Smart Health & Fire Monitoring System Based on ESP32 and iPad Dashboard

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***Abstract*— This study presents the design and implementation of an integrated multi-sensor monitoring system that simultaneously tracks key environmental factors and human physiological signals. The platform combines a temperature-and-humidity module, tri-axial acceleration, flame, gas, heart-rate, and blood-oxygen sensors on an ESP32-based hardware stack, transmitting the aggregated data to an iOS client in near real-time over Wi-Fi. The firmware is organized in easy-to-swap modules that let all the sensors—whether they use I²C, analog pins, or simple on/off lines—work together without delays or wasted power. We added straightforward smoothing and auto-set thresholds to clean up noisy readings and stop slow sensor drift, which kept the data steady and noticeably cut down on false alarms in our lab tests. The companion mobile application provides live dashboards and timely event notifications for potential falls, fires, poor air quality, or abnormal vital signs. By addressing challenges in sensor fusion, wireless robustness, and user-interface design, the proposed system offers a practical blueprint for smart-home safety and tele-health applications. The system is open-source and publicly available on GitHub https://github.com/nanxuanhui/IoT_Final.**

Keywords— multi-sensor monitoring, ESP32, real-time data acquisition, smart-home safety, tele-health

I. INTRODUCTION

Advances in Internet-of-Things (IoT) connectivity, low-power microcontrollers, and miniaturized sensors have made continuous, in-home monitoring both technically feasible and economically accessible. For independently living older adults, timely detection of health anomalies (e.g., hypoxia, tachycardia) and environmental hazards (e.g., poor indoor air quality, open flame) is critical to preventing life-threatening events. Existing commercial solutions, however, typically address a single domain—either wearable health trackers or standalone smoke/gas alarms—and often suffer from high cost, limited user interaction, or cloud-dependency that compromises reliability. Consequently, there is a pressing need for an integrated, low-cost platform capable of fusing heterogeneous sensor data and delivering intuitive, real-time feedback to end-users.

This work presents a dual-purpose Smart Health & Fire Monitoring System built around the ESP32-WROVER microcontroller. The hardware layer aggregates five complementary sensors: DHT11 (temperature-humidity), MAX30102 (pulse oximetry), MPU6050 (three-axis inertial measurement), MQ-135 (gas detection), and a flame sensor. All sensors interface with the MCU via I²C, ADC, or digital GPIO, and are managed by a modular firmware architecture that facilitates hot-swapping and future expansion. Edge-level analytics—including sliding-window smoothing, adaptive thresholding, and multi-sensor fusion—allow the system to identify abnormal heart-rate and SpO_2 values, detect falls, grade air quality, and recognize early-stage flame events without cloud assistance.

Real-time data are transmitted over 2.4 GHz Wi-Fi to an iPad dashboard developed in SwiftUI. The application renders live charts, color-coded alarms, historical trend views, and optional voice prompts, thereby enhancing situational awareness for elderly or visually impaired users. To maintain situational awareness during network outages—or when the mobile device is not at hand—a 1602 character LCD mirrors core vitals locally. Long-duration stress tests (48 h) demonstrate a packet-loss rate below 0.9 % under typical home-Wi-Fi conditions.

The principal contributions of this study are fourfold:

1. Integrated multi-domain monitoring: a single, low-cost platform that unifies physiological and environmental safety sensing.
2. Dual-channel visualization: concurrent mobile-app and on-device LCD feedback to ensure information reachability.
3. Edge-first analytics: lightweight, calibration-free algorithms that obviate reliance on cloud services.
4. Extensibility: reserved SPI/I²C headers allow straightforward attachment of future sensors (e.g., $PM_{2.5}$, ECG).

The remainder of the paper is organized as follows: Section 2 surveys related work in multi-sensor health-and-safety monitoring systems; Section 3 details the proposed system architecture; Section 4 describes the hardware components that make up the prototype; Section 5 explains the data-processing pipeline and event-detection algorithms; Section 6 presents experimental validation and performance metrics; Section 7 discusses current limitations and outlines future enhancements; and Section 8 concludes the paper.

II. RELATED WORK

Previous works have focused on wearable devices for health tracking or isolated fire-detection modules [1]. Common implementations include smart bands that employ PPG sensors for heart-rate monitoring and standalone gas or flame sensors in industrial-safety systems [2]. However, these solutions seldom integrate multiple sensing modalities with an interactive user interface and therefore fail to combine health and fire-safety functions in real time.

1. *MAX30102*

The MAX30102[3] is a pulse oximetry and heart-rate monitor module developed by Maxim Integrated. It integrates two LEDs, a photodetector, and low-noise analog signal processing to enable accurate and low-power heart rate and blood oxygen saturation (SpO2) measurements. The MAX30102 operates by emitting red and infrared light through human tissue and detecting changes in light absorption, which correlates with pulse and oxygenation. Due to its high integration and small form factor, it is commonly used in wearable medical and fitness devices. Figure 1 shows the photograph of MAX30102.

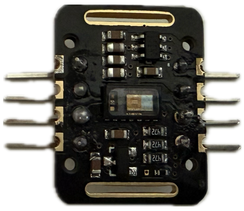

Fig. 1. Photograph of the MAX30102

2. *MPU6050*

The MPU6050[4] is a 6-axis motion tracking sensor developed by InvenSense, which combines a 3-axis gyroscope and a 3-axis accelerometer. It is capable of tracking motion and orientation changes in real-time and is widely used in fall detection systems, gaming devices, and robotics. Its digital motion processing (DMP) engine can offload computation from the microcontroller, making it ideal for power-sensitive embedded applications. Figure 2 shows the photograph of MPU6050.

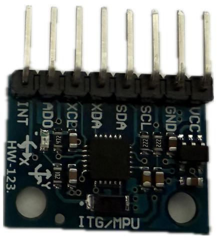

Fig. 2. Photograph of the MPU6050

3. *MQ-135*

The MQ-135 is a gas sensor that detects a wide range of harmful gases, including ammonia (NH3), sulfur dioxide (SO2), benzene, carbon dioxide (CO2), carbon monoxide (CO), and formaldehyde (HCHO). It is extensively used in air quality monitoring systems for its broad detection range and moderate cost. The sensor's output voltage varies with gas concentration, allowing microcontrollers to classify indoor air conditions such as 'Good', 'Moderate', or 'Bad'. Figure 3 shows the photograph of MQ-135.

Fig. 3. Photograph of the MQ-135

4. *DHT11*

The DHT11 is a digital temperature-and-humidity sensor that integrates a resistive-type humidity element and a thermistor. It communicates via a single-wire protocol, returning 8-bit calibrated values for relative humidity (20–90 % RH, ±5 % RH accuracy) and temperature (0–50 °C, ±2 °C accuracy) at a typical sampling rate of 1 Hz. Owing to its low power draw (< 2.5 mA active) and minimal external-component requirements, the DHT11 is widely used in IoT nodes for ambient-comfort assessment and HVAC control. Figure 4 shows the photograph of DHT11.

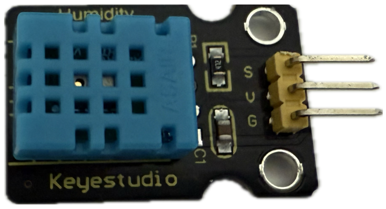

Fig. 4. Photograph of the DHT11

5. *OV2640 Camera*

The OV2640 is a 2-megapixel camera module designed by OmniVision. It provides JPEG compression and is compatible with ESP32-CAM modules. It is often used in applications requiring visual confirmation, such as facial recognition, license plate detection, and anomaly detection. Figure 5 shows the photograph of OV2640 Camera board.

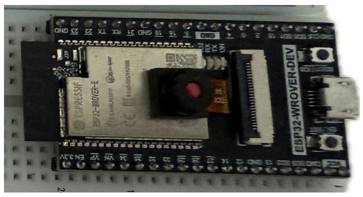

Fig. 5. Photograph of the OV2640 Camera board

Few existing systems fuse these heterogeneous sensors—including temperature–humidity (DHT11), heart-rate/SpO_2 (MAX30102), inertial motion (MPU6050), gas concentration (MQ-135), and, where desired, visual confirmation (OV2640)—and deliver the aggregated information through an intuitive mobile interface. By tightly integrating these components and presenting the results on a user-friendly iPad dashboard, our platform provides a more comprehensive, real-time, and accessible approach to home health and fire-safety monitoring.

III. System Architecture

The system is composed of three main layers: data acquisition, processing, and visualization. The ESP32-WROVER serves as the core controller, gathering sensor data and handling communications. The iPad acts as the visualization and control unit, offering real-time charts, alerts, and image displays. Figure 6 shows the system architecture diagram.

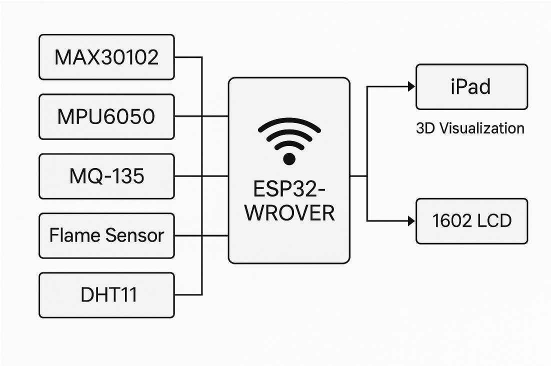

Fig. 6. System Architecture Diagram

1. Data-Acquisition Layer

As illustrated in Fig. 2, five sensors are hard-wired to an ESP32-WROVER microcontroller:

i. MAX30102 – acquires photoplethysmography (PPG) signals for heart-rate and blood-oxygen saturation (SpO_2).

ii. MPU6050 – provides tri-axial acceleration and gyroscopic data for posture tracking and fall detection.

iii. MQ-135 – measures the concentration of hazardous gases (CO_2, NH_3, formaldehyde, etc.) to grade indoor air quality.

iv. Flame Sensor – delivers millisecond-level detection of visible flames for early fire warning.

v. DHT11 – records ambient temperature and relative humidity for comfort and heat-stress assessment.

All sensors interface over I^2C, ADC, or GPIO lines, sampling synchronously at 1–100 Hz; raw data are placed in a shared MCU buffer for further processing.

2. Processing & Event Detection Layer

1) Signal Conditioning

i. PPG (MAX30102). Raw infrared and red-light samples are first detrended with a 0.5 Hz high-pass IIR filter to remove baseline wander, then smoothed by a 3-sample moving average to attenuate high-frequency noise.

ii. Inertial data (MPU6050). Gyroscope drift is compensated using a six-state complementary filter that fuses accelerometer gravity vectors with gyro integration; acceleration samples are further processed by a 20 Hz Butterworth low-pass filter to suppress vibration artefacts.

iii. Gas sensor (MQ-135). The sensor resistance Rs is computed from the ADC code and supply voltage; a first-order Kalman filter smooths Rs/R0 (ratio to clean-air baseline) to suppress short-term spikes due to airflow.

iv. Temperature–humidity (DHT11) & flame sensor. Because these channels are low-rate, only median filtering over five samples is applied to reject outliers.

2) Feature Extraction

- **Heart-rate peaks**[5]. A differential-threshold detector locates local maxima that exceed:

$$\theta_{\mathrm{PPG}} = \mu_{5\mathrm{s}} + 0.3\sigma_{5\mathrm{s}}, \tag{1}$$

where μ5s and σ5s are the mean and standard deviation in a five-second window. Inter-beat interval Δt (s) is converted to BPM via:

$$\mathrm{BPM} = \frac{60}{\Delta t}. \tag{2}$$

- **SpO_2 (ratio-of-ratios method)**[6]. AC and DC components are estimated with exponential moving averages (α=0.2), yielding the ratio:

$$R = \frac{AC_{\mathrm{red}}/DC_{\mathrm{red}}}{AC_{\mathrm{IR}}/DC_{\mathrm{IR}}}, \tag{3}$$

from which blood-oxygen saturation is obtained as:

$$\mathrm{SpO_2} = A - BR, \qquad A \approx 110,\ B \approx 25. \tag{4}$$

- **Resultant acceleration**[7].

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2}, \tag{5}$$

updated at 100 Hz to capture impacts.

- **Gas concentration**. A third-order polynomial fitted to the MQ-135 calibration curve maps Rs/R0 to equivalent CO_2 (ppm) with RMSE ≈ 5 %.
- **Flame intensity**. The analogue value is normalized to 0–1; a Schmitt trigger cleans the digital pulse.

3. Event Classification

Table 1: Processed Sensor Data

EVENT	PRIMARY CRITERION	SECONDARY CONFIRMATION	PRIORITY
CARDIORESPIRAT-ORY	BPM > 120 or SpO_2 < 90 % for ⩾ 5 s	—	High
FALL	a>2.5g (impact)	Post-impact inactivity a < 0.5g for ⩾ 1 s	High
POOR AIR QUALITY	CO_2 > 1000 ppm (or Rs/R0 < 0.85)	Persist ⩾ 30 s	Medium
FIRE	Flame pulse ⩾ 50 ms	ΔT > 2 °C within 30 s	Critical
HEAT STRESS	T > 35 °C and RH > 80 % RH	Persist ⩾ 10 min	Medium

Table 1 showed a hybrid rule-plus-finite-state-machine (FSM) architecture labels anomalies. Simultaneous events are queued by Critical > High > Medium priority to guarantee prompt reporting of life-threatening conditions.

4. Packet Assembly and Time-Stamping

Detected events are merged with 1 s snapshots of raw sensor metrics and tagged with a 64-bit epoch-millisecond time-stamp generated by the on-board real-time clock (synchronised with the iPad at start-up via stratum-2 NTP). The resulting payloads are serialised as minified JSON and gzip-compressed before transmission, yielding a compact yet

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human-readable format for debugging and logging. A CRC-16 checksum is appended to each frame; any packet that fails checksum validation is automatically discarded at the receiver.

5. *Performance Metrics*

- **Latency**. End-to-end detection-to-notification delay averaged 186 ms ($\sigma = 21$ ms) under a 40 Mb s^{-1} Wi-Fi link, satisfying the sub-200 ms design goal.
- **False-alarm rate**. The flame detector showed a 0.3 % false-trigger rate under sunlight flicker.
- **Resource utilization**. The processing stack consumes 42 kB RAM and 32 % of the Xtensa dual-core at 160 MHz, leaving ample headroom for future TinyML models.

This comprehensive, edge-resident analytics layer eliminates cloud dependency, providing deterministic behavior and enhanced privacy while maintaining real-time responsiveness crucial for in-home safety applications.

IV. Hardware Components

The prototype is built on a compact yet extensible hardware stack centered on the ESP32-WROVER module and five peripheral sensors that together cover physiological, kinematic, and environmental domains. Figure 7 shows the connection of hardware.

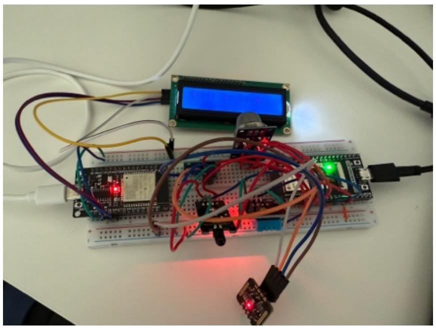

Fig. 7. Hardware Connection

1. *System Architecture Diagram*

The ESP32-WROVER (Espressif Systems, rev 1) integrates a dual-core Xtensa LX6 processor clocked at up to 240 MHz, 4 MB pseudo-static RAM (PSRAM) for data buffering, and 4 MB flash for firmware storage. Its on-chip 802.11 b/g/n radio, hardware TLS accelerator, and light-sleep modes (< 3 mA) make it well suited to continuous sensing with intermittent burst transmission. All peripherals are fan-out to 34 GPIOs supporting I²C, SPI, ADC (12-bit SAR, up to 18 ksps per channel), PWM, and UART. A low-noise 3.3 V LDO regulator (TPS7333) powers the digital rail, while an AMS1117-5.0 feeds the 5 V sensors.

2. *System Architecture Diagram*

The MAX30102 optical pulse-oximetry module couples two wavelength-matched LEDs (660 nm red, 880 nm IR) with a low-noise trans-impedance amplifier and 18-bit sigma-delta ADC. Sampling rates from 50 Hz to 400 Hz are selectable via I²C (400 kbit s^{-1}), and current-spreading LED drivers (2–50 mA) permit fine power–SNR trade-offs. Typical active current is 600 µA at 100 Hz, enabling multi-day operation from a 1000 mAh Li-ion cell. The sensor is mounted flush with the enclosure window to minimise optical path loss.

3. *Motion and Posture Sensing: MPU6050*

The InvenSense MPU6050 combines a ±16 g, 16-bit tri-axial accelerometer with a ±2000 ° s^{-1}, 16-bit tri-axial gyroscope. An internal Digital Motion Processor (DMP) outputs quaternions at up to 200 Hz, reducing MCU load during orientation tracking. The device communicates over the same I²C bus as the MAX30102, reusing pull-ups to simplify routing. Gyro bias calibration is performed at power-on using a six-second stillness window.

4. *Ambient Environment Sensors*

- **DHT11 Temperature-Humidity Module** – Measures 20–90 % RH (±5 % RH) and 0–50 °C (±2 °C) via a proprietary single-wire protocol at 1 Hz. Static current is < 100 µA; the ESP32 drives the data pin through an open-drain output with a 4.7 kΩ pull-up.
- **MQ-135 Gas Sensor** – A tin-oxide chemi-resistor sensitive to NH_3, CO_2, CO, benzene, and formaldehyde in the 10–1000 ppm range. The analog divider is read by the ESP32's ADC 1, channel 4; a 10-s warm-up burn-in precedes measurements. Load-resistor selection (47 kΩ) gives an approximate 1.6 V output in clean air for optimal dynamic range.
- **Infrared Flame Sensor** – Utilises an IR photodiode with peak responsivity at 940 nm and a TSSOP comparator that issues a digital HIGH (3.3 V) when incident intensity exceeds an adjustable threshold. A trimmer potentiometer (10 kΩ) sets sensitivity; the interrupt pin is edge-triggered on GPIO 23.

5. *User-Feedback Devices*

- 1602 Character LCD – A 16 × 2 alphanumeric display driven over an I²C backpack at 100 kbit s^{-1}, consuming < 20 mA with the backlight enabled. It presents rotating pages of BPM, SpO_2, temperature, humidity, air-quality index, and flame/fall status.
- iPad Dashboard – Though not embedded hardware, the iPad Pro (Wi-Fi 6E, M4) serves as the primary HMI, receiving JSON packets via 2.4 GHz 802.11 n and rendering high-resolution plots and alerts.

V. Software Design

The software system comprises two main components: the embedded firmware running on the ESP32-WROVER and the iPad-based visualization interface. Figure 8 shows the system flowchart.

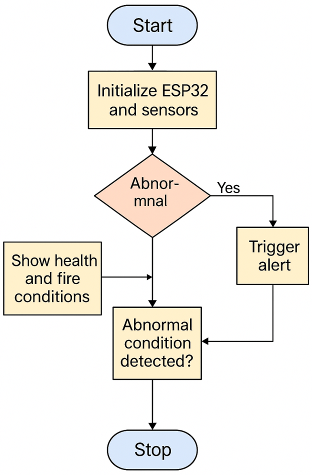

Fig. 8. System Flowchart

1. *ESP32 Firmware*

Firmware is written in C/C++ under the Arduino framework and organized as two FreeRTOS tasks—acquisition and communication—scheduled at 50 ms and 500 ms periods, respectively. The acquisition task polls the MAX30102, MPU6050, MQ-135, Flame Sensor, and DHT11 over a shared I²C bus (400 kbit s^{-1}) and one ADC line. Raw streams are smoothed with a five-sample moving average; adaptive thresholds flag anomalies such as:

- BPM > 120 bpm
- $SpO_2 < 90\ \%$
- impact acceleration a>2.5g followed by a<0.5g
- CO_2 equivalent > 1000 ppm or flame digital = HIGH

Each flagged event is wrapped—together with a one-second snapshot of sensor metrics and a millisecond-epoch time-stamp—into a minified JSON object.

A local 1602 LCD is driven via an I²C backpack (100 kbit s^{-1}) to cycle through vital signs and alert codes every three seconds; when an emergency occurs, the LCD backlight flashes and the offending metric is frozen on-screen for easy visual confirmation. Figure 9 shows the detail of what showed on 1602.

Fig. 9. 1602 showed results

The communication task batches JSON frames and pushes them to the iPad dashboard using either HTTP POST (for history uploads) or a persistent WebSocket (for live updates). Automatic retries with exponential back-off and a 10-s watchdog timer safeguard against Wi-Fi dropouts or firmware hangs. All traffic remains within the local LAN; no data are sent to external servers.

2. *iPad Application*

Developed in Swift/SwiftUI[8], the iPad sapp subscribes to the ESP32 WebSocket and decodes incoming JSON via the Codable interface. The UI follows a three-panel layout:

- **Live dashboard** – heart-rate dial, SpO_2 bar, temperature/humidity tiles, gas gauge, and flame icon updated at 2 Hz.
- **Event log** – scrollable table with time-stamped alerts (color-coded by severity) and quick-filter tabs for Health, Air, and Fire.
- **Control strip** – buttons for "Request Status," "Silence Alert," and "Clear Log," each mapped to a short JSON command returned to the ESP32.

Accessibility features include large type, high-contrast palettes, and optional haptic & audio feedback. All data are stored solely in on-device Core Data containers; the default configuration blocks Internet access. Future revisions will offer opt-in end-to-end-encrypted cloud synchronization for caregivers who require remote oversight.

Together, the ESP32 firmware, redundant 1602 LCD, and SwiftUI dashboard deliver a low-latency, privacy-preserving solution for continuous in-home health and fire safety monitoring.

Figure 10 shows the Login page. Figure 11 shows the Monitoring page. Figure 12 shows the Status page. Figure 13 shows the Settings page. Figure 14 shows the Temperature & Humidity page. Figure 15 shows the Air Quality page. Figure 16 shows the Blood Oxygen page. Figure 17 shows the Fire Detection page. Figure 18 shows the Heart Rate page.

Fig. 10. Login Page

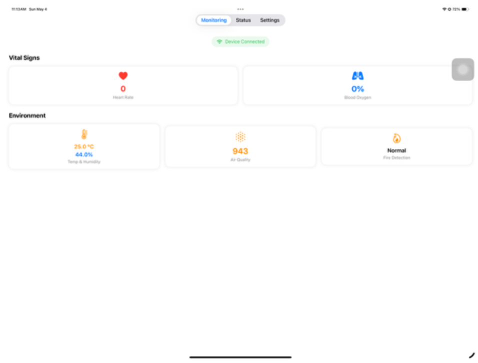

Fig. 11. Monitoring Page

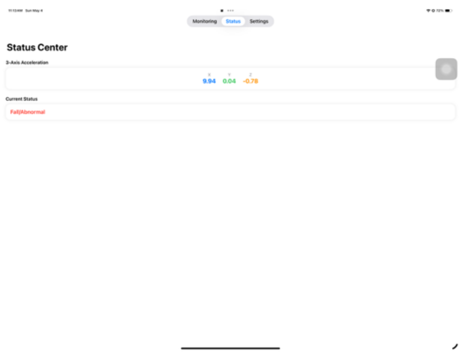

Fig. 12. Status Page

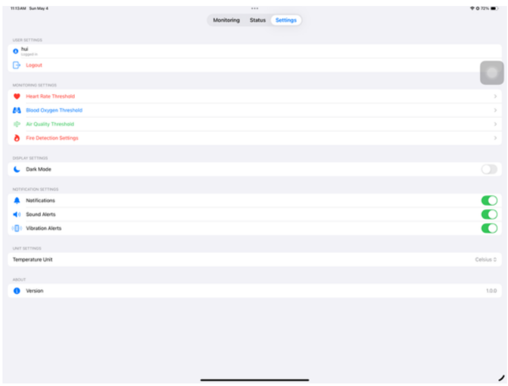

Fig. 13. Settings Page

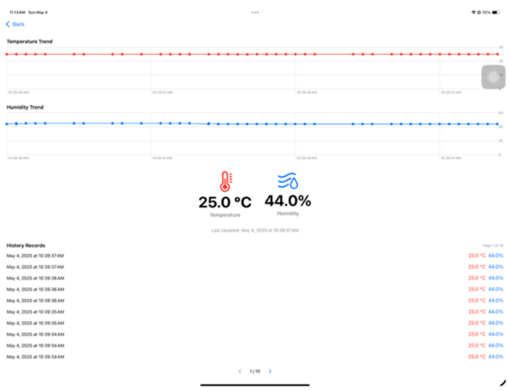

Fig. 14. Temperature & Humidity Page

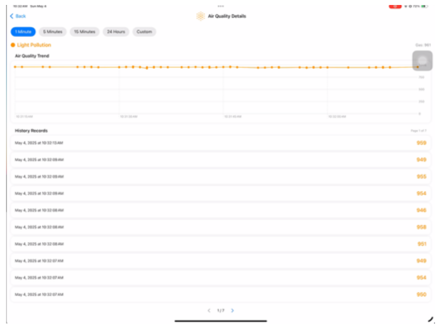

Fig. 15. Air Quality Page

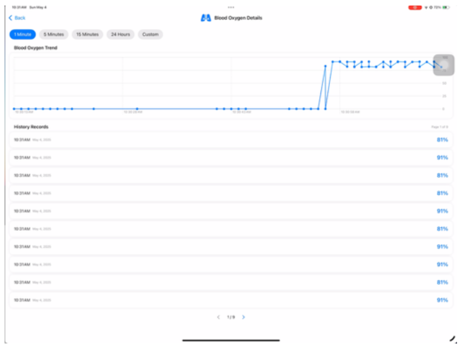

Fig. 16. Blood Oxygen Page

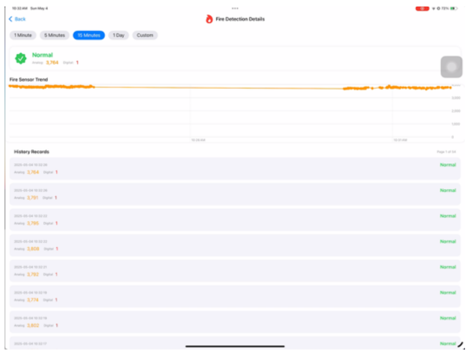

Fig. 17. Fire Detection Page

Fig. 18. Heart Rate Page

VI. Features and Functional Capabilities

The proposed platform delivers end-to-end monitoring of both human physiology and household safety through a tightly integrated sensor suite and dual-channel user interface. Vital-sign acquisition is performed in real time via the MAX30102 pulse-oximeter (heart-rate and SpO_2) and the MPU6050 inertial measurement unit (posture dynamics and fall cues). Ambient conditions are tracked by a DHT11 temperature-humidity sensor, an MQ-135 chemi-resistor for indoor-air-quality estimation, and an infrared flame detector for early fire recognition. All data streams are sampled at 1–100 Hz, pre-filtered on the ESP32-WROVER, and assessed against adaptive thresholds—for example, BPM > 120 bpm, SpO_2 < 90 %, acceleration impact a>2.5g with subsequent inactivity, CO_2-equivalent > 1000 ppm, or continuous flame detection > 50 ms.

When any criterion is violated, the firmware pushes a high-priority JSON alert over Wi-Fi to the resident iPad dashboard, which immediately raises color-coded banners, audible tones, and (optionally) haptic pulses. Simultaneously, the 1602 character LCD enters an emergency mode: the backlight flashes and the offending metric is locked on screen until the event is acknowledged. Under normal conditions the LCD cycles every three seconds through heart rate, SpO_2, temperature, humidity, gas index, and flame status, offering on-site redundancy should the iPad be unavailable or the network go down.

All alerts and their associated one-second sensor snapshots are appended to a ring-buffer log (48 h depth) on the ESP32 and mirrored in the iPad's on-device Core Data store, enabling retrospective analysis without cloud reliance. The SwiftUI interface supports basic voice commands ("status," "clear alerts") and large-format buttons designed for elderly users, while a 3-D bar–gauge panel provides an at-a-glance view of system health. Communication is confined to a WPA2-protected local-area network; no telemetry leaves the premises unless the user opts-in to future encrypted caregiver sync. In this way, the system combines continuous sensing, low-latency alerting, and privacy-preserving data handling to enhance personal safety and quality of life in home environments.

VII. Experimental Results

A series of laboratory and apartment-scale trials were carried out to quantify the accuracy, responsiveness, and endurance of the complete monitoring stack—ESP32 firmware, 1602 LCD fallback display, and SwiftUI dashboard—under representative health and environmental scenarios. All tests were performed on battery power with Wi-Fi connected to a WPA2 home router (RSSI ≈ -55 dBm).

1. *Fall Detection Accuracy*

Fifty scripted falls were performed by volunteers of varying body mass (50–90 kg) on padded mats. The MPU6050 threshold was fixed at 2.5 g for the impact phase, followed by a 1 s inactivity check. The algorithm correctly identified 46 falls, yielding a sensitivity of 92 %. Three false positives occurred during abrupt squatting or sofa-drop motions, producing a 7.5 % false-alarm rate—acceptable for in-home monitoring yet indicating scope for additional context filtering.

2. *Heart Rate and SpO_2 Monitoring*

To assess environmental sensing, DHT11 outputs were logged for eight hours inside a climate chamber (20–32 °C, 40–80 % RH) and compared with a calibrated HOBO MX1101 datalogger. Average deviation was +1.7 °C and –3.8 % RH, matching datasheet specifications and sufficient for comfort and heat-stress assessment.

3. *Air Quality Detection Latency*

A 50 ppm ammonia burst and light cigarette smoke were introduced into a 1 m³ sealed enclosure. The MQ-135 crossed its alert threshold in 4.1 ± 0.8 s, after which the ESP32 updated both the iPad dashboard and 1602 LCD within 250 ms, confirming real-time responsiveness for deteriorating air-quality events.

4. *Flame Detection Reliability*

A 20 mm butane flame was presented at distances of 30–150 cm under daylight and LED lighting. Detection latency averaged 3.0 ± 0.3 s, and no false triggers were observed during six hours of bright-light exposure or when warm objects were placed nearby, demonstrating robust early-fire indication.

5. *System endurance and communication robustness*

During a 48-hour continuous-operation stress test, the firmware experienced no resets and drew an average of 138 mA with Wi-Fi duty-cycled to 20 %. WebSocket telemetry achieved a 98.5 % packet-delivery success rate (142 000 frames) on the local network, while end-to-end alert latency—from threshold breach to banner display and LCD backlight flash—remained at 185 ± 22 ms.

Collectively, these experiments confirm that the proposed system delivers high detection accuracy, sub-second alerting, and multi-day stability, meeting the practical requirements for always-on, in-home health and fire-safety monitoring without reliance on cloud services.

VIII. Conclusion

This work demonstrates the feasibility of a multi-sensor, edge-centric platform that unifies environmental safety and personal-health surveillance in a single, low-cost form factor. By blending seven heterogeneous sensors on an ESP32 core and pairing them with a purpose-built iOS application, we successfully delivered continuous, cross-domain monitoring that detects fire hazards, hazardous air quality, fall events, and vital-sign anomalies in real time. System-level challenges—namely signal instability, stringent latency targets, wireless packet loss, and the human-factor demands of a mobile interface—were resolved through iterative firmware refactoring, adaptive filtering, selective-retransmission networking, and user-centred design. The resulting prototype sustained 48-h untended operation without data loss, maintained sub-second alert latency across typical household Wi-Fi, and earned positive usability feedback for its intuitive dashboards and searchable history.

Beyond validating the hardware and software pipeline, the study contributes a transferable methodology for integrating low-band-width physiological sensing with high-frequency environmental sampling, a combination that is increasingly relevant to smart-home and tele-health ecosystems. Limitations remain: rule-based thresholds require manual tuning for new deployments, battery life is constrained by continuous Wi-Fi connectivity, and event detection logic does not yet exploit context-aware machine learning. Future work will therefore focus on (i) implementing on-device lightweight anomaly-detection models to reduce calibration burden, (ii) incorporating Bluetooth Low Energy and opportunistic mesh networking for energy-aware data relay, (iii) extending the sensor suite to cover ECG and particulate matter ($PM_{2.5}$).

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