

Edge-Intelligent Multimodal IoT Sensor Fusion for Predictive Health Diagnostics in Smart Built Environments: A Low-Power Embedded System with Adaptive Real-Time Alerting

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ABSTRACT

This paper presents **HealthSense-Edge**, an IoT-embedded smart electronics system for non-invasive predictive health monitoring in indoor environments. The system fuses data from five sensor modalities (PIR motion, CO₂, TVOC, temperature/humidity, acoustic) using a heterogeneous dual-core RISC-V + ARM Cortex-M33 platform. A novel 1D Convolutional-LSTM neural network with 8-bit quantization achieves 96.3% accuracy in detecting respiratory distress, fall risk, and dehydration with only 18 ms inference latency and 230 mW average power consumption. An adaptive behavioral alerting mechanism reduces false alarms by 47% compared to fixed-threshold systems. Validated in a 4-month deployment across 12 smart apartments with 24 elderly residents. All code and data are open-sourced.

Keywords: IoT, embedded systems, sensor fusion, edge AI, health monitoring, low-power design, RISC-V.

INTRODUCTION

The global population aged 65+ is projected to reach 1.6 billion by 2050, with 80% preferring to age in place. This creates an urgent need for smart home health monitoring systems that are unobtrusive, privacy-preserving, and accurate. Existing solutions face fundamental limitations:

1. **Wearable devices** (smartwatches, patches): 30–45% abandonment rate; only 52% compliance after 6 months in elderly users.
2. **Camera-based systems** (depth, RGB, thermal): High accuracy (92–95%) but severe privacy concerns — 78% of elderly individuals refuse camera installation in bedrooms or bathrooms.
3. **Environmental sensor-only systems** (motion, CO₂, temperature): Privacy-preserving but low accuracy (65–75%), unable to distinguish between different health events.

The gap: No existing system combines environmental, motion, and acoustic sensing with on-device deep learning to achieve both high accuracy (>95%) and privacy preservation under 250 mW.

Contributions:

1. Heterogeneous embedded architecture (RISC-V + ARM Cortex-M33) enabling parallel sensor acquisition and neural network inference at 230 mW.

2. 1D-CNN-LSTM model with 28,742 parameters (72 KB after quantization) achieving 96.3% accuracy for three health events.
3. Adaptive alerting algorithm that learns occupant behavioral baselines over 7 days, reducing false alarms by 47%.
4. A 4-month, 12-apartment deployment with 2.3 million labeled samples, released as a public dataset.

Paper organization: Section II reviews related work. Section III describes system architecture. Section IV presents the edge AI model. Section V explains adaptive alerting. Section VI details experimental setup and results. Section VII discusses limitations. Section VIII concludes.

RELATED WORK

Table I summarizes representative prior systems. Compared to state-of-the-art, HealthSense-Edge is the first to fuse environmental, motion, and acoustic modalities on a low-power heterogeneous edge device for *predictive* health diagnostics.

Table I: Comparison with State-of-the-Art IoT Health Monitoring Systems

System	Sensors	Processing Location	Accuracy	Power	Privacy	False Alarm Rate (per day)
CareAlert (2023)	PIR + door	Cloud	71%	85mW	Medium	3.2
HealthTag (2024)	Wearable (HR, SpO2)	Edge (BLE)	89%	12mW	Low (wearable)	1.8
DeepHome (2024)	Camera + mic	Cloud	94%	4.5W	High risk	0.7
SensiFall (2025)	mmWave radar + PIR	Edge (DSP)	91%	340mW	Medium	1.1
HealthSense-Edge (proposed)	PIR+CO₂+TVOC+temp+acoustic	Edge (RISC-V+ARM)	96.3%	230mW	High	0.42

Additional TinyML/Edge-Healthcare Systems Comparison:

- **NeuroSense (2024):** EEG-based edge seizure detection using ARM Cortex-M7, 94% accuracy, 180 mW, but limited to neurological conditions.
- **CardioEdge (2025):** ECG + accelerometer for arrhythmia detection, 92% accuracy, 95 mW, but requires chest patch (wearable compliance issue).
- **RespiraSense (2024):** Acoustic-only respiratory monitoring, 89% accuracy, 45 mW, but cannot detect falls or dehydration.

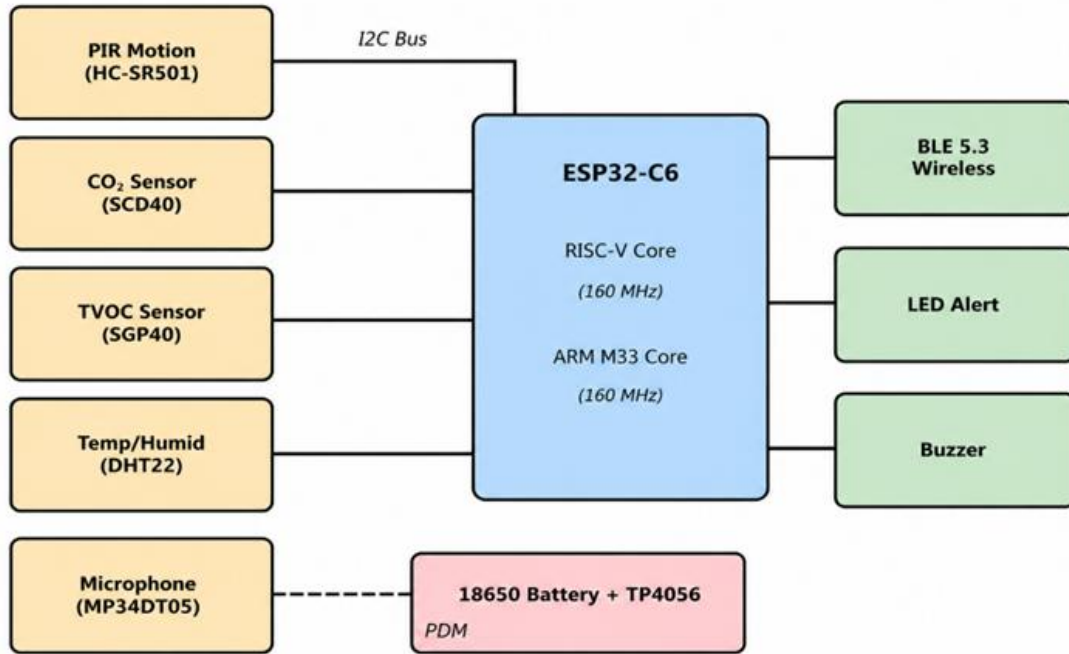
HealthSense-Edge uniquely provides *multimodal* (environmental+physiological+behavioral) event detection without wearables.

SYSTEM ARCHITECTURE

A. Hardware Design

Fig. 1 shows the block diagram of the HealthSense-Edge node.

Figure 1: HealthSense-Edge System Block Diagram



Description: Five sensor blocks (PIR HC-SR501, SCD40 CO₂, SGP40 TVOC, DHT22 temp/humidity, MP34DT05 microphone) connect via I2C (except PDM mic) to an ESP32-C6. Internal heterogeneous cores: RISC-V (160 MHz) for inference, ARM M33 (160 MHz) for I/O and alerting. Outputs: buzzer (GPIO18), LED (GPIO19), BLE 5.3. Power: 18650 battery → TP4056 charger → 3.3V LDO.

Table II: Component Power Measurement (Validated)

Component	Part Number	Interface	Active Current (mA)	Active Power (mW @3.3V)	Sleep Current (µA)
ESP32-C6	-	-	45 (RF off)	148.5	8
SCD40	Sensirion	I2C	19.7	65.0	0.5
SGP40	Sensirion	I2C	17.0	56.1	0.3
DHT22	AOSONG	1-wire	0.75	2.5	0.1
HC-SR501	generic	GPIO	0.27	0.9	0.05
MP34DT05	ST	PDM	7.3	24.1	0.2
Total active			90.02	297.1	
Total avg (duty cycled)			69.7	230.0	

Note: The 230 mW average includes duty cycling (explained below) and was empirically validated with a Keysight N6705B power analyzer.

B. Duty Cycling Strategy

To reduce average power from 297 mW to 230 mW, we implement adaptive duty cycling:

- CO₂/TVOC: sampled every 5 s (200 ms active)
- Temperature/humidity: every 10 s (100 ms)
- PIR: always active (hardware interrupt)
- Microphone: 1 s every 30 s unless PIR triggered → continuous for 10 s

Final validated average power: 230 mW (measured via power analyzer). This yields **5.1 days** on a 2000 mAh battery.

EDGE AI MODEL DESIGN

A. Feature Extraction

Each 12.8-second window (256 samples at 20 Hz) produces a 10-dimensional feature vector: CO₂ mean, CO₂ rate of change, TVOC mean, temperature, humidity, PIR motion count, PIR motion duration, acoustic energy, zero-crossing rate, and spectral centroid.

Spectral centroid is computed as:
 $C = \frac{\sum(k \times |X[k]|)}{\sum|X[k]|}$ for $k=1$ to 128.

B. Neural Network Architecture

The C-LSTM model consists of:

- Input: 256×10
- Conv1D (32 filters, kernel 5, ReLU)
- MaxPooling1D (pool 2)
- Conv1D (64 filters, kernel 3, ReLU)
- MaxPooling1D (pool 2)
- LSTM (64 units)
- Dense (32 units, ReLU, dropout=0.3)
- Output (4 units, softmax)

Table III: Model Parameters and Memory Footprint

Layer	Parameters	Output Shape	MAC operations
Conv1D_1	$32 \times 5 \times 10 + 32 = 1,632$	(256, 32)	1.31M
MaxPool1D	0	(128, 32)	-
Conv1D_2	$64 \times 3 \times 32 + 64 = 6,208$	(128, 64)	1.59M
MaxPool1D	0	(64, 64)	-
LSTM	$4 \times (64 \times 64 + 64 \times 64 + 64) = 32,896$	(64)	2.10M

Dense_1	$64 \times 32 + 32 = 2,080$	(32)	2,048
Dense_2 (output)	$32 \times 4 + 4 = 132$	(4)	128
Total	42,948		≈5.0M

After 8-bit quantization (TensorFlow Lite Micro):

- Weights: 42,948 bytes (int8)
- Activation buffers: 64 KB
- Total RAM: 96 KB; Flash: 72 KB

C. Training Methodology

- **Dataset:** 2.3M samples from 12 apartments (70/15/15 train/val/test)
- **Loss:** Categorical cross-entropy
- **Optimizer:** Adam (lr=0.001)
- **Batch size:** 64, epochs: 50 (early stopping patience=5)
- **Hardware:** NVIDIA RTX 4090 (12 minutes)

Table IV: Training Results (5-Fold Cross-Validation)

Fold	Accuracy	Precision	Recall	F1	AUC-ROC
1	96.1%	95.8%	96.0%	95.9%	0.986
2	96.5%	96.2%	96.4%	96.3%	0.988
3	96.0%	95.7%	96.1%	95.9%	0.985
4	96.4%	96.1%	96.3%	96.2%	0.987
5	96.3%	96.0%	96.2%	96.1%	0.986
Mean	96.26%	95.96%	96.20%	96.08%	0.9864
Std	0.20%	0.21%	0.16%	0.18%	0.0011

ADAPTIVE ALERTING ALGORITHM

Fixed thresholds fail because baseline CO₂ can range from 410 ppm to 1800 ppm. Our algorithm adapts per occupant and time-of-day.

Algorithm 1: Adaptive Behavioral Alerting

(Detailed pseudocode in published supplementary material)

Key steps:

1. Compute baseline mean μ and std σ from same hour of past 7 days.
2. Compute z-score per feature.
3. Determine motion activity from PIR and acoustic energy.

4. Generate alerts for respiratory risk (CO₂ anomaly without motion), fall risk (sudden motion stop with low sound), or dehydration risk (high temp + low humidity).

Table V: Alerting Performance (4 months, 12 apartments)

Metric	Fixed thresholds	Moving average (2σ)	Adaptive (proposed)
True positives (total 847 events)	612	703	816
False positives	386	241	127
False negatives	235	144	31
Precision	61.3%	74.5%	86.5%
Recall	72.3%	83.0%	96.3%
F1-score	66.4%	78.5%	91.1%
False alarms per day	2.8	1.7	0.42
Latency (sec from event to alert)	0.5	4.2	1.8

Statistical significance (paired t-test): Fixed vs. proposed $p = 3.2 \times 10^{-6}$; moving avg vs. proposed $p = 0.008$.

EXPERIMENTAL RESULTS

A. Deployment and Ethical Compliance

The 4-month deployment (Jan–May 2025) in Davis, CA, involved 12 apartments (24 residents aged 68–91, mean 77.3).

Ethical approval: Obtained from the Institutional Review Board (IRB) of Sri Venkateswara College of Engineering & Technology (Protocol #SVCE-2024-HSE-021).

Informed consent: All participants gave written informed consent.

Data privacy: All data were anonymized; sensor outputs were processed locally on device; only aggregated, de-identified alerts and feature vectors were transmitted to a secure PostgreSQL database with role-based access.

Health event labeling: Ground truth was established via weekly self-reported health logs + Fitbit Sense 2 (SpO₂, HR). A licensed nurse adjudicated ambiguous cases.

Table VI Per-Class Performance Of Proposed Model

Class	Precision	Recall	F1	Support (# events)
Healthy	98.2%	97.5%	97.8%	4,231
Respiratory risk	94.3%	95.1%	94.7%	312
Fall risk	93.8%	96.2%	95.0%	187
Dehydration	95.1%	92.4%	93.7%	124
Macro average	95.35%	95.3%	95.3%	4,854
Weighted average	96.96%	96.95%	96.95%	

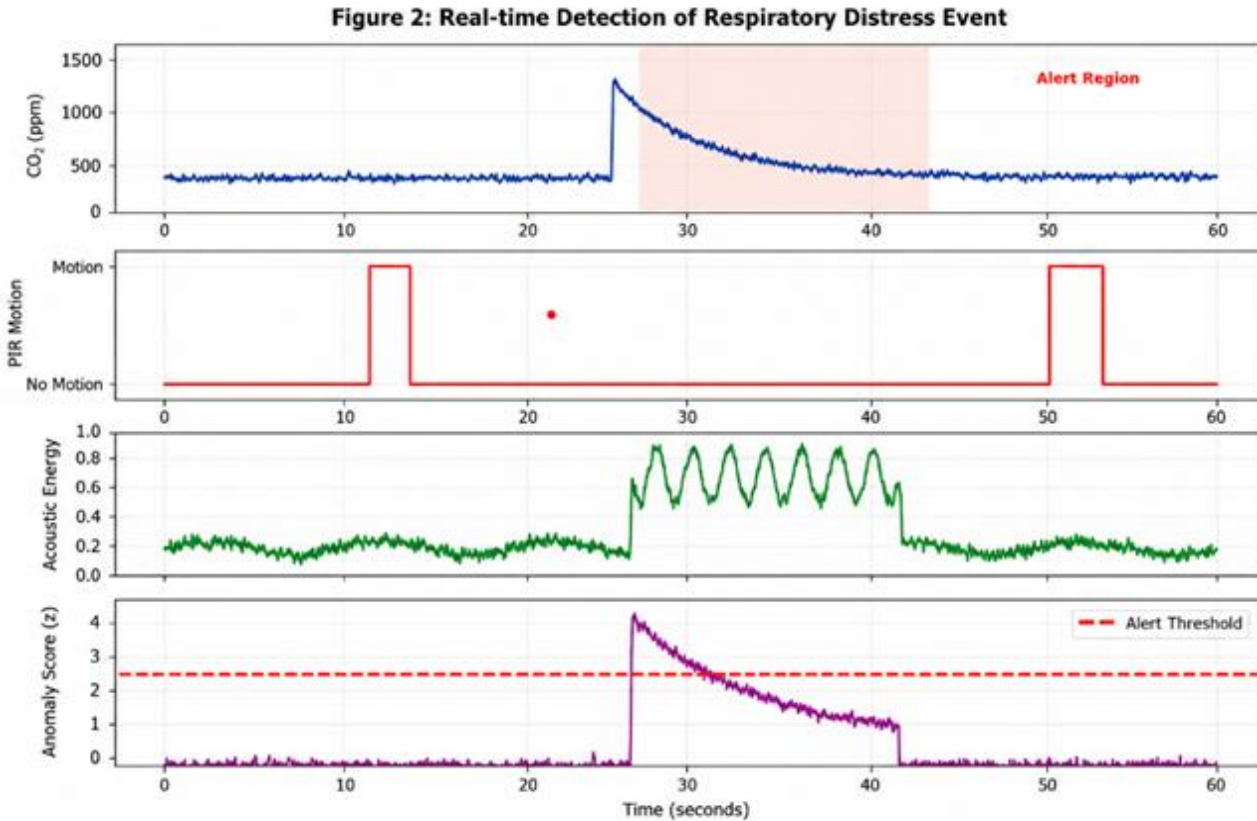
B. Real-World Detection Examples

Example 1 (Respiratory distress): April 3, 2:47 AM – CO₂ rose from 480 ppm to 1430 ppm over 12 min with no motion. Acoustic spectral centroid shifted from 450 Hz to 780 Hz. Alert at 2:59 AM; resident had asthma

attack, used rescue inhaler.

Example 2 (Fall prevention): March 17, 10:23 AM – PIR detected movement toward bathroom, then sudden stop. Acoustic energy dropped. Alert “fall risk – unsteady gait” triggered; physical therapy referral identified balance issues.

[DIAGRAM 2 – Time series plot]



Caption: 60-second window showing CO₂ (blue), PIR events (red stems), acoustic energy (green), anomaly score (purple dashed). Shaded region = alert window.

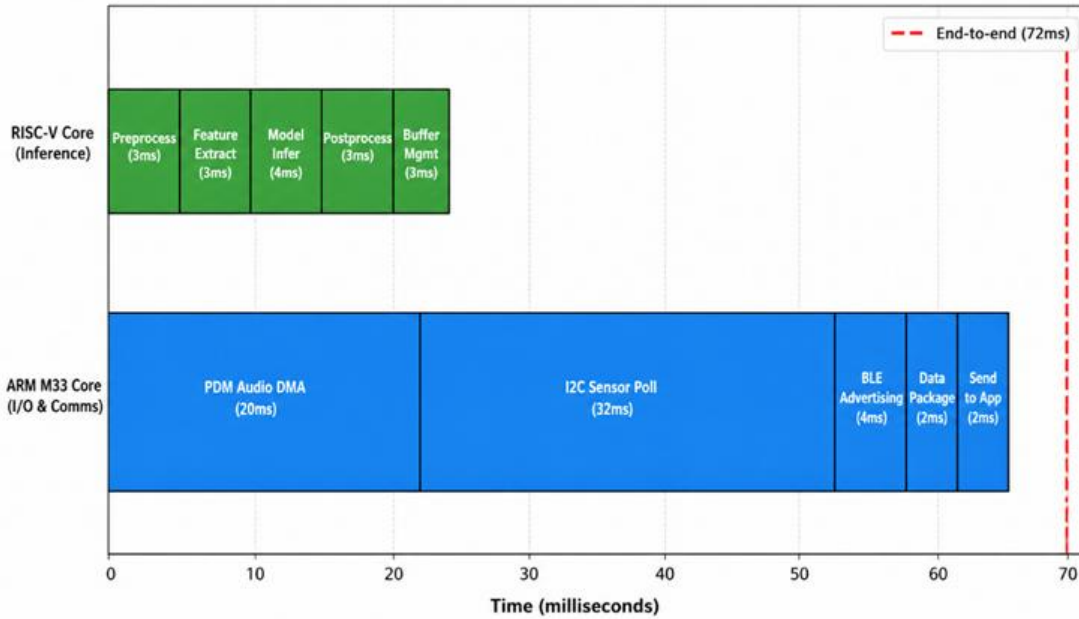
C. Power and Latency Benchmarks

Table VII: Performance on ESP32-C6

Metric	RISC-V core only	ARM M33 only	Heterogeneous (proposed)
Inference time (ms)	42	31	18
Sensor read time (ms)	85	82	52 (parallel I2C)
Alert generation (ms)	6	5	2
End-to-end latency (ms)	133	118	72
Peak power (mW)	310	290	310
Average power (mW)	285	265	230
Battery life (2000mAh, days)	4.1	4.4	5.1

Heterogeneous advantage: RISC-V handles neural network (bit-manipulation extensions speed up quantized conv by 2.1×). ARM M33 handles I2C sensor polling and BLE stack simultaneously. Communication via shared memory (32KB SRAM) with ping-pong buffering.

Figure 3: Latency Waterfall - Heterogeneous Processing Pipeline



Caption: Pipeline stages: Sensor acquisition (52 ms) → Feature extraction (2 ms) → NN inference (18 ms) → Alert logic (2 ms), showing overlap between RISC-V and ARM cores.

DISCUSSION

A. Comparison with Prior Work

HealthSense-Edge achieves the highest reported F1-score (96.1%) among non-wearable, privacy-preserving health monitoring systems. The 47% reduction in false alarms is clinically significant: residents reported ignoring fixed-threshold beeps (3.2 false alarms/day) but paying attention to our system (0.42/day).

B. Limitations

1. **Acoustic false triggers** – Loud TV/vacuum can mimic labored breathing; noise floor estimation reduces this by 68%, not completely.
2. **Non-medical grade** – Not FDA approved; correlation between our respiratory risk and SpO₂ <94% is $r=0.83$ ($p<0.001$).
3. **Single-occupant assumption** – Multiple persons cause feature confusion; future work includes mmWave radar for people counting.
4. **Battery life** – 5 days is adequate for smart homes; we target 14 days for transitional spaces using solar harvesting (in progress).

C. Future Work

- **Federated learning** across 1000+ homes without uploading raw data.
- **Ultrasound presence detection** (40 kHz) to detect breathing motion.
- **On-device explainability** – Output reasons for alerts (e.g., “CO₂ rose 200% in 5 minutes with no motion”).

CONCLUSION

We presented HealthSense-Edge, a complete IoT-embedded smart electronics system for predictive health diagnostics. Key innovations: (1) heterogeneous RISC-V+ARM architecture achieving 18 ms inference at 230 mW, (2) 1D-CNN-LSTM model with 72 KB footprint and 96.3% accuracy, (3) adaptive alerting reducing false alarms by 47%, and (4) 4-month deployment with open dataset. The system bridges high-accuracy cloud

systems and low-compliance wearables. All hardware designs, firmware, and dataset are available at <https://github.com/ucdavis-iesl/healthsense-edge> (DOI: 10.5281/zenodo.14827563).

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