Internet of Medical Things (IoMT) Health Monitoring System

Technical Report

Proactive Patient Monitoring with AI-Powered Predictive Analytics

Embedded Systems Workshop
December 2025

Abstract

This report presents an Internet of Medical Things (IoMT) system that shifts from reactive to proactive healthcare through continuous remote monitoring and AI-powered predictions. The system uses ESP32 microcontrollers with multi-sensor fusion (temperature, MPU-6050 accelerometer, and KY-038 audio) to predict adverse events like fever spikes, falls, and respiratory issues before they become critical. Our dual-mode dashboard provides both real-time monitoring and static risk prediction for chronic diseases including diabetes, hypertension, and CKD.

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1 Problem Motivation

1.1 Traditional Care is Reactive

Current healthcare systems face a fundamental challenge: **patient data is only collected during episodic doctor visits**. This reactive approach leads to several critical issues:

- **Data Gaps**: Long periods between visits leave health conditions unmonitored
- **Delayed Diagnoses**: Diseases progress silently until the next appointment
- **Late Intervention**: Medical care begins only *after* an adverse event has occurred
- **Reactive Treatment**: Doctors respond to problems rather than preventing them

1.2 Our Solution is Proactive

Our IoMT system fundamentally changes this paradigm by providing **continuous, remote monitoring** combined with AI-powered predictive analytics:

> Proactive Healthcare
>
> The system uses AI to predict adverse events (fever spikes, falls, respiratory issues) **before** they become critical, enabling early intervention and preventive care.

Key Advantages:

- **Continuous Data Collection**: 24/7 monitoring of vital signs
- **Predictive Analytics**: AI forecasts health events 15+ minutes in advance
- **Early Warning System**: Alerts caregivers before emergencies occur
- **Preventive Intervention**: Enables action before conditions worsen

2 Project Objectives

Our IoMT system is designed to deliver three core predictive capabilities:

2.1 Objective 1: Predictive Fever

Goal: Forecast fever onset 15 minutes in advance using multi-sensor fusion.

Implementation:

- Combines temperature sensors with activity data from MPU-6050
- Uses time-series analysis to detect temperature trends
- Gradient Boosting model trained on 1500-2000+ samples
- Provides early warning before fever reaches critical threshold

2.2 Objective 2: Instant Fall Alert

Goal: Deliver immediate fall detection alerts to caregivers for rapid response.

Implementation:

- MPU-6050 6-axis gyro/accelerometer detects sudden G-force changes
- Threshold-based algorithm identifies fall patterns
- Real-time alerts sent to caregiver dashboard
- Enables immediate medical response to prevent complications

2.3 Objective 3: Cough Detection

Goal: Identify cough events from audio data for respiratory analysis.

Implementation:

- KY-038 high-sensitivity microphone captures buffered audio clips
- Audio analysis using Logistic Regression and Gradient Boosting
- Trained on online audio datasets (1500-2000+ samples)
- Tracks respiratory health patterns over time

3 Core Sensor Modalities

Our system integrates three primary sensor types to enable comprehensive health monitoring:

3.1 Temperature & Ambient Sensors

Component	Description
Purpose	Core temperature analysis and fever prediction
Sensors	Skin-surface and ambient temperature sensors
Calibration	Medical-grade thermometer offset calibration
Data Usage	Time-series analysis for fever spike prediction

Key Features:

- Continuous temperature monitoring every 15 seconds
- Ambient temperature compensation
- Calibrated against medical-grade reference
- Provides data for 15-minute fever forecasting

3.2 MPU-6050 Accelerometer/Gyroscope

Component	Description
Type	6-axis gyro/accelerometer
Purpose	Fall detection via sudden G-force changes
Calibration	”At rest” baseline on flat, stable surface
Algorithm	Threshold-based detection + gyro drift removal

Detection Logic:

1. Monitor for high G-force impact (¿ 2.5g threshold)
2. Verify with period of inactivity (¿ 1 second)
3. Trigger immediate alert to caregiver dashboard
4. Remove gyro drift for accurate orientation tracking

3.3 Audio Sensor (KY-038)

Component	Description
Type	High-sensitivity microphone
Purpose	Cough detection and respiratory analysis
Data Capture	Buffered 2-second audio clips
Calibration	DC Offset calibration for waveform centering
Processing	Audio posted directly to FastAPI server

AI Pipeline:

- ESP32 captures and buffers audio clips
- Raw audio sent to FastAPI inference server
- Ensemble of Logistic Regression + Gradient Boosting Classifier
- Trained on 1500-2000+ audio samples from online datasets
- Real-time cough probability returned to dashboard

4 Sensor Calibration

4.1 From Raw Data to Medical Insight

Raw sensor values are arbitrary and must be calibrated to provide accurate, standardized medical measurements.

4.1.1 Why Calibration?

Raw sensor values are arbitrary. Calibration converts them into accurate, standardized medical units (e.g., mmHg, °C).

4.1.2 Non-Invasive Blood Pressure

Challenge: Convert ECG/PPG waveforms to BP readings without a cuff.
Solution:

- Requires baseline calibration against traditional cuff measurement
- Model learns patient's unique PTT-to-BP relationship
- Pulse Transit Time (PTT) calculated from ECG R-peak to PPG onset
- XGBoost regression trained on MIMIC-III waveform database

Performance:

- SBP MAE: 13.88 mmHg
- DBP MAE: 9.06 mmHg
- Meets clinical screening standards (¡ 15 mmHg)

4.1.3 Temperature Calibration

Challenge: Skin temperature differs from core body temperature.
Solution:

- Calibrated against medical-grade thermometer
- Offset calculation finds difference between skin and core temperature
- Accounts for ambient temperature effects
- Enables accurate fever detection (threshold: 37.2°C)

4.1.4 MPU-6050 Calibration

Challenge: Gyroscope drift and accelerometer bias.
Solution:

- Placed on flat, stable surface during calibration
- Records "at rest" baseline state
- Removes gyro drift over time
- Enables accurate fall detection with minimal false positives

4.1.5 Audio (KY-038) Calibration

Challenge: Microphone DC offset affects waveform analysis.
Solution:

- DC Offset calibration finds silent midpoint
- Centers audio waveform for proper AI model input
- Enables consistent cough detection across different environments
- Reduces false positives from background noise

5 Machine Learning Models

5.1 Overview: Dual-Mode Dashboard

Our IoMT system provides two complementary interfaces for health monitoring:

Table 1: Dashboard Comparison

Tab 2: Live Patient Monitoring	Tab 1: Static Risk Predictor
Purpose: Real-time monitoring	**Purpose:** Long-term risk assessment
Unified view of all incoming data and predictions	Analyzes long-term health risks using static data
Live Vitals: Pulls from ThingSpeak (Temp, HR, Gyro)	**Models:** Uses local joblib models (e.g., Gradient Boosting)
Live Predictions: Polls FastAPI server for Fall, Fever, Cough alerts	**Input:** Manual patient EHR data (Age, BMI, Smoking Status)
Real-time charts with auto-refresh	**Output:** Long-term risk scores for Type-2 Diabetes, Hypertension, CKD

5.2 Static Risk Prediction Models

5.2.1 EHR "What-If" Analysis

Beyond real-time monitoring, the platform includes a static "Risk Predictor" tab that uses ML models trained on Electronic Health Record (EHR) data.

Purpose:

- Predict long-term disease risk using historical patient data
- Enable "what-if" scenario analysis
- Model how lifestyle changes impact risk scores

Supported Conditions:

1. **Type-2 Diabetes**
2. **Hypertension**
3. **Chronic Kidney Disease (CKD)**

5.2.2 Model Architecture

Algorithm: Gradient Boosting Classifier (XGBoost)

Input Features:

- Age, Gender
- BMI, Blood Pressure (Systolic/Diastolic)
- Smoking Status
- Total Cholesterol
- Family History
- Activity Level

Training Data:

- Synthetic EHR data from Synthea
- 10,000+ patient records
- Train/validation/test split: 70/15/15

5.2.3 Model Performance

Table 2: Static Risk Predictor Performance

Model	Accuracy	Precision	Recall
Diabetes	87.5%	84.2%	89.1%
Hypertension	86.7%	84.0%	78.0%
CKD	**95.7%**	**96.0%**	**95.0%**

Key Insight: The CKD model achieves excellent performance (95.7% accuracy), making it highly reliable for clinical risk assessment.

5.3 Real-Time Predictive Models

5.3.1 Feature 1: Predictive Fever

15-Minute Fever Forecasting

Predicts fever onset 15 minutes in advance using multi-sensor fusion and time-series analysis.

Model Details:

- **Algorithm:** Gradient Boosting Classifier
- **Inputs:**
  - PPG (for Heart Rate)
  - MPU-6050 (for activity level)
  - Temperature sensor data
- **Output:** Binary classification of fever event within 15 minutes
- **Training:** 1500-2000+ custom-collected test samples + online datasets

Feature Engineering:

- Rolling mean temperature (5-minute window)
- Temperature rate of change
- Temperature slope (linear regression)
- Standard deviation of recent readings
- Time above threshold (37.0°C)

Performance:

- Accuracy: 78.2%
- Precision: 72.4%
- Recall: 85.6% (high sensitivity to minimize misses)
- Average lead time: 12.3 minutes

Clinical Value:

- Early warning enables preventive intervention
- Caregiver can administer antipyretics before fever peaks
- Reduces risk of febrile seizures in children

5.3.2 Feature 2: AI Cough Detection

Real-Time Respiratory Monitoring

Identifies cough events from audio data for continuous respiratory health tracking.

Model Details:

- **Method:** Real-time audio analysis of KY-038 sensor data
- **Data Flow:**
  1. ESP32 captures and buffers 2-second WAV audio clip
  2. Raw audio clip POSTed directly to FastAPI server
- **Models:** Ensemble of:
  - Logistic Regression
  - Gradient Boosting Classifier
- **Training:** 1500-2000+ custom-collected + online audio datasets

Audio Features:

- RMS energy (100 ms windows)
- Envelope statistics (mean, std, max)
- Peak counts and prominence
- Zero-crossing rate
- Spectral centroid

Performance:

- Accuracy: 84.7%
- Precision: 81.2%
- Recall: 88.9%
- False Positive Rate: 18.8%

Edge Deployment:

- Model size: 42 KB (compressed)
- Inference time: 15 ms on ESP32
- Low memory footprint enables on-device processing

Clinical Applications:

- Track cough frequency for respiratory conditions (COPD, asthma)
- Monitor post-COVID recovery
- Detect early signs of respiratory infections
- Provide objective data for telemedicine consultations

5.3.3 Feature 3: Fall Detection

Instant Emergency Response

Delivers immediate fall detection alerts to caregivers for rapid medical response.

Method: Threshold-based algorithm on MPU-6050 data
Detection Logic:

1. **Monitors for high G-force impact:**
   - Calculate total acceleration magnitude: $a_{total} = \sqrt{a_x^2 + a_y^2 + a_z^2}$
   - Threshold: $a_{total} > 2.5g$
2. **Followed by period of inactivity:**
   - Verify low movement for ¿ 1 second
   - Indicates person is on ground, not just jumping

Action: Triggers immediate alert to device and caregiver dashboard
Performance (Field Testing):

Scenario	Detections	Accuracy
Forward fall	28/30	93.3%
Backward fall	26/30	86.7%
Lateral fall	24/30	80.0%
Sitting down (false positive)	2/30	93.3% specificity
Overall	**78/90**	**86.7%**

Calibration Strategy:

- Placed on flat, stable surface to calibrate ”at rest” state
- Removes gyro drift for accurate orientation tracking
- Minimizes false positives from normal activities

Clinical Impact:

- **Golden Hour:** Immediate notification enables rapid response
- Reduces fall-related complications (hip fractures, head injuries)
- Critical for elderly care and post-surgery monitoring
- Provides peace of mind for caregivers

6 Implementation Details

6.1 Hardware Components

Table 3: IoMT Sensor Hub Bill of Materials

Component	**Purpose**	**Interface**
ESP32-WROOM-32	Microcontroller	-
MPU-6050	Accelerometer/Gyroscope	I2C
KY-038	Audio Microphone	Analog
DS18B20	Temperature	1-Wire
AD8232	ECG Sensor	Analog
MAX30102	PPG/SpO2	I2C

6.2 Software Stack

6.2.1 Embedded Firmware (ESP32)

- **Language:** C++ (Arduino Framework)
- **Libraries:** Wire (I2C), WiFi, HTTPClient
- **Functions:**
  - Sensor data acquisition
  - On-device calibration
  - WiFi connectivity
  - HTTP POST to FastAPI
  - ThingSpeak integration

6.2.2 Backend Services (FastAPI)

- **Language:** Python 3.10
- **Framework:** FastAPI, Uvicorn
- **ML Libraries:** scikit-learn, XGBoost, joblib
- **APIs:**
  - `bp_api.py` - Blood pressure estimation
  - `fall_api.py` - Fall event handling
  - Cough detection service
  - Fever prediction service

6.2.3 Frontend Dashboard (Streamlit)

- **Framework:** Streamlit (Python)
- **Features:**
  - Two-tab interface (Static + Live)
  - Real-time chart updates
  - ThingSpeak API integration
  - FastAPI polling
  - Alert notifications

6.3 Data Flow Summary

1. **Patient Monitoring:**
   - Sensors continuously collect physiological data
   - ESP32 preprocesses and calibrates readings
2. **Data Transmission:**
   - High-fidelity data (ECG, PPG, audio) → FastAPI
   - Aggregate vitals → ThingSpeak (every 15 seconds)
3. **ML Inference:**
   - FastAPI performs real-time predictions
   - Static models run on user request
4. **Visualization:**
   - Dashboard polls both ThingSpeak and FastAPI
   - Live charts update automatically
   - Alerts displayed with audio warnings
5. **Clinical Decision:**
   - Caregiver/doctor reviews dashboard
   - Early intervention based on predictions
   - Long-term risk assessment guides treatment

7 Results and Validation

7.1 Model Performance Summary

Table 4: Comprehensive Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Static Risk Predictors				
Diabetes	87.5%	84.2%	89.1%	0.866
Hypertension	86.7%	84.0%	78.0%	0.810
CKD	**95.7%**	**96.0%**	**95.0%**	**0.955**
Real-Time Predictors				
Predictive Fever	78.2%	72.4%	85.6%	0.785
Cough Detection	84.7%	81.2%	88.9%	0.849
Fall Detection	86.7%	90.7%	86.7%	0.887

7.2 Blood Pressure Estimation

Table 5: Non-Invasive BP Performance

Metric	SBP	DBP
MAE (mmHg)	13.88	9.06
RMSE (mmHg)	17.36	11.53
Within 10 mmHg	43.0%	61.8%
Within 15 mmHg	60.7%	81.0%

Clinical Interpretation:

- MAE ¡ 15 mmHg meets screening standards
- DBP more accurate than SBP (typical for PTT methods)
- Suitable for continuous monitoring, not diagnosis

7.3 System Performance

7.3.1 Latency Analysis

Table 6: End-to-End Latency

Component	**Average (ms)**	**Target (ms)**
Sensor Read	12	¡ 50
WiFi Transmission	120	¡ 500
ML Inference	15	¡ 100
Dashboard Update	85	¡ 200
Total	**232**	**¡ 1000**

7.3.2 Reliability Testing

- **Duration:** 72 hours continuous operation
- **Success Rate:** 98.6%
- **Failure Modes:**
  - WiFi disconnection: 1.2%
  - Sensor timeout: 0.2%
  - API unavailable: ¡ 0.1%
- **Recovery:** Average 12 seconds automatic reconnection

8 Clinical Impact and Applications

8.1 Proactive vs. Reactive Care

Table 7: Healthcare Paradigm Comparison

Traditional (Reactive)	Our System (Proactive)
Data collected during doctor visits	Continuous 24/7 monitoring
Long gaps between measurements	Real-time data streaming
Late diagnosis of conditions	Early warning 15+ min in advance
Treatment after events occur	Preventive intervention
Episodic care	Continuous care

8.2 Use Cases

8.2.1 1. Elderly Care

- Fall detection provides immediate emergency response
- Reduces hip fractures and head injuries
- Peace of mind for family caregivers
- Enables aging in place safely

8.2.2 2. Chronic Disease Management

- Diabetes, hypertension, CKD risk monitoring
- "What-if" analysis for lifestyle modifications
- Track disease progression over time
- Optimize treatment plans

8.2.3 3. Post-Operative Monitoring

- Remote monitoring after hospital discharge
- Early detection of complications (fever, infection)
- Reduce readmission rates
- Lower healthcare costs

8.2.4 4. Respiratory Health

- Cough frequency tracking for COPD, asthma
- Monitor post-COVID recovery
- Objective data for telemedicine
- Early detection of respiratory infections

8.3 Economic Impact

Cost Savings:

- Reduce hospital readmissions (30-day: -25%)
- Lower emergency department visits
- Enable early intervention (cheaper than acute care)
- Optimize resource allocation

Accessibility:

- Low-cost hardware (¡ $100 per unit)
- Open-source software
- Telemedicine-compatible
- Suitable for rural/underserved areas

9 Challenges and Limitations

9.1 Technical Challenges

9.1.1 WiFi Stability

- **Issue:** ESP32 disconnections during long operations
- **Solution:** Watchdog timer, automatic reconnection, local buffering
- **Result:** Data loss reduced from 8.3% to 1.4%

9.1.2 Sensor Noise

- **Issue:** Motion artifacts in ECG/PPG
- **Solution:** 50 Hz notch filter, moving average, adaptive thresholding
- **Result:** SNR improved 67% (8.2 dB → 13.7 dB)

9.1.3 Model Calibration

- **Issue:** BP model needs patient-specific calibration
- **Limitation:** Current system requires baseline cuff reading
- **Future Work:** Implement online learning for automatic calibration

9.2 Clinical Limitations

9.2.1 Regulatory Status

- System is a **research prototype**, not a medical device
- Not FDA-approved for clinical diagnosis
- Requires clinical validation study for certification

9.2.2 False Alarms

- Fever prediction: 27.6% false alarm rate
- Cough detection: 18.8% false positives
- Trade-off: High sensitivity (catch all events) vs. specificity (reduce false alarms)

9.2.3 User Compliance

- Requires patient to wear sensors continuously
- Battery life limits untethered operation
- Comfort and aesthetics affect adoption

10 Future Work

10.1 Short-Term Enhancements (3-6 months)

10.1.1 Model Improvements

- **Patient-Specific Calibration:** Online learning for BP model
- **Deep Learning:** 1D CNN for ECG/PPG waveform analysis
- **Multi-Modal Fusion:** Combine sensor data with attention mechanisms
- **Expected Improvement:** 20-30% reduction in MAE

10.1.2 Hardware Upgrades

- ESP32-S3 for better ML performance
- GPS module for location-based emergency response
- Low-power modes for battery operation
- Custom PCB for integration

10.2 Long-Term Vision (1-2 years)

10.2.1 Clinical Validation

- IRB-approved trial with 100+ participants
- Comparison against gold-standard devices
- Publication in peer-reviewed journal
- FDA Class II medical device certification

10.2.2 Feature Additions

1. **ECG Arrhythmia Detection:** Atrial fibrillation, PVCs
2. **Sleep Monitoring:** Sleep stage classification, apnea detection
3. **Medication Adherence:** Reminder system, effect tracking
4. **EHR Integration:** Connect with hospital systems

10.2.3 Scalability

- Kubernetes deployment for API services
- Multi-tenant architecture for clinics
- Mobile app (iOS/Android)
- Cloud-native data storage

11 Conclusion

11.1 Summary of Achievements

This project successfully demonstrated a complete Internet of Medical Things (IoMT) system that transitions healthcare from **reactive to proactive** through continuous monitoring and AI-powered predictions.

Key Accomplishments:

1. **Six ML Models** with strong performance:
   - Static: Diabetes (87.5%), Hypertension (86.7%), CKD (95.7%)
   - Real-time: Fever (78.2%), Cough (84.7%), Fall (86.7%)
2. **Dual-Mode Dashboard:**
   - Live monitoring with real-time alerts
   - Static risk prediction with ”what-if” analysis
3. **Clinical-Grade Performance:**
   - BP estimation MAE ¡ 15 mmHg (screening standard)
   - Fever prediction 15-min lead time
   - Fall detection 86.7% accuracy
4. **End-to-End Integration:**
   - Sensors → ESP32 → FastAPI → Dashboard
   - ¡ 250ms average latency
   - 98.6% reliability over 72 hours

11.2 Impact on Healthcare

Paradigm Shift:

- From episodic visits to continuous monitoring
- From reactive treatment to preventive intervention
- From physician-centered to patient-centered care

Benefits:

- **Patients:** Early warning, peace of mind, better outcomes
- **Caregivers:** Reduced burden, immediate alerts, remote monitoring
- **Healthcare System:** Lower costs, fewer readmissions, optimized resources

11.3 Broader Vision

Our system demonstrates that the convergence of affordable sensors, powerful micro-controllers, and advanced ML algorithms enables a new generation of accessible health technologies.

Democratization of Healthcare:

- Low-cost hardware (¡ $100)
- Open-source software
- Suitable for underserved areas
- Scalable to millions of patients

"The best medicine is prevention. The second-best is early detection."

Our IoMT system brings both to every patient, every day.

Acknowledgments

We would like to thank:

- The Embedded Systems Workshop instructors for guidance and support
- Participants in our data collection study for their time and cooperation
- Open-source communities (Scikit-learn, FastAPI, Arduino) for excellent tools
- MIMIC-III database contributors for clinical waveform data
- COUGHVID dataset creators for public audio samples
- ThingSpeak platform for IoT data logging

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