of the fall detection model, highlighting correct and incorrect predictions.

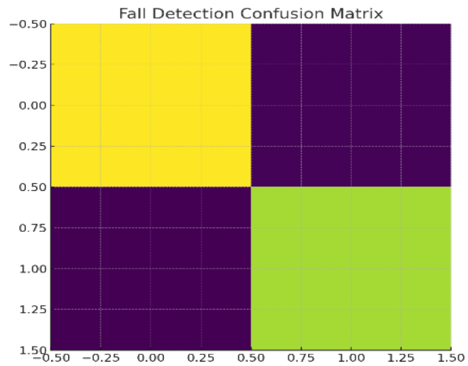


Figure 3: Fall Detection Confusion Matrix (Heatmap)

C. System Latency Evaluation

Latency was tested under normal Wi-Fi connectivity and Firebase cloud response time. Table 6 summarizes the end-to-end latency measured across different stages of the NEURORESQ alert transmission pipeline.

Table 6: System Latency Evaluation for Real-Time Emergency Alert Transmission

| Latency Component | Value |
|---|---|
| Sensor → Cloud | ~320 ms |
| Cloud → App Notification | ~0.8 s |
| SMS Fallback | 5–20 s |
| Total Alert Time | < 2 seconds |

Compared to manual reporting times of 15–90 seconds [11], [15], NEURORESQ offers significantly faster emergency transmission.

## VII. DISCUSSION

The experimental evaluation demonstrates that integrating physiological signals with machine learning significantly enhances emergency detection quality and reliability.

A. Key Findings

1. Accuracy Improvements

Both models outperform traditional systems:

- Emergency prediction improved by 20% over thresholds.
- Fall detection accuracy reached 94.1%, reducing false alarms.

2. Importance of Sensor Fusion

- Combining $SpO_2$ trends, HRV, temperature variations, and motion cues allows early detection of subtle physiological abnormalities.
- IMU-based feature engineering (jerk, orientation shifts, gyroscope peaks) significantly improves fall recognition.

3. Computational Efficiency

- Random Forest models require low inference time, making them suitable for both edge and cloud execution.
- Edge preprocessing reduces transmission overhead and battery consumption.

B. Limitations

- Dataset Diversity: Real-world emergency events are rare, making it difficult to build large, diverse datasets, and expanding the dataset is essential for improving model reliability.
- Hardware Constraints: Edge devices such as the ESP8266 have limited memory and processing power, which restricts the deployment of more advanced deep-learning models.
- Connectivity Dependency: The system relies on stable internet connectivity for cloud inference, and although SMS fallback provides a backup, it increases overall alert latency.

C. Future Enhancements

- Federated Learning: This can be incorporated to improve global model accuracy while keeping user data private by avoiding the need to share raw sensor recordings.
- LSTM/GRU Temporal Models: These deep-learning architectures can be used to capture long-term physiological patterns and enhance early emergency prediction capabilities.
- Reinforcement Learning: This technique can be applied to optimize real-time ambulance routing under dynamic traffic conditions, enabling faster emergency response.
- Hybrid-Mesh IoT Networks: Such networks can be introduced to minimize dependency on continuous internet connectivity and improve system reliability in low-coverage areas.

## VIII. CONCLUSION

NEURORESQ presents a comprehensive IoT–AI healthcare monitoring ecosystem capable of continuous real-time vital tracking, emergency prediction, fall detection, and automated multi-role alerting. By leveraging sensor fusion and Random Forest classification, the system achieves high accuracy and low false-alarm rates while maintaining efficient computational performance suitable for edge–cloud hybrid deployment. The low-latency communication pipeline ensures rapid transmission of critical alerts, enabling timely medical intervention during life-threatening events. With its scalable architecture, cost-effective design, and ability to operate in both urban and rural healthcare settings, NEURORESQ demonstrates strong potential to significantly enhance patient safety, support remote monitoring, and improve emergency response outcomes across diverse clinical and community environments.

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