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A Multi-Node Wearable Monitoring System for Firefighters With Edge AI and LoRa-BLE Heterogeneous Communication

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ABSTRACT

Firefighters working in high-risk environments, such as building fires and chemical accidents, are exposed to extreme thermal, toxic, and physical stressors, making real-time monitoring of physiological and environmental states essential for safety assurance. This study proposes a multinode wearable monitoring system tailored for firefighting scenarios, featuring a distributed architecture composed of chest, wrist, and environmental nodes. A heterogeneous communication framework combining Bluetooth Low Energy (BLE) and LoRa is adopted to support collaborative sensing and long-range data backhaul. A lightweight one-dimensional convolutional neural network (1D-CNN) is deployed on the ESP32-S3 platform to enable real-time edge-side recognition of six representative firefighter postures. In parallel, an adaptive Physiological Strain Index (aPSI) model is implemented to quantify heat-stress load through the fusion of chest temperature, wrist temperature, and heart rate. The environmental node monitors representative hazardous fireground gases and provides local audible and visual alarms for safety redundancy. Experimental results indicate stable communication performance and effective multimodal monitoring, demonstrating the system's engineering feasibility for firefighter safety support in complex operational environments.

1 | Introduction

In recent years, the increasing frequency of emergencies, such as earthquakes, explosion, chemical accident, and building fire, have severely threatened urban safety, as well as human lives and property [1]. As the primary force in the emergency response chain, firefighters are often required to perform search-and-rescue and fire suppression operations under extreme conditions, during which they are exposed to multiple hazards, including intense thermal radiation, dense smoke, toxic gas leakage, limited visibility, and unstable structures [2].

These factors increase the physical and psychological burden on firefighters and significantly elevate the risk of accidents. Numerous studies indicate that heat stress, heart rate overload, fall injuries, and disorientation are typical causes of injury during firefighting missions [3–5], making firefighters one of the occupational groups with the highest casualty rates worldwide [6]. Although traditional protective equipment and radio voice communication have improved survival rates and coordination efficiency to some extent, they still fall short of enabling precise individual status monitoring and timely anomaly warnings

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under high-pressure and information-asymmetric fireground conditions [7, 8]. It is therefore crucial to develop an individual firefighter monitoring system with real-time, comprehensive, and intelligent capabilities to enhance emergency response efficiency and safety assurance, as this has become a key focus in the field of public safety [9].

The rapid advancements in wearable sensors, edge artificial intelligence (Edge AI), and low-power wide-area networks (LPWANs) have significantly contributed to the development of intelligent monitoring systems for firefighters, highlighting a clear trend toward the integration of multidimensional technologies [2, 10, 11]. In the area of vital-sign monitoring, existing studies have extensively employed sensing technologies to capture key indicators such as heart rate, body temperature, and galvanic skin response, aiming to build quantitative models of health risks for firefighters under extreme workloads and to introduce multisource data fusion mechanisms that improve the accuracy of heat-stress assessment [12–14]. Meanwhile, intelligent sensing of operational behavior has become another research hotspot. Numerous studies have employed inertial measurement units (IMUs) to extract spatiotemporal motion features and develop classification schemes for tactical actions and fall events, using either statistical methods or deep learning algorithms [5, 15, 16]. More recent efforts have further explored the lightweight deployment of neural networks on embedded platforms to address real-time inference challenges for wearable devices under limited computing resources [17, 18]. Beyond individual-state sensing, ensuring reliable wide-area connectivity in fireground environments is equally critical. Related research studies have analyzed the complex composition of gases in fire scenes [19]. Other studies have systematically compared the channel attenuation characteristics of BLE, Wi-Fi, and LoRa in building environments to establish transmission links capable of crossing floor barriers [11, 20, 21]. In addition, to close the data-value loop, recent schemes have begun to integrate sensor networks with visualization terminals, promoting the evolution of systems from single-point data collection to real-time situational awareness [22, 23].

Despite continuous technological advances, existing systems still face critical challenges when moving toward practical deployment. First, most physiological risk assessment models remain at the level of single-parameter warnings, making it difficult to comprehensively capture the complex heat-stress responses of individuals in high-temperature environments. Second, although multimodal recognition systems have improved sensing accuracy, they typically rely on high-computing-power platforms (e.g., Raspberry Pi), which are constrained by power consumption and physical size in real wearable applications, thereby making long-term operation difficult to achieve. In addition, short-range communication methods are severely limited in environments with high temperature, high humidity, and complex occlusions, which can result in high packet loss rates and large latency, thereby compromising the stability of mission-critical data links. Moreover, the lack of real-time interaction between the command center and frontline personnel remains a major obstacle to practical deployment. Therefore, there is a need for a complete system that features high integration and scalability. Such

a system should provide multimodal fusion sensing of physiology, posture, and environment and support remote communication and command linkage, thereby bridging the current technical gap.

In this work, a multinode intelligent monitoring system tailored for firefighter operational tasks is presented to address the aforementioned challenges. Through the construction of a heterogeneous LoRa–BLE framework, reliable data backhaul from deep within the fireground to the remote command center is enabled. A lightweight 1D-CNN model is deployed on the edge node for the real-time recognition of six typical motion postures, allowing that fall-related events to be promptly reported to the incident commander. Furthermore, an adaptive Physiological Strain Index (aPSI) model integrated with environmental sensing is introduced to dynamically evaluate physiological stress and toxicity risks. Finally, when combined with an application-based visualization terminal, a validated engineering solution for enhancing situational awareness and operational safety is provided.

2 | System Architecture and Hardware Design

2.1 | Overall System Architecture

In this study, a multidimensional firefighter status monitoring system is proposed based on a hierarchical Internet of Things (IoT) architecture. Heterogeneous sensor networks are integrated with remote monitoring terminals to enable end-to-end monitoring of physiological signs, motion postures, and the operational environment. From a logical perspective, the system is organized into three layers: the perception and edge computing layer, the network transmission layer, and the application service layer. The overall system architecture is illustrated in Figure 1.

In the perception and edge computing layer, a “master–slave” distributed wireless body sensor network (WBSN) topology is adopted, in which three wearable nodes collaboratively provide the data basis for the aPSI physiological–environmental fusion model. The chest node is deployed on the inner torso layer of the protective suit as the system coordinator, where multimodal sensing and a lightweight inference model are integrated to enable real-time edge-side motion posture recognition [24]. By performing inference locally, the uplink load associated with raw high-frequency data is reduced. Acting as the master controller, the chest node synchronizes and aggregates heterogeneous data from the wrist node (physiological sensing) and the environment node (environmental sensing) through BLE. Local spatiotemporal alignment, multisource fusion, and frame encapsulation are then performed to generate unified data frames for subsequent heat-stress assessment and long-range transmission.

The wrist node is secured to the inner wrist area of the protective suit and provides peripheral physiological information for individual-state assessment. Blood oxygen saturation (SpO_2), heart rate, and peripheral skin temperature are measured to capture variations in physical workload during high-intensity operations, thereby serving as key inputs for heat-stress evaluation within the aPSI framework. The environment node is



FIGURE 1 | Overall system architecture.

mounted on the exterior of the protective suit to monitor hazardous environmental conditions. To enhance individual safety under harsh and unreliable communication conditions, an autonomous local alarm mechanism is incorporated. When environmental indicators or fused physiological risk metrics exceed predefined thresholds, audible and visual warnings are triggered locally, ensuring immediate hazard feedback even in the event of uplink interruption.

In the network transmission layer, a dual-mode heterogeneous communication mechanism is adopted to balance high-frequency body-area data exchange and long-distance transmission. Bluetooth Low Energy (BLE) is used for low-power short-range communication within the wireless body sensor network, supporting continuous data synchronization among wearable nodes. For wide-area uplink transmission, LoRa spread-spectrum communication is employed to transmit fused and structured data frames from the chest node to the remote monitoring terminal, providing stable connectivity in complex fireground environments.

In the application service layer, the remote monitoring terminal receives LoRa data streams through a USB-connected receiver and performs real-time packet parsing and device identification. Based on the incoming data, functions, including anomaly detection and multiparameter visualization, are implemented, enabling commanders to monitor the physiological status, motion states, and environmental exposure of multiple firefighters. This layer completes the closed loop from front-end perception and edge computing to back-end decision support.

2.2 | Hardware Circuit Design

The detailed hardware implementation is illustrated in Figure 2a,b, which show the PCB layout of the chest node and its integration into the firefighter turnout gear. Serving as the system's computing core and communication gateway, the chest

node is designed to support real-time edge inference, reliable wireless transmission, and continuous power supply. A single-board integration scheme is adopted, with an ESP32-S3-WROOM-1 module employed as the main control unit. This system-on-chip integrates a 240 MHz dual-core Xtensa LX7 processor, 16 MB Flash, and 8 MB PSRAM, enabling sensor interfacing, windowed IMU preprocessing, and on-device inference of the lightweight posture recognition model. Motion data are acquired using a QMI8658A 6-axis IMU connected over an I²C interface, whereas core body temperature is measured by a TW117 digital temperature sensor. Long-range communication is supported by an SX1278-based Ai-Thinker Ra-02 LoRa module interfaced through SPI. Power is provided by a 1500 mAh HJX852080 lithium-polymer battery with LDO regulation and multistage decoupling to ensure stable operation under peak loads.

The wrist node hardware implementation is illustrated in Figure 2c,d, which show its PCB layout and placement at the cuff region of the protective suit. The node is designed for fine-grained physiological monitoring in dynamic operational environments, with emphasis on lightweight construction and stable skin-contact signal acquisition. To minimize wearing burden and accommodate the limited cuff space, a chip-level minimum system design is adopted. The node is built around an ESP32-C3 RISC-V system-on-chip, operating with an external 40 MHz crystal oscillator and an RF matching network to support Bluetooth Low Energy (BLE 5.0) communication while reducing PCB area. Physiological signals are acquired using an ADI MAX30102 reflective PPG sensor, which integrates red/IR LEDs, a photodetector, and ambient light cancellation to mitigate motion-induced interference. Peripheral skin temperature is measured using a TW117 digital temperature sensor shared on the I²C bus. The node is powered by a 450 mAh HJX403040 lithium-polymer battery with independent 3.3 and 1.8 V LDO-regulated rails. The final device weighs approximately 10 g and occupies a 30 × 27 mm board area.

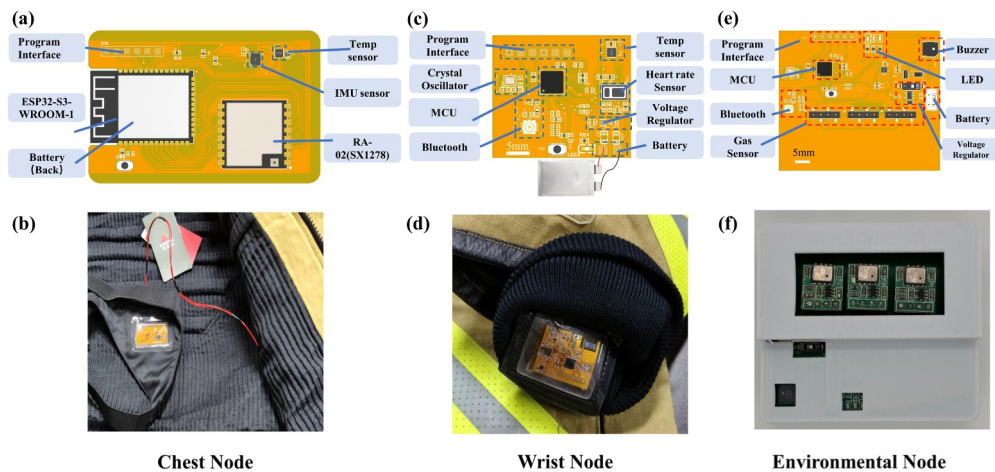


FIGURE 2 | (a) PCB layout of the chest node. (b) chest node integrated into firefighter turnout gear. (c) PCB layout of the wrist node. (d) wrist node worn at the cuff region. (e) PCB layout of the environmental node. (f) Environmental node mounted externally.

The hardware implementation of the environmental node is illustrated in Figure 2e,f, showing its PCB layout and external deployment on the firefighter protective equipment. This node is designed for real-time monitoring of hazardous gases and ambient environmental parameters, with emphasis on sensing scalability and autonomous alarm redundancy. A modular micro-electro-mechanical systems (MEMS) gas-sensor interface based on a Qwiic-compatible I²C connector is adopted to support the JED001 series of digital sensors, including volatile organic compounds, carbon monoxide, smoke, and propane, allowing plug-and-play replacement according to mission requirements. The MEMS sensors operate at low power and output calibrated gas-concentration data through the I²C interface. An environmental temperature sensor is integrated to capture thermal variations in the fireground. For safety reinforcement, a local audible-visual alarm loop is implemented using a passive piezoelectric buzzer and high-brightness LEDs. Distinct alarm patterns are generated through pulse width modulation control to indicate high-temperature, toxic-gas, and low-battery conditions. When predefined thresholds are exceeded, alarms are triggered locally without dependence on the host system. The node is powered by a 1500 mAh HJX852080 lithium-polymer battery regulated to 3.3 V through an LDO stage.

This MCU configuration is task-driven: the chest node requires higher computing and memory resources for concurrent edge inference, BLE-based data aggregation, and LoRa backhaul, whereas the wrist and environmental nodes mainly perform local sensing and periodic BLE upload, making the lower-power ESP32-C3 more appropriate for these subordinate nodes. Under the current battery configuration, the estimated continuous operating time is approximately 37 h for the chest node, approximately 11 h for the wrist node, and approximately 37 h for the environmental node. These operating durations are sufficient to support multiple firefighting or training missions under typical usage conditions.

3 | Software Architecture and Algorithm Design

Building upon the previously constructed multinode distributed hardware architecture, this section describes the core algorithms and software architecture that support efficient system

operation. The overall software workflow is organized around four core modules: physiological-environmental risk modeling, edge-side intelligent inference, heterogeneous communication orchestration, and command-side visualization, forming a closed loop from front-end sensing and acquisition to back-end decision support. An adaptive Physiological Strain Index (aPSI) model and gas-concentration hazard levels are constructed based on data collected from the wearable nodes, enabling real-time quantitative assessment of physiological load and environmental exposure. Subsequently, the chest node performs edge-side inertial-data preprocessing and lightweight deep learning inference to achieve local recognition of motion postures. A BLE-LoRa heterogeneous communication mechanism is then used to aggregate data from the body-area network and deliver structured information to the long-distance uplink. Finally multisource data are parsed, fused, and visualized by the host system, thereby enabling real-time assessment of physiological load and environmental hazards at the command side.

3.1 | Physiological Strain and Environmental Exposure Modeling

To quantitatively assess the physiological load and exposure risk of firefighters in high-temperature, low-ventilation, and complex smoke environments, a dual-dimensional physiological-environmental hazard model is developed based on multinode wearable data. The model integrates physiological indicators, including core body temperature, skin temperature, and heart rate, with typical hazardous gas concentrations (CO, H₂S, and VOCs) to enable dynamic risk characterization of operational status. The model design is derived from the Physiological Strain Index (PSI) proposed by Moran et al. [25] and the adaptive PSI framework reported by Buller et al. [26], with engineering-oriented adaptations introduced to accommodate wearable deployment constraints and the specific sensor configuration adopted in this study.

In physiological stress modeling, the chest node is positioned close to the torso, and the temperature measured at this location is commonly used as a proxy for core body temperature in wearable systems. Previous studies have shown that chest-worn temperature measurements correlate well with rectal or

esophageal temperature in simulated firefighting tasks [13], making them suitable for noninvasive core temperature estimation. Accordingly, chest temperature T_{chest} is adopted in this study as an approximation of core temperature, and an engineering bias compensation is applied to define the estimated core temperature $T_{\text{core}}^{\text{est}}$ as follows:

$$T_{\text{core}}^{\text{est}} = T_{\text{chest}} + 0.5. \quad (1)$$

Wrist temperature T_{wrist} reflects peripheral heat dissipation capacity and I exhibits higher sensitivity to environmental temperature variations, consistent with the role of peripheral sites in multipoint skin-temperature models. In this study, a simplified estimate of the mean skin temperature, denoted as $T_{\text{skin}}^{\text{mean}}$ is defined using a weighted average of chest and wrist temperatures as follows:

$$T_{\text{skin}}^{\text{mean}} = 0.6T_{\text{chest}} + 0.4T_{\text{wrist}}. \quad (2)$$

Furthermore, the core-to-skin temperature gradient, defined as $\Delta T = T_{\text{core}}^{\text{est}} - T_{\text{skin}}^{\text{mean}}$, is introduced to characterize the balance between deep-body heat production and peripheral heat dissipation. Buller et al. [26] systematically evaluated this gradient under thermoneutral conditions, routine exercise loads, and scenarios involving protective equipment. Results indicate that this gradient typically maintains around 4°C in thermal neutral and routine exercise scenarios. However, when wearing insulated clothing, experiencing restricted ventilation, or being exposed to high-temperature heat flux environments, skin temperature rises rapidly, causing the gradient to shrink significantly, reflecting restricted heat dissipation and increased risk of heat accumulation. Based on these observations, a temperature-gradient-driven dynamic core temperature threshold, denoted as T_{crit} is adopted in this study as follows:

$$T_{\text{crit}} = 39.5 + \frac{\Delta T - 4}{4}. \quad (3)$$

The dynamic core temperature threshold T_{crit} is constrained within the range of 38.5°C–40.5°C to ensure physiological plausibility. For the cardiovascular component, the normalized heart-rate term from the original Physiological Strain Index proposed by Moran et al. is adopted to quantify cardiovascular load. According to heat-stress literature, the resting heart rate of healthy adults typically ranges from 60 to 80 bpm, whereas heart rate during firefighting or military operations may increase to 170–190 bpm [25, 27]. Accordingly, 70 and 180 bpm are selected as the lower and upper bounds for heart-rate normalization. By combining the core-temperature component with the normalized heart-rate component, the adaptive Physiological Strain Index (aPSI) is formulated on a standardized 0–10 scale as follows:

$$\text{aPSI} = 5 \frac{T_{\text{core}}^{\text{est}} - 37.0}{T_{\text{crit}} - 37.0} + 5 \frac{\text{HR} - 70}{180 - 70}. \quad (4)$$

This index comprehensively reflects changes in core temperature, heat-dissipation capacity, and cardiovascular load. It is employed as the primary physiological risk indicator for evaluating firefighter heat stress and can be further classified into graded risk levels, ranging from mild to severe strain, according to its numerical value.

For environmental hazard modeling, this study focuses on gases commonly encountered in firegrounds and chemical incidents, including carbon monoxide (CO), hydrogen sulfide (H₂S), and volatile organic compounds (VOCs). The concentrations of these gases indicate air toxicity and can be used to infer the fire development stage, local ventilation conditions, and combustible gas accumulation. For example, rapid accumulation of CO often corresponds to smoldering or restricted ventilation processes, elevated VOC levels suggest material thermal decomposition or combustible gas buildup, and the presence of H₂S is frequently associated with poor ventilation in underground spaces or confined structures, posing a significant asphyxiation hazard. According to exposure limits recommended by NIOSH and OSHA (e.g., CO: 35 ppm REL and 200 ppm ceiling; H₂S: 10 ppm ceiling) [7], this study classifies gas concentrations into four hazard intervals. These intervals are used to describe progressive environmental risk states from safe to acute health threat while also addressing risk-alert requirements for personnel with incomplete protection or prolonged exposure.

Two independent dimensions are established by the physiological strain index and environmental gas levels to characterize the physiological load on personnel and the hazardous evolution of the operational environment, respectively. Together, a foundational software-level hazard characterization framework for the proposed system is formed. Based on different combinations of these two dimensions, corresponding risk-alert strategies are derived by subsequent modules, thereby enabling dynamic safety management and graded early warning during firefighter operations.

3.2 | Edge-Side Lightweight AI Implementation

To enable prompt recognition of postural anomalies during high-intensity firefighter operations, including falls, incapacitation, and sudden collapse caused by heat stress, a real-time activity recognition function is deployed on the chest node, and edge-side AI inference is implemented on the ESP32-S3 platform. The chest node is positioned near the core of the torso, where global body posture changes can be effectively captured. By performing activity recognition locally, the transmission of high-frequency IMU data to the uplink is avoided, allowing rapid response to sudden postural changes with minimal latency under potentially unstable communication conditions in fireground environments. In contrast to conventional IMU-based approaches that depend on attitude angles or fixed thresholds and exhibit limited robustness under intense motion and environmental interference, the lightweight deep learning model adopted in this study extracts multilevel temporal features directly from raw inertial time-series signals, enabling reliable identification of safety-critical postural transitions, such as abrupt shifts from continuous activity to abnormal stillness or lying states. Recognition of typical actions, including standing, walking, going upstairs, going downstairs, sitting, and laying, is thereby achieved [28, 29], and deviations from normal operational modes are reflected through continuous variations in action sequences. It should be noted that the present model is intended for the recognition of representative safety-related posture states in firefighter monitoring, rather than for exhaustive coverage of all task-specific firefighting movements. To satisfy these requirements, an MCU-adapted training and

deployment pipeline is constructed, enabling real-time inference to be performed on the resource-constrained chest node. The overall process and model structure are illustrated in Figure 3.

Three-axis acceleration and three-axis angular velocity signals from the UCI HAR dataset are used during the data processing phase, with representative raw waveforms shown in Figure 3a. To ensure consistency between training and inference, a fixed input window of $[128 \times 6]$, is adopted, which is expanded to a static tensor of $[1, 128, 6]$ on the embedded side to match the ESP-DL static-graph inference interface. All input signals are subjected to Z-score normalization to accelerate model convergence and reduce discrepancies in input distributions. A sliding window of 128 samples with 50% overlap is then applied to generate continuous temporal segments, providing sequence inputs that capture temporal dependencies. As the UCI HAR dataset is presynchronized and presegmented, no additional filtering is applied. The windowed data are directly used to construct the input data structure for edge inference, as illustrated in Figure 3b.

In the model design phase, a lightweight 1D-CNN network architecture optimized for MCU deployment is constructed, as shown in Figure 3b. The network is composed of three convolutional layers with progressively increasing channel numbers ($16 \rightarrow 32 \rightarrow 64$) to extract multiscale motion features. Each convolutional layer is followed by a max-pooling operation to compress the temporal dimension and reduce the computational burden during inference. The resulting feature maps are flattened and fed into a fully connected layer, where dropout with a rate of 0.3 is applied to mitigate overfitting. Finally, a softmax layer is used to generate the probability distribution over six predefined action classes. Owing to its shallow structure and limited parameter count, millisecond-level inference latency is achieved on the ESP32-S3 platform [30], satisfying the requirements of real-time response and energy efficiency for wearable applications.

To efficiently execute the aforementioned model on the embedded platform, a quantization and deployment pipeline is constructed, as shown in Figure 3c [31, 32]. First, the FP32 model trained in PyTorch is exported as an ONNX file with static input shapes, and the ESP-PPQ toolchain is used for 8-bit post-training quantization (PTQ). To minimize quantization errors, a calibration set consisting of 200 window samples is created to statistically analyze the activation dynamic range of each network layer. A power-of-two scaling strategy is adopted, enabling quantization coefficients to be implemented through integer shifts, thereby significantly enhancing computational efficiency on the ESP32-S3. The quantized model is then exported as a FlatBuffers-based .espd file, which can be loaded by the ESP-DL runtime using a zero-copy mechanism.

During deployment, model weights are preloaded into external PSRAM to reduce on-chip SRAM usage, ensuring memory stability while the node performs concurrent communication, sensing, and inference tasks. In actual board-level operation, the chest node samples 3-axis acceleration and angular velocity data at 50 Hz and writes it to a circular buffer of length 128. When the buffer is full, a $[1, 128, 6]$ input tensor is constructed, and ESP-DL is invoked to perform a single forward inference pass. The result is then encapsulated into the LoRa data frame, along with physiological and environmental parameters, enabling continuous real-time tracking of the firefighter's motion state.

3.3 | Heterogeneous Communication Protocol

To maintain reliable data backhaul in complex fireground building environments, a heterogeneous communication architecture combining Bluetooth Low Energy (BLE) and Long Range (LoRa) wireless technologies is adopted. Through this architecture, multimodal physiological, environmental, and posture data are transmitted in a stable manner during firefighter operations. The overall communication process is coordinated by the chest node, which is configured as a BLE central

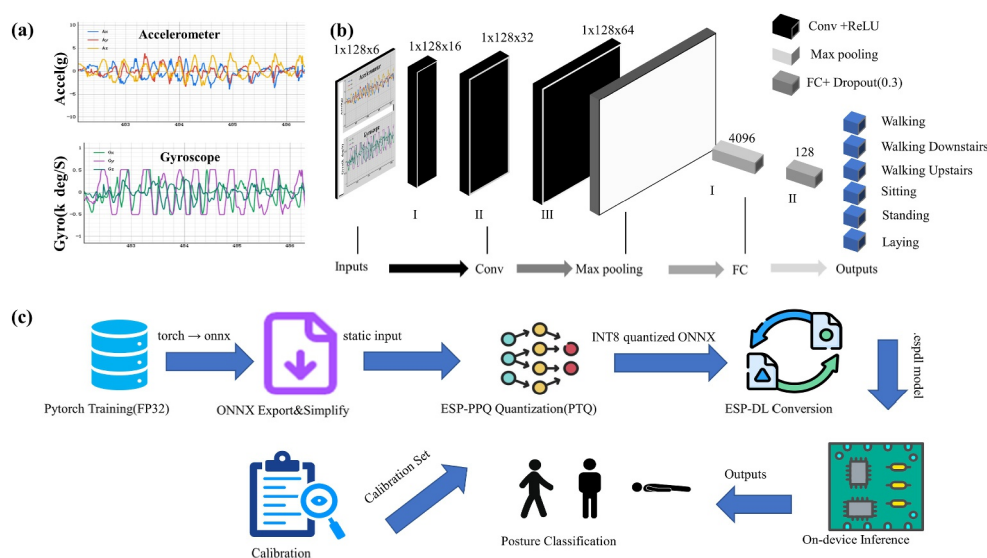


FIGURE 3 | (a) Raw IMU data. (b) Architecture of the proposed lightweight 1D-CNN model for firefighter motion recognition. (c) Quantization and deployment pipeline for the proposed 1D-CNN model on the ESP32-S3 platform.

to manage the wrist physiological node and the external gas node operating as BLE peripherals. In this configuration, short-range data acquisition and aggregation are performed within the body-area network. In addition, a unique node ID is assigned to each set of firefighting equipment, enabling the host computer to distinguish physiological load, environmental exposure, and activity recognition results across different personnel [20, 21]. The overall workflow of the proposed BLE-LoRa heterogeneous communication mechanism is illustrated in Figure 4.

As shown in Figure 4, in the BLE near-field communication link, low power consumption, short connection establishment latency suitable for dynamic wearable devices, and flexible connection maintenance mechanisms are exploited to maintain stable access for the two peripheral nodes during continuous firefighter movement. After system startup, the chest node performs BLE device discovery and establishes independent GATT connections with the wrist node and the environmental node. Physiological data, including heart rate, blood oxygen saturation, and peripheral skin temperature, are periodically transmitted by the wrist node through the GATT Notify property, whereas gas concentration data such as VOCs, smoke, and CO are uploaded by the environmental node in a similar manner. Through the GATT Notify-based subscription mechanism, multisource sensor data are continuously aggregated in a deterministic format with low transmission latency, and a complete local status buffer is constructed to provide unified input for subsequent uplink encapsulation.

Subsequently, fused physiological data, environmental data, and edge-side activity recognition results, together with the unique node ID, are encapsulated into a structured status packet by the chest node and transmitted over a long-distance uplink using LoRa. In contrast to short-range communication protocols such as Wi-Fi or BLE, chirp spread spectrum (CSS) modulation is employed in LoRa, enabling reliable demodulation under low signal-to-noise ratio (SNR) conditions. As a result, communication reliability is maintained in fireground environments characterized by multistory structures, dense smoke, and nonline-of-sight propagation, demonstrating strong resistance to interference and effective penetration capability. Accordingly, LoRa is selected for long-distance uplink transmission, supporting continuous monitoring across multiple floors and complex operational areas commonly encountered during firefighting missions.

Through the BLE-LoRa collaborative communication architecture, high-frequency and low-latency data acquisition, as well as stable fusion of multimodal sensor data, are achieved in the near field. Meanwhile, long-range coverage provided by LoRa is used in the far field to support reliable status reporting, thereby

establishing a network foundation with real-time capability, robustness, and scalability for multifirefighter monitoring.

3.4 | Host Software Design

The host monitoring program is positioned as the core component of the application layer and is designed to provide real-time monitoring and decision support for the incident commander (IC). The program is developed using the Flutter framework and is deployed on Windows computers and Android tablets, through which a unified interface for monitoring the status of multiple firefighters is provided [33]. The real-time monitoring interface of the system is shown in Figure 5.

At the data access layer, serial communication is first established between the host and an external LoRa receiver through a USB interface, and structured data frames uploaded by the chest node are continuously received. Each data frame is composed of a unique firefighter ID, a timestamp, physiological parameters, gas concentration measurements, and the motion state inferred at the edge. An automatic mapping index is constructed based on the identity information associated with each firefighting suit, enabling concurrent monitoring of multiple firefighters. The parsed data stream is subsequently forwarded to the backend processing pipeline.

A visualization scheme combining dashboard elements with multichannel time-series curves is adopted to dynamically display trends in heart rate, blood oxygen saturation, core temperature, skin temperature, and representative hazardous gas concentrations. Through this interface, individual physiological load and environmental exposure during missions can be intuitively assessed by commanders. The time-series curves are equipped with dragging and temporal backtracking functions, enabling rapid identification of abnormal fluctuations at critical moments. Potential risks are adjudicated in real time based on the integrated aPSI model, physiological threshold rules, and gas hazard level model. When abnormal conditions are detected, real-time feedback on danger levels is provided through interface pop-up warnings, audible alerts, and color-coded indicators (e.g., red/yellow/green), thereby establishing a stable risk-prompting mechanism.

In addition, all received status data are persistently stored locally, enabling efficient querying during missions and supporting post-event export in CSV format for subsequent in-depth analysis. Based on the complete mission dataset, structured PDF reports are automatically generated by the host system, providing a data foundation for after-action reviews, training evaluation, and long-term health monitoring. Owing to the component-based architecture of the Flutter framework, strong

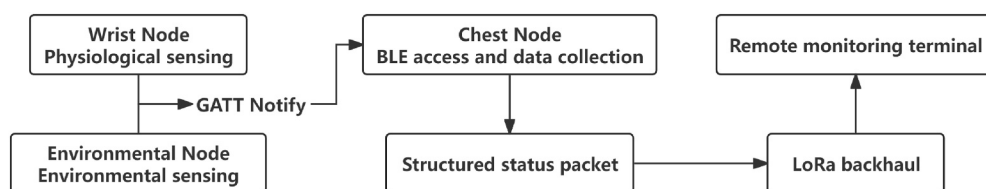


FIGURE 4 | BLE-LoRa communication workflow.

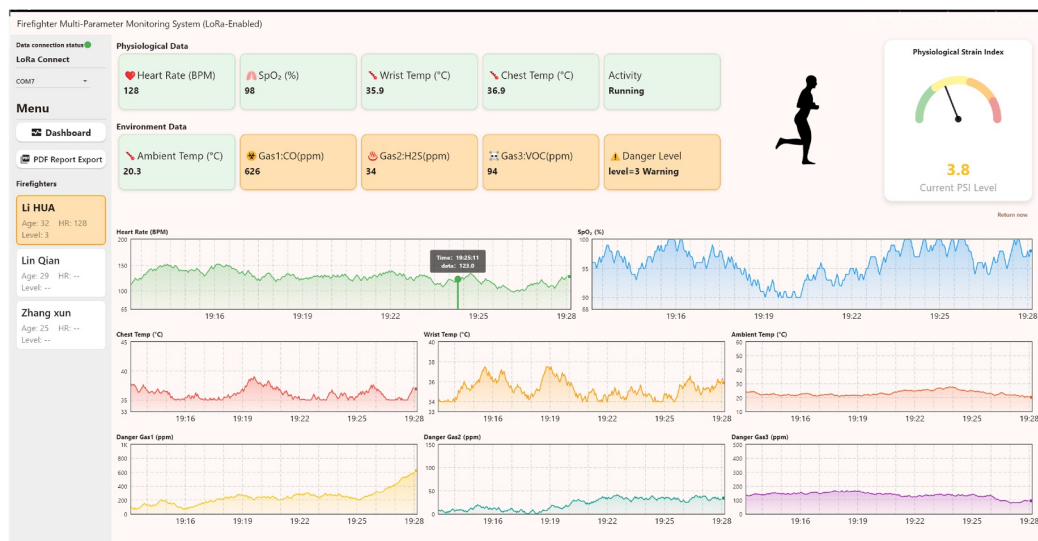


FIGURE 5 | Upper-computer monitoring interface.

cross-platform compatibility and extensibility are achieved, allowing seamless integration of additional sensor types or intelligent analysis algorithms in future system iterations.

4 | System Evaluation and Validation

A rigorous experimental environment was established to comprehensively evaluate the system's overall performance in simulated operational scenarios, with particular emphasis placed on two dimensions: vertical spatial coverage and horizontal long-range transmission. As shown in Figure 6a, a volunteer was equipped with the chest, wrist, and environment node consistent with actual firefighter gear, thereby replicating the physical load and wearing conditions encountered during rescue operations. The experiments were conducted in a 21-story student apartment building, whose internal layout—characterized by dense load-bearing walls, metal structural components, and narrow stairwells—effectively reproduced the severe nonline-of-sight (NLOS) propagation conditions commonly observed at fire-ground scenes [34, 35] (Figure 6b). The LoRa receiver was deployed in an open area approximately 750 m away from the building, thereby establishing a hybrid link defined by “deep indoor floor penetration” and “urban long-range uplink”. This setup allowed for a comprehensive verification of system availability and stability under extreme communication conditions.

During the experiment, a male volunteer (height: 175 cm, weight: 70 kg) was instructed to perform a standardized sequence of actions—including walking, stair ascent, stair descent, sitting, standing, and laying (simulated falling)—on multiple floors within the stairwell, with each action maintained for approximately 2 min. Throughout the test, LoRa link quality metrics (RSSI and SNR), edge-side AI inference results, and dynamic variations in physiological parameters were synchronously recorded by the system. Through this experimental protocol, communication performance, edge inference capability, and physiological monitoring accuracy were simultaneously evaluated. In addition, the reliability of the algorithmic model under realistic wearable conditions and the overall system performance under compounded factors—such as dynamic

motion, posture transitions, and floor switching—were systematically assessed [36, 37].

4.1 | Lightweight Edge AI Inference Performance

In this section, the on-device runtime performance and classification accuracy of the lightweight 1D-CNN model on the ESP32-S3 platform are evaluated using measured data. Owing to INT8 post-training quantization (PTQ), operator fusion strategies, and the FlatBuffers-based zero-copy model loading mechanism, a flash footprint of only 534 KB is required by the model [38], whereas the peak SRAM usage during runtime is approximately 22 KB. This memory consumption represents only a small fraction of the available MCU resources, leaving sufficient capacity for BLE and LoRa protocol stacks as well as real-time sensing tasks. In addition, an average inference latency of approximately 46.6 ms per sample is achieved, corresponding to 3.6% of the sliding-window update period ($128 \text{ samples} \times 100 \text{ Hz} \approx 1.28 \text{ s}$). The core performance metrics of edge-side inference are summarized in Table 1, demonstrating the feasibility and engineering practicality of deploying the proposed model on resource-constrained hardware platforms.

With respect to classification accuracy, the confusion matrix of the model across six action classes is presented in Figure 6c. High recognition accuracy is achieved for both static and dynamic behaviors, with a recall rate of 95.0% obtained for the laying category. As this category is commonly associated with high-risk conditions, such as firefighter falls, loss of consciousness, or heat-stress-induced incapacitation, its recognition performance is directly related to the effectiveness of the system's safety alerting function and is therefore treated as a key monitoring target in this study. Although confusion of approximately 30% is observed between the upstairs and downstairs classes—primarily attributed to the limitation of a single chest-mounted IMU in fully decoupling subtle variations in the vertical gravitational component—the model is shown to reliably distinguish normal activity patterns from static or hazardous states, satisfying the real-time and reliability requirements of tactical safety monitoring.

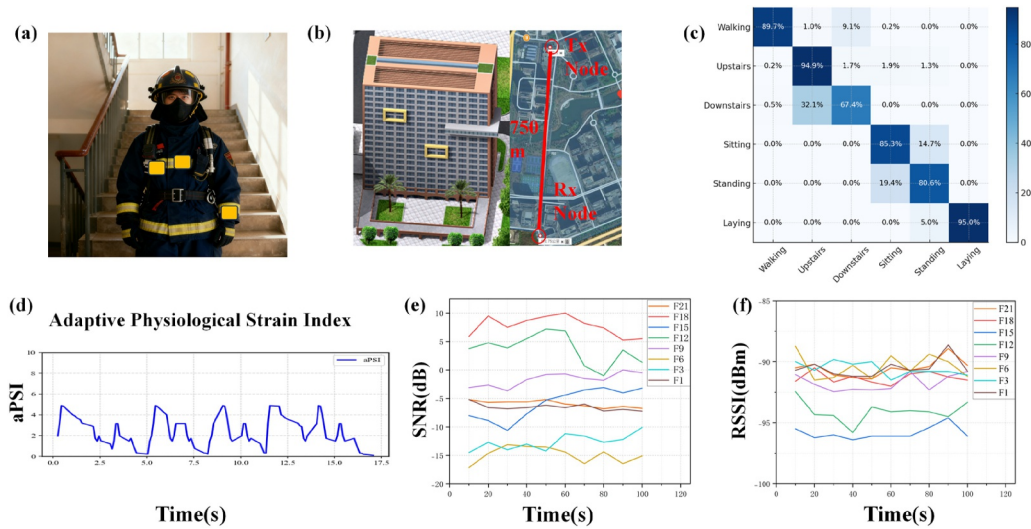


FIGURE 6 | (a) Wearable deployment during stairwell experiments. (b) Test topology showing vertical coverage and a 750 m horizontal link. (c) Confusion matrix for edge-side activity recognition. (d) Real-time aPSI response curve. (e) LoRa SNR variation across floors. (f) LoRa RSSI variation across floors.

TABLE 1 | Model deployment resources and inference performance metrics.

Metric	Value	Notes
Model size (Flash)	534 KB	Stored in Flash memory via ESP-DL
RAM usage (SRAM)	~22 KB	Includes variables and runtime buffers
Average inference time	46.6 ms	Measured on ESP32-S3 (single core, INT8 inference)
Inference frequency	Once per 1.28 s	Sliding window with 50% overlap
Deployment framework	ESP-DL v2.1.1	Based on PPQ quantized ONNX model

4.2 | Physiological Heat Stress Assessment

To verify the practical operational effectiveness of the proposed physiological–environmental fusion hazard model, the aPSI curve calculated by the host computer based on real-time returned data is presented in Figure 6d. The experimental results indicate that dynamic variations in aPSI are highly consistent with changes in the volunteer's exercise intensity. During high-intensity activity phases, such as continuous stair climbing or rapid movement, heart rate and metabolic load are observed to increase rapidly, resulting in a pulse-like rise in aPSI. In contrast, during rest or low-intensity activity phases, the index is observed to decrease markedly and reach a stable level.

As the experiment was conducted in a room-temperature environment, lacking the high thermal radiation and continuous heat accumulation found in a real fireground, the variation amplitude of the core-to-skin temperature gradient ΔT was limited [39–41]. Consequently, the contribution of the heat-stress component remained relatively small, and the overall aPSI peak was maintained within the low-to-moderate stress range, without reaching the high-risk alarm threshold of 6.5. Nevertheless, the aPSI curve was observed to exhibit a high degree of responsiveness, accurately reflecting variations in physical exertion, thermo physiological trends, and fatigue accumulation, thereby confirming the engineering applicability of this indicator for real-time firefighter monitoring scenarios [42].

4.3 | Communication Reliability in Complex Building Environments

To address the severe signal attenuation introduced by the 21-story building structure, the propagation stability and antifading performance of the LoRa uplink were further analyzed across different floor heights. The LoRa transmission parameters were configured as SF12, a bandwidth of 125 kHz, and a transmit power of 20 dBm to maximize the link budget under high-attenuation conditions. In this configuration, priority was assigned to coverage reliability rather than data rate, which is consistent with the practical communication requirements of firefighter operations in complex indoor environments.

The temporal variation of SNR across different floors is shown in Figure 6e. Under conditions involving multiple floor slabs, multipath reflections, and structural obstructions, pronounced SNR fluctuations are observed along the vertical propagation path. Relatively higher SNR levels are maintained on upper floors (e.g., F18–F21), whereas severe signal degradation is observed on lower floors (e.g., F3 and F6), with SNR values frequently dropping into the negative range (approximately -10 to -17 dB). Nevertheless, prior studies indicate that reliable demodulation is supported by LoRa configured with SF12 at SNR levels as low as -20 dB [43, 44]. As all measured values remain above this critical threshold throughout the experiment, stable demodulation is maintained despite deep fading conditions. The corresponding RSSI distribution across floors is

shown in Figure 6f, where values are maintained between -90 and -95 dBm, which is substantially higher than the receiving sensitivity of the SX1278 transceiver (approximately -135 dBm), indicating sufficient link margin. Across the entire 21-story test, the packet loss rate is maintained below 10%, confirming stable long-term uplink operation in high-attenuation building environments and enabling continuous backhaul of critical physiological and environmental data from deep indoor locations.

5 | Conclusion

A multisource wearable monitoring system targeting the physiological and environmental states of firefighters in high-risk operational scenarios was designed and implemented in this study. The proposed system is composed of chest, wrist, and environmental nodes and integrates physiological sensing, edge-side posture recognition, hazardous gas monitoring, and long-range wireless data backhaul within a unified architecture. An adaptive physiological strain index (aPSI) model was established to quantify firefighter heat stress through the fusion of multi-point body temperature and heart-rate information, enabling the real-time characterization of physiological load under varying activity intensities. For motion monitoring, a lightweight 1D convolutional neural network was deployed on the ESP32-S3 platform to perform edge-side recognition of six representative firefighter actions. A recall rate of 95% was achieved for the laying category, which is closely associated with safety-critical conditions such as falls or incapacitation. In terms of communication performance, a high-spreading-factor LoRa configuration was adopted and validated through nonlinear-of-sight transmission experiments conducted in a 21-story building, where stable RSSI and SNR levels were maintained and the packet loss rate remained below 10%. In addition, a local audible-visual alarm mechanism was integrated into the environmental node to provide immediate risk notification in the event of communication interruptions. It should be noted that the current validation was conducted under ambient-temperature building conditions, and further evaluation under extreme fireground environments is required to comprehensively assess system robustness. Overall, the proposed system provides a validated engineering reference for integrating multimodal wearable sensing, edge intelligence, and long-range communication in firefighter safety monitoring applications.

Author Contributions

Chongyuan Ni: validation, investigation, software, data curation, formal analysis, writing – original draft, writing – review and editing, visualization. **Saihua Jiang:** conceptualization, funding acquisition, project administration, methodology, resources, supervision. **Shun Li:** software, validation. **Hongyi Guo:** validation, software. **Luyao Huang:** validation, software. **Jianjun Xia:** supervision, project administration, resources. **Yang Lan:** supervision. **Zhijun Zheng:** supervision, resources. **Zhiwei Tan:** supervision, project administration.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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