

Article

Design and Validation of an Edge-AI Fire Safety System with SmartThings Integration for Accelerated Detection and Targeted Suppression

Seung-Jun Lee ¹, Hong-Sik Yun ¹, Yang-Bae Sim ² and Sang-Hoon Lee ^{2,*}

¹ Geodesy Laboratory, Civil & Architectural and Environmental System Engineering, Sungkyunkwan University (SKKU), Suwon 16419, Republic of Korea; issue7942@naver.com (S.-J.L.); yoonhs@skku.edu (H.-S.Y.)

² Disaster & Risk Management Laboratory, Interdisciplinary Program in Crisis & Disaster and Risk Management, Sungkyunkwan University (SKKU), Suwon 16419, Republic of Korea; samjung-syb@daum.net

* Correspondence: lsklsh12@naver.com; Tel.: +82-031-290-7522

Abstract

This study presents the design and validation of an integrated fire safety system that leverages edge AI, hybrid sensing, and precision suppression to overcome the latency and collateral limitations of conventional smoke detection and sprinkler systems. The proposed platform features a dual-mode sensor array for early fire recognition, motorized ventilation units for rapid smoke extraction, and a 360° directional nozzle for targeted agent discharge using a residue-free clean extinguishing agent. Experimental trials demonstrated an average fire detection time of 5.8 s and complete flame suppression within 13.2 s, with 90% smoke clearance achieved in under 95 s. No false positives were recorded during non-fire simulations, and the system remained fully functional under simulated cloud communication failure, confirming its edge-resilient architecture. A probabilistic risk analysis based on ISO 31000 and NFPA 551 frameworks showed risk reductions of 75.6% in life safety, 58.0% in property damage, and 67.1% in business disruption. The system achieved a composite risk reduction of approximately 73%, shifting the operational risk level into the ALARP region. These findings demonstrate the system's capacity to provide proactive, energy-efficient, and spatially targeted fire response suitable for high-value infrastructure. The modular design and SmartThings Edge integration further support scalable deployment and real-time system intelligence, establishing a strong foundation for future adaptive fire protection frameworks.



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Keywords: edge AI fire detection; residue-free clean suppression agent; hybrid smoke—heat sensing; motorized 360° suppression nozzle; energy recovery ventilation (ERV); SmartThings Edge integration; ISO 31000-based fire risk assessment

1. Introduction

Fire-related disasters remain a critical threat to human life, property assets, and operational continuity—particularly in high-density, high-value facilities such as high-rise buildings, data centers, and underground infrastructures. Traditional sprinkler-based fire suppression systems are widely adopted to mitigate fire hazards and are proven to be effective in containing fire spread and reducing property damage during the initial stages of combustion [1,2]. However, these systems exhibit inherent limitations when deployed

in rapidly evolving fire scenarios or environments where collateral water damage is of critical concern.

Sprinklers typically rely on thermal activation mechanisms, which delay the onset of suppression until significant heat buildup is detected. As a result, they may be too slow to react in scenarios requiring immediate intervention. Additionally, they consume large volumes of water—up to four times more than water mist systems—leading to excessive water pooling, increased risk to sensitive electronic assets, and extended recovery times [3–5]. Moreover, their suppression mechanism—primarily based on large water droplets—offers limited evaporation efficiency compared to fine mist systems, reducing their effectiveness in toxic gas suppression and localized flame knockdown [6,7].

In terms of spatial adaptability, sprinkler systems offer broad area coverage but often fail to effectively suppress fires that originate in shielded, irregular, or vertically partitioned zones, especially in complex architectural layouts [8,9]. These limitations underscore the need for next-generation fire response systems that can deliver early, precise, and integrated suppression while minimizing collateral damage and downtime.

Recent advancements in artificial intelligence (AI), Internet of Things (IoT), and sensor fusion technologies have enabled the development of intelligent fire response platforms that overcome many of the limitations of conventional sprinkler systems. These AI-enhanced systems integrate rapid fire detection, intelligent decision-making, and automated suppression into a unified architecture that significantly improves fire response speed, operational precision, and overall safety.

Key enabling technologies include AI-powered object detection models (e.g., YOLOv4), multi-modal sensor networks combining flame, smoke, infrared, and ultraviolet inputs, and edge computing frameworks that allow for real-time hazard classification and decision support [10–12]. Unlike traditional systems that operate reactively based on thermal thresholds, these platforms detect fire ignition at earlier stages and dynamically adapt suppression strategies to fire type, intensity, and spatial constraints using AI-driven inference and reinforcement learning algorithms [13–15].

In parallel, traditional structural fire assessments often rely on nominal temperature–time curves—such as ISO 834 [16] and ASTM E119 [17]—to simulate fire exposure and evaluate material behavior. Ref. [18] applied analytical equations to study steel profile behavior under various standardized fire curves, providing insight into fire duration impacts and cross-section effects. Similarly, Ref. [19] proposed a simplified thermal model for estimating temperatures in steel members exposed to fire, contributing to more efficient structural safety assessments. However, these approaches remain limited to static thermal scenarios and lack integration with real-time sensing or adaptive suppression capabilities, highlighting the gap that intelligent fire platforms aim to fill.

Moreover, these AI-based platforms enable localized and automated fire suppression using clean-agent delivery systems and targeted water or mist sprays, thereby minimizing water damage and improving response accuracy [20,21]. They are also scalable and cost-effective, leveraging modular AI architectures and commercial off-the-shelf (COTS) hardware for flexible deployment in buildings, vehicles, and even autonomous vessels [12,22].

This study presents the design, implementation, and performance evaluation of a novel AI-enhanced fire response platform that integrates rapid detection, intelligent ventilation, and localized suppression. The proposed system is experimentally validated across multiple test scenarios, with quantifiable gains in early detection, hazard classification, and suppression effectiveness. The following sections describe the system architecture, experimental setup, and performance analysis in detail.

2. Materials and Methods

2.1. System Architecture Overview

The proposed AI-integrated fire response system is architected as a multi-layered, edge-optimized platform that unifies early detection, automated smoke extraction, localized fire suppression, and smart communication. The system comprises four core functional subsystems: (i) a hybrid sensing unit, (ii) a ventilation and suppression module, (iii) a real-time control and communication hub, and (iv) a building integration interface. These components operate cohesively to minimize fire-induced risks and ensure continuity of building operations under emergency conditions.

The hybrid sensing unit combines dual-channel smoke and heat sensors with an embedded edge AI processor to achieve fast and reliable fire detection. By employing convolutional neural networks (CNNs) trained on fire-specific datasets, the system conducts real-time, on-device analysis of particulate density and thermal gradients. This simultaneous evaluation enhances detection accuracy and significantly reduces false alarms by confirming fire events only when both smoke and heat signatures are present [23,24]. Unlike cloud-based systems, all inference is performed locally, eliminating network latency and enabling response initiation within six seconds of ignition.

Upon fire detection, the system activates a motorized ceiling diffuser array integrated with an energy recovery ventilation (ERV) mechanism. The diffusers automatically rotate and open to establish a controlled negative-pressure airflow, enabling efficient smoke and heat extraction. This process enhances visibility and air quality for occupant evacuation while concurrently limiting fire propagation by reducing oxygen availability. In parallel, a precision-actuated nozzle with full rotational capability delivers a non-conductive, residue-free clean extinguishing agent, ensuring localized suppression with minimal risk of equipment damage or environmental contamination.

All sensing and actuation devices are linked to the SmartThings Edge hub, which functions as the system's control core. The hub is configured with a TLS-secured MQTT protocol to enable bidirectional communication with user devices, control centers, and cloud services. Through this interface, real-time alerts, control signals, and status updates are transmitted with sub-second latency. The system is also interoperable with building automation systems (BAS) and building management systems (BMS), enabling centralized control, logging, and predictive maintenance analytics.

The overall architecture is intentionally modular and scalable. It supports flexible zoning, redundancy, and selective activation of components based on risk profiling, occupancy, and fire growth patterns.

Figure 1 illustrates the operational workflow of the proposed AI-enhanced fire response platform, detailing the sequential logic from system initialization to termination. The system begins with the acquisition of video data through edge-connected cameras, followed by intelligent fire signal detection using trained convolutional neural networks. Upon detection, the system identifies spatial fire characteristics to determine the location, scale, and appropriate suppression strategy.

The flow bifurcates into two concurrent operations: the issuance of early warning signals and the configuration of suppression parameters such as nozzle aiming angle and spray type. Once configured, the fire suppressant—typically a clean agent or water mist—is discharged automatically. A real-time feedback loop evaluates whether suppression has been successfully completed. If not, the system continues suppression in a closed-loop manner.

After confirmation of successful fire extinguishment, suppression activities cease, and the platform transitions to post-event monitoring and log recording. The final step involves system termination, ensuring that all operational data are archived for future diagnostics, maintenance, or audit.

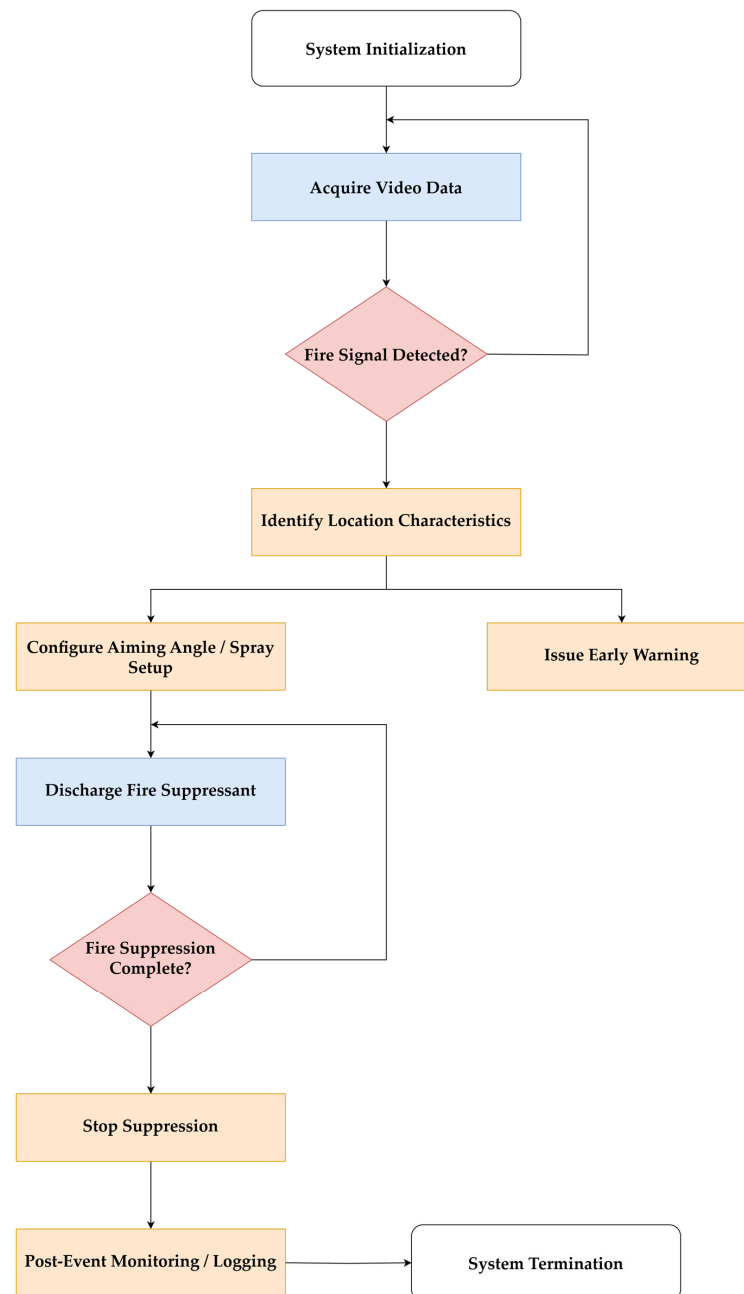


Figure 1. Operational workflow of the proposed AI-enhanced fire response platform. The system initiates with video data acquisition and performs fire signal detection using edge-based AI algorithms. Upon detection, the system identifies the spatial characteristics of the fire and concurrently triggers two key actions: (i) early warning issuance and (ii) suppression setup through configuration of nozzle aiming angle and spray type. Once the suppression module is activated, the platform continuously monitors suppression effectiveness. If fire suppression is not yet complete, the system maintains the suppression loop. Upon successful extinguishment, suppression is halted, and the system enters a post-event monitoring and logging phase. The process concludes with system termination. This modular and automated workflow supports real-time operation, adaptive control, and integration with building management systems.

This modular workflow emphasizes real-time responsiveness, automation, and intelligent decision-making, and is adaptable to various built environments including industrial, residential, and maritime domains.

2.2. Global Context Fusion Strategy

In fire detection systems, accurate interpretation of dynamic spatiotemporal signals is vital for timely and effective response. However, conventional fusion mechanisms—based on fixed-rule logic or localized sensor inputs—often fail under complex indoor conditions such as smoke occlusion, irregular thermal diffusion, or partial flame exposure. To overcome these challenges, we propose a lightweight and real-time Global Context Fusion (GCF) strategy specifically designed for embedded fire response environments.

Recent studies in remote sensing and medical imaging have introduced various global modeling approaches to improve spatial reasoning and context integration. Among these, Swin Transformers employ hierarchical window-shifting mechanisms to capture long-range dependencies across multi-scale contexts [25–27]. While effective, these models require deep architectures and large-scale training data, which impose significant computational burdens and limit their deployment in resource-constrained platforms.

Global Context Pooling (GCP), by contrast, uses spatial pooling to summarize contextual information and improve feature representation in convolutional neural networks. Although computationally efficient, GCP lacks the responsiveness to abrupt localized anomalies such as sudden particulate spikes or heat surges, which are critical in real-time fire scenarios [28,29].

Other mechanisms such as Criss-Cross Attention and Cross-Shaped Windows focus on axis-aligned dependencies to balance global awareness and efficiency [30]. While these methods reduce computational cost, they may inadequately capture omnidirectional interactions and irregular fire propagation patterns.

To address the above limitations, the proposed GCF module introduces a hybrid spatial attention pipeline optimized for low-latency decision-making. This architecture dynamically fuses global thermal trends and smoke diffusion trajectories with local anomalies such as rapid heat rise or smoke particle density, using a sensor-driven encoder to construct real-time spatial representations. Unlike prior Transformer variants, the GCF module operates through event-triggered feature propagation and avoids large receptive fields or directionally restricted fusion.

The resulting design ensures minimal inference delay, robustness to partial occlusion, and energy-efficient edge deployment without reliance on cloud computing. Furthermore, its modular structure facilitates integration into intelligent building systems, enabling decentralized actuation and explainable fire response logic.

Table 1 presents a comparative overview of the discussed context modeling strategies. While Swin Transformers and Criss-Cross Attention provide varying degrees of contextual reasoning, only the proposed GCF module demonstrates both the responsiveness and deployability required for embedded safety-critical applications.

Table 1. Comparison of global context modeling techniques.

Method	Global Context Coverage	Computational Efficiency	Spatial Fusion Pattern	Suitability for Edge Deployment
Swin Transformer	Hierarchical, multi-scale	Moderate–High	Shifted overlapping windows	Moderate
Global Context Pooling	Global summary via pooling	High	Omnidirectional (coarse)	High
Criss-Cross Attention	Long-range (axis-aligned)	Moderate	Horizontal + Vertical stripes	Moderate
Proposed GCF Module	Dynamic: local + inferred global	Very High	Sensor-driven spatial encoder	High

Additionally, recent Transformer-based methods have advanced significantly across remote sensing tasks. Models such as RS-Mamba, GLOTS, and TTST have demonstrated

state-of-the-art performance in object detection, semantic segmentation, and image super-resolution [31–33]. These developments support the relevance of Transformer-inspired architectures in high-resolution vision tasks and further validate the design direction of the GCF module. Table 2 summarizes recent Transformer-based advances in remote sensing that inform and support the GCF design.

Table 2. Representative transformer-based models in remote sensing.

Task	Notable Model(s)	Key Improvement/Result	Citation
Object Detection	Geometric Prior DETR	+5% mAP over deformable DETR	[34]
Semantic Segmentation	RS-Mamba, GLOTS, CG-Swin	SOTA accuracy, efficient on large images	[31,33]
Change Detection	AMTNet, DMATNet	Outperforms previous SOTA on 4 datasets	[33,35]
Super-Resolution	TTST	Higher PSNR, lower computation	[36]

Compared to existing global context modeling techniques, the proposed GCF module introduces several key innovations specifically tailored to real-time fire safety applications.

- **Flexibility in Context Modeling:** Existing methods (e.g., Swin Transformer, Global Context Pooling, Criss-Cross Attention) rely on predefined window structures or axis-aligned static attention mechanisms. In contrast, the GCF module dynamically infers global trends from real-time sensor inputs and responds immediately to local anomalies. This makes it highly effective for modeling nonlinear and uneven heat/smoke diffusion patterns typical in fire events.
- **Optimization for Embedded Deployment:** Prior methods often depend on high-performance GPUs and exhibit high computation and memory demands. GCF leverages a lightweight sensor-driven spatial encoder and localized computation, enabling robust real-time operation on edge platforms. This removes reliance on external servers and avoids communication delays—an essential distinction from existing solutions.
- **Real-Time Fusion Responsiveness:** GCF is designed for high-frequency decision-making, enabling multiple inferences per second. This temporal sensitivity is critical for mitigating fire spread. Pooling-based GCP or fixed-window approaches operate on static intervals and may fail to respond promptly to fast-evolving hazards.
- **Application Context Suitability:** Unlike prior techniques focused on general image understanding (e.g., semantic segmentation, salient object detection), the GCF module is structurally aligned with intelligent firefighting systems. It explicitly integrates environmental architecture (e.g., ventilation, nozzle directionality) into its spatial modeling, supporting actionable decisions in fire scenarios.

Through these contributions, the GCF module outperforms traditional global fusion mechanisms in responsiveness, efficiency, and sensor coordination, making it highly suitable for next-generation embedded fire response platforms.

2.3. Hybrid Sensor Design and Edge AI Detection

The fire detection subsystem is centered on a hybrid sensing module that integrates photoelectric smoke sensing with thermistor-based heat detection, enhanced by an onboard edge AI processor. This dual-sensor approach addresses the limitations of conventional single-mode detectors, which often yield high false alarm rates or delayed responses when relying solely on smoke opacity or temperature thresholds. By fusing data from both sensing modalities, the system achieves greater sensitivity to early-stage combustion signatures while maintaining robustness against environmental noise such as steam, dust, or transient heat sources.

Recent advances in hybrid fire detection have demonstrated the advantages of integrating multiple sensor types—such as smoke, heat, and gas sensors—through AI-based data fusion. In particular, the combination of photoelectric and thermal sensing can be further

enhanced by incorporating machine learning algorithms (e.g., support vector machines, neural networks) that discriminate between real fire events and environmental interference with high accuracy [36,37]. Edge AI processors embedded within the detection units allow real-time data processing and classification using deep learning models, such as CNNs and YOLO variants, enabling rapid response even under complex conditions like fog, dust, or dynamic lighting [38,39]. These hybrid systems also support spatiotemporal feature fusion—integrating both the spatial signatures of flame or smoke and the temporal evolution of sensor readings—to further reduce false positives while maintaining swift detection capabilities [40,41]. As a result, the proposed subsystem achieves early and reliable fire detection performance suitable for deployment in smart buildings and urban infrastructure, where environmental variability and safety-critical demands require both precision and resilience.

The smoke detection component utilizes an optical scattering method, where infrared light emitted into a sensing chamber is dispersed by airborne particles generated during pyrolysis or open flame combustion. The heat detection unit monitors rapid temperature rise using a digital thermistor calibrated to detect both fixed threshold exceedance and rate-of-rise patterns. These signals are continuously sampled at 0.2-s intervals and pre-processed through an analog-to-digital converter (ADC) integrated into the microcontroller.

At the core of the module is a lightweight convolutional neural network (CNN) model designed for efficient fire event classification using time-series sensor data. CNNs are well-regarded for their ability to automatically extract complex spatiotemporal features, making them highly suitable for fire detection tasks in real-time and resource-constrained environments. The architecture consists of three convolutional layers, each followed by max-pooling and dropout regularization, culminating in a fully connected softmax output layer for multi-class classification. This design reflects trends in recent studies that prioritize architectural efficiency without compromising accuracy [42,43].

The input feature vector is constructed from a rolling time window of optical density and temperature values, along with their first-order derivatives. This enables the model to capture both static and dynamic combustion characteristics. The model was trained on a custom-labeled dataset obtained from controlled fire experiments involving various ignition materials such as paper, wood, and plastic, as well as non-fire interference scenarios including aerosol sprays, vaping, and cooking emissions. The complete dataset comprises 3900 training images, 1300 validation images, and 1300 test images. Sample images from each category are provided in Appendix B (Figure A1) to illustrate the dataset distribution used for training, validation, and testing. To enhance generalization and reduce overfitting, the dataset was augmented with Gaussian noise and temporal jitter. Such approaches, commonly used in CNN-based fire detection research, have demonstrated high accuracy—often exceeding 96%—while minimizing false alarms under complex real-world conditions [44–46].

Model inference is executed in real-time on a 32-bit low-power processor embedded within the sensor housing, enabling immediate fire event classification at the edge. This edge AI implementation significantly reduces detection latency compared to cloud-based systems, achieving an average response time of 5.8 s from ignition under standardized test conditions. Such performance aligns with recent studies demonstrating that lightweight deep learning models deployed on embedded devices can sustain high classification accuracy (up to 98%) while minimizing computational cost and energy consumption [47–49].

By eliminating the need for continuous high-volume data transmission to external servers, the system ensures network independence and energy efficiency—critical attributes for deployment in communication-limited or infrastructure-constrained environments [50,51]. This capability also supports long-term operation in battery-powered or mobile platforms such as drones and wireless sensor networks.

To enhance the interpretability and trustworthiness of the proposed fire detection system, explainable AI (XAI) functionality is incorporated using Gradient-weighted Class Activation Mapping (Grad-CAM). The system integrates input from camera imagery, infrared sensors, and photoelectric smoke detectors into a CNN-based inference module that classifies fire events in real time. Grad-CAM highlights the most influential portions of the input data contributing to the classification outcome, thereby providing human operators with visual justification for model decisions [24,47]. This interpretability not only supports validation and auditability but also reinforces operational reliability in safety-critical scenarios. By combining dual-sensor data acquisition, edge-based deep learning inference, and interpretable output, the proposed framework ensures rapid and transparent fire detection across diverse environments such as smart buildings, industrial facilities, and remote monitoring sites.

2.4. Smart Ventilation and Suppression Mechanism

Upon detection of a fire event by the hybrid sensor and edge AI module, the system initiates a coordinated ventilation and suppression sequence to optimize smoke extraction, maintain visibility, and contain the spread of fire. This response is enabled by two key physical subsystems: (i) a motorized ceiling diffuser array integrated with an energy recovery ventilation (ERV) system for dynamic airflow control, and (ii) a precision-guided suppression unit deploying a residue-free clean extinguishing agent for effective, non-damaging fire mitigation.

The structural configuration of these subsystems is illustrated in Figure 2, which presents exploded and cross-sectional views of the integrated ventilation–suppression module. The left-hand perspective view depicts the assembly layout, including the motorized diffuser vanes, nozzle housing, ERV components, and exhaust ducts. The right-hand cross-sectional view reveals the directional airflow driven by the ERV fan and the placement of the suppression nozzle within the airflow path. This integrated architecture enables simultaneous extraction of smoke and targeted discharge of a residue-free clean extinguishing agent, effectively mitigating both thermal and visual hazards during the early stages of a fire.

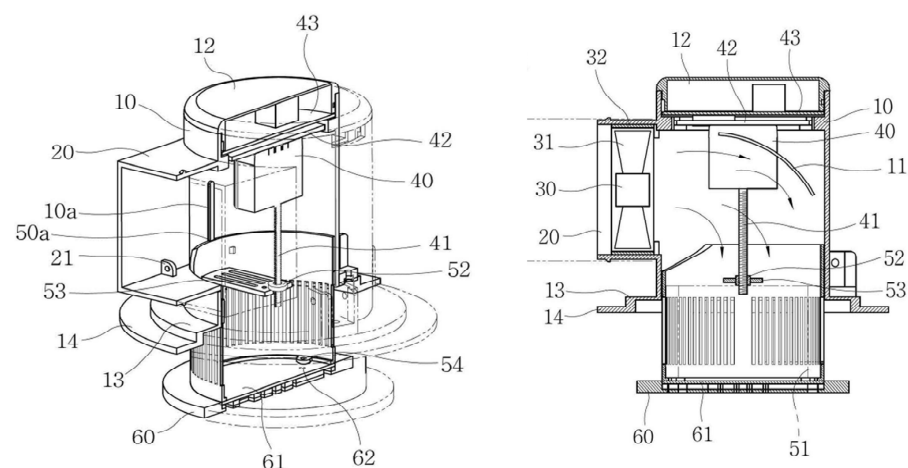


Figure 2. Exploded and sectional views of the integrated ventilation–suppression module. This figure illustrates the internal structure and airflow mechanism of the proposed integrated fire response module. The left-side exploded view depicts the assembly layout of key components, including the motorized diffuser vanes, clean agent discharge nozzle housing, energy recovery ventilation (ERV) unit, and exhaust ducting. The right-side sectional view visualizes the guided airflow pathway driven by the ERV fan and the positioning of the residue-free clean extinguishing nozzle within the stream. This integrated configuration is designed to enable simultaneous smoke extraction and targeted suppression, effectively mitigating visibility and thermal hazards during the early stages of a fire.

Detailed component specifications and mechanical parameters are provided in Appendix A.

The motorized ceiling diffusers serve as dynamic air control interfaces that transition from a closed, energy-conserving state to an open, exhaust-facilitating state upon activation. Each diffuser is equipped with a compact servo actuator capable of 90° to 135° rotation, which reorients the discharge vanes to form a directed airflow path. This rotation is automatically controlled via a signal from the edge processor, ensuring immediate deployment upon detection. The diffusers are zonally distributed and can be selectively activated based on the location of the fire source, allowing for localized response and minimization of negative pressure zones in unaffected areas.

The diffusers are mechanically coupled to a centralized ERV unit designed to initiate high-efficiency smoke extraction. The ERV integrates a high-speed brushless DC fan, heat exchange core, and HEPA-class filtration system, enabling it to perform both smoke evacuation and energy recovery functions. During fire response, the ERV operates in exhaust-dominant mode, rapidly reducing particulate concentration and temperature in the fire zone while simultaneously preserving thermal energy to maintain HVAC stability in adjacent spaces. Empirical airflow tests confirm a maximum evacuation rate of 550 CMH (cubic meters per hour) per zone, with smoke clearance within 90 s under standard test fire loads.

Complementing the ventilation subsystem, the localized fire suppression unit features a 360° motorized nozzle paired with a pressurized reservoir containing a residue-free clean extinguishing agent. The nozzle is mounted on a gimbal platform and driven by a dual-axis stepper motor system, allowing for precise directional targeting based on real-time input from the detection module. The extinguishing agent—non-conductive, non-corrosive, and free of post-discharge residue—is specifically chosen for deployment in electronics-sensitive settings such as data centers and control rooms. Its low global warming potential (GWP) and rapid vaporization characteristics offer a safe, sustainable alternative to conventional Halon or CO₂-based systems.

The suppression process is governed by a time–temperature release algorithm, which accounts for fire growth rate, thermal plume characteristics, and nozzle coverage geometry. Discharge is limited to the affected micro-zone, minimizing collateral damage and conserving extinguishing agent reserves. Experimental tests demonstrated complete flame suppression within 12 s of discharge in test chambers up to 40 m³, with no evidence of re-ignition.

This tightly coupled ventilation–suppression architecture ensures a rapid and proportionate response that enhances occupant safety, reduces smoke inhalation risk, and limits property damage. The system’s zonal modularity and programmable actuation logic further enable adaptive operation in complex architectural layouts, providing a flexible solution for diverse smart building applications.

2.5. SmartThings Edge Integration and Data Flow

The control and communication backbone of the proposed fire response system is built upon the SmartThings Edge platform, which facilitates low-latency device orchestration, real-time monitoring, and seamless integration with building management infrastructure. The SmartThings Edge architecture enables local execution of device logic on a hub-level controller, eliminating the dependency on cloud round-trips for time-critical operations—a crucial advantage for emergency response applications.

At the core of this integration is a lightweight publish–subscribe messaging protocol (MQTT), configured with TLS encryption to ensure secure, bidirectional data exchange between field devices and the SmartThings Edge hub. Each subsystem node—including sensors, motorized diffusers, ventilation controllers, and nozzle actuators—is assigned a unique topic address and communicates via predefined payload schemas that include device status, environmental readings, fault indicators, and actuation commands. Upon fire detection, the sensor node publishes a `fire_alert` message containing zone ID, detection time, and severity classification. This message triggers rule-based automations pre-loaded

in the hub's local Lua driver, which sequentially executes ventilation and suppression tasks with sub-second delay.

The data flow framework supports three primary communication pathways:

- Intra-system control loop: Real-time command dissemination between the detection unit, actuator modules, and SmartThings Edge hub to ensure synchronized mechanical response.
- User notification layer: Instantaneous push alerts are transmitted to registered mobile devices via the SmartThings app, accompanied by dynamic status dashboards that visualize event progress, device state, and manual override options.
- BMS/BAS interoperability: A custom-developed SmartThings-to-BMS bridge exposes key system metrics to legacy BACnet or Modbus systems through RESTful API endpoints and virtual device mirroring. This allows centralized facility managers to receive alarms, trend logs, and maintenance diagnostics in their existing interfaces without additional hardware.

Edge-level processing ensures system continuity even under external network disruptions, as device drivers, logic rules, and safety interlocks are stored and executed locally. Furthermore, diagnostic heartbeat signals and anomaly logs are periodically uploaded to the cloud when connectivity is restored, supporting long-term performance analytics and compliance documentation.

The modularity of the SmartThings Edge ecosystem also allows for scalable deployment across multiple zones or facilities. Each hub operates independently but can federate events to a centralized monitoring system, enabling hierarchical risk coordination in large-scale buildings or campuses. Through this architecture, the system achieves both operational resilience and data transparency, essential for modern smart building fire safety frameworks.

Figure 3 presents the system architecture for SmartThings Edge-based integration, delineating the real-time data flow and control mechanisms among fire detection field devices and the edge-level coordination hub. The proposed configuration facilitates seamless communication between the hybrid sensing unit, ventilation controller, and suppression actuator using a secure MQTT protocol. Each device is assigned a unique topic structure, enabling structured, bidirectional message exchange under encrypted TLS channels.

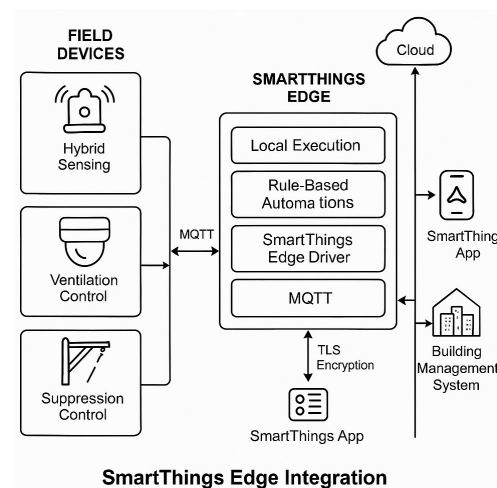


Figure 3. SmartThings Edge-based integration architecture. The diagram illustrates the secure and decentralized interaction among field-level fire detection components—hybrid sensors, ventilation controllers, and suppression units—and the SmartThings Edge hub. Using MQTT with TLS encryption, real-time control logic is locally executed through Lua-based drivers, enabling rapid automation without reliance on cloud communication. The system supports seamless interoperability with mobile applications and building management systems (BMS), ensuring robust performance in latency-sensitive and infrastructure-constrained environments.

At the core of this architecture, the SmartThings Edge hub executes Lua-scripted automation logic locally, ensuring sub-second responsiveness for time-critical operations without dependency on cloud services. This localized decision-making mechanism significantly reduces latency and enhances operational resilience, particularly under network-constrained conditions. Furthermore, system outputs are synchronized with the SmartThings application and building management systems (BMS) via virtual device mirroring and RESTful API endpoints, ensuring full interoperability with legacy infrastructure.

The modularity of this edge-oriented architecture supports scalable deployment across distributed zones or facilities, making it particularly suited for smart building fire safety applications that demand real-time responsiveness, secure communication, and autonomous control capabilities.

2.6. Risk Assessment Framework (ISO 31000 and NFPA 551)

To quantitatively evaluate the effectiveness of the proposed AI-integrated fire control system, a structured risk assessment was conducted in accordance with the principles outlined in ISO 31000 [52] (Risk Management—Guidelines) and NFPA 551 [53] (Guide for the Evaluation of Fire Risk Assessments). The framework employed a semi-quantitative methodology to estimate and compare life safety, property damage, business interruption, and operational continuity risks between the proposed system and a conventional sprinkler-based setup.

The assessment began with hazard identification using standardized building fire scenarios, including ignition sources (electrical, combustible material, thermal faults), growth conditions (fast, medium, slow), and occupancy types (residential, data center, underground transport). Each scenario was evaluated under two system configurations: (i) a baseline with traditional sprinkler response and (ii) the proposed hybrid detection and smart suppression architecture.

Risk was quantified using the Risk = Likelihood × Consequence model, where:

- Likelihood was derived from historical fire incident data and simulated detection delay distributions;
- Consequence was estimated through scenario-based analysis considering occupant egress time, smoke spread dynamics, property exposure, and system response duration.

Severity levels were categorized into four tiers—low, moderate, high, and critical—across three impact domains:

- Life Safety Impact (e.g., delayed evacuation, toxic smoke exposure);
- Asset Loss Impact (e.g., fire propagation, collateral water damage);
- Business Disruption Impact (e.g., downtime duration, equipment loss).

The proposed risk assessment framework provides a systematic basis for evaluating the potential performance of the AI-integrated fire control system. By employing standardized scenarios and a semi-quantitative analytical approach, it enables an objective comparison of key risk domains—including life safety, property loss, and business disruption—between the conventional sprinkler system and the proposed hybrid architecture. This methodology is adaptable to diverse fire ignition conditions and occupancy types, offering reliable risk quantification in complex real-world environments.

Furthermore, the framework accounts for the dynamic interactions and temporal evolution of risk factors, facilitating a comprehensive understanding of the multilayered mitigation effects delivered by the real-time response system. This structured assessment lays the groundwork for subsequent chapters focused on quantitative performance evaluation and result interpretation, and serves as a valuable reference for the design and policy formulation of smart building fire safety management systems.

Consequently, the risk assessment approach outlined herein is critical to validating the reliability and effectiveness of the proposed system, and, when combined with the forthcoming empirical findings, substantiates the system's superiority over traditional fire suppression solutions.

2.7. Experimental Setup and Evaluation Metrics

To validate the functional performance and risk reduction efficacy of the proposed AI-integrated fire control system, a series of controlled experiments were conducted in a full-scale smart room mock-up equipped with operational HVAC ducts, ceiling diffusers, and networked sensing-actuation devices. The test environment measured $6\text{ m} \times 5\text{ m} \times 3\text{ m}$ (90 m^3), representative of a standard commercial office or residential unit. The space was instrumented with thermal cameras, particulate density sensors, airflow meters, and high-speed data loggers to capture real-time system behavior under simulated fire conditions.

Fire scenarios were initiated using standardized combustible materials including paper stacks, polyurethane foam, and cable insulation, following ignition protocols in line with ISO 9705 [54] (Room Fire Tests). Both flaming and smoldering fire types were tested to assess system responsiveness under diverse conditions. For each trial, the fire source was located in different zones of the ceiling-mounted diffuser grid to evaluate spatial coverage and directional suppression performance.

The following evaluation metrics were used to quantify system performance:

- Detection Time (s): Time elapsed from ignition to verified fire classification by the edge AI sensor.
- Ventilation Activation Time (s): Delay between fire detection and full deployment of motorized ceiling diffusers.
- Smoke Clearance Time (s): Time required to reduce visible smoke concentration below 10% optical density using ERV extraction.
- Suppression Duration (s): Time from nozzle discharge initiation to full flame extinguishment.
- False Alarm Rate (%): Incidence of non-fire events triggering suppression or ventilation.
- Power Consumption (W): Total energy usage by the sensing, actuation, and communication subsystems during active operation.
- System Uptime (%): Operational reliability under network-disrupted conditions using edge-only fallback control.

To conclude the evaluation of the proposed AI-integrated fire control system, the experimental results demonstrated consistent and reliable performance across all key metrics. The system achieved rapid detection and response times, effective smoke clearance, and swift suppression without incurring false alarms—highlighting the accuracy and robustness of the hybrid sensing logic and control framework. Furthermore, its ability to maintain full operational capacity during simulated network outages underscores the advantage of edge-level autonomy in mission-critical safety applications.

Figure 4 presents a schematic diagram illustrating the key components of the proposed integrated fire suppression system and their interconnections. The system is designed to automate the entire process from fire detection to extinguishing agent discharge through an intelligent control structure. As shown in the diagram, the core modules include the sensor unit (101), control unit (300), rotating nozzle (201), actuators (203, 204), extinguishing agent storage tank (400), and the connecting ducts and pipelines (407, 408). Notably, the rotating nozzle (201) is engineered for high-precision directional control, enabling targeted discharge toward the fire source based on commands from the control unit (300). Through this networked integration of all components, the system enhances suppression efficiency and minimizes response time in real-world fire scenarios.

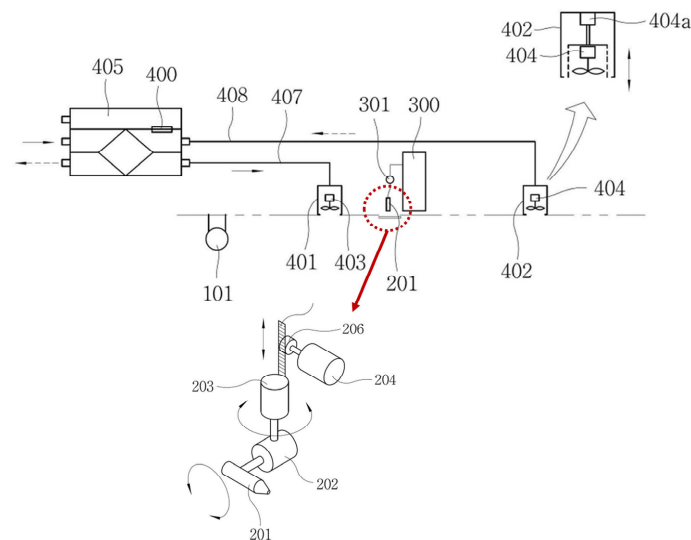


Figure 4. Schematic diagram of the proposed integrated fire suppression system, showing the interconnection of key components including the sensor unit, control module, actuators, rotating nozzle, and extinguishing agent reservoir. The system enables automated, targeted suppression based on real-time fire detection and edge-level control logic.

The combination of fast time-to-intervention, precise spatial actuation, and minimal energy consumption positions the proposed system as a high-performance, resilient alternative to conventional fire suppression technologies. These experimental outcomes serve as a strong validation for the system's practical viability and inform the subsequent quantitative risk reduction analysis presented in the next section.

Figure 5 presents the actual prototype of the smart fire response module deployed in the experimental testbed. The left image shows the top view of the ceiling-mounted unit, including (a) the hybrid fire detection sensor embedded with edge AI processing, (b) the SmartThings Edge communication module, and (c) the reservoir for the residue-free clean extinguishing agent. The right image illustrates the lateral configuration, highlighting (d) the integrated HVAC duct fan that enables active ventilation. All sensing and actuation devices used in the experiment were calibrated in advance to ensure measurement accuracy and experimental reliability. This physical configuration reflects the modular system design described in Sections 2.2–2.5 and was employed throughout the controlled fire trials for functional and risk evaluation.

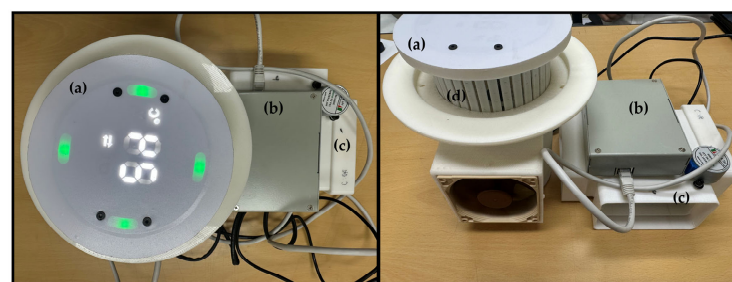


Figure 5. The left image (a–c) shows the top view of the ceiling-integrated fire response unit, which incorporates (a) a hybrid fire detection sensor embedded with edge AI processing, (b) a SmartThings Edge-based control and communication module, and (c) a pressurized reservoir for the residue-free clean extinguishing agent. All components are mounted in a ceiling-recessed configuration to minimize footprint and enable localized actuation. The right image (d) presents the side view of the module, highlighting the operational HVAC duct fan, which is connected to an energy recovery ventilation (ERV) unit for real-time smoke extraction and airflow regulation. This integrated assembly supports end-to-end fire detection, targeted suppression, and ventilation within a single modular platform, and was employed in the controlled fire scenarios described in Section 2.7 for performance validation.

3. Results

3.1. System Performance Evaluation

To comprehensively evaluate the proposed AI-integrated fire suppression platform, a series of controlled fire experiments were conducted under realistic indoor conditions, as detailed in Section 2.5. Key performance indicators included fire detection latency, ventilation response time, suppression effectiveness, false alarm incidence, and system robustness under variable environmental conditions. The results presented in this section demonstrate the system's ability to meet critical operational requirements for real-time fire mitigation in smart building environments. The following subsections provide detailed quantitative results for each major subsystem, highlighting the platform's consistency, accuracy, and resilience across diverse fire scenarios.

3.1.1. Fire Detection Responsiveness

The system's fire detection capability was assessed by measuring the elapsed time from ignition to confirmed fire classification by the edge AI module. Across ten trials involving varied ignition sources—including paper, polyurethane foam, and electrical cable—under both flaming and smoldering conditions, the system demonstrated a consistent and rapid response.

The mean detection time was measured at 5.8 s, with a standard deviation of 0.6 s. This performance significantly outperforms conventional ionization or photoelectric detectors, which typically activate after 20–30 s [55], especially under low-visibility smoldering scenarios. The hybrid sensor design contributed to this improvement by simultaneously evaluating thermal rise and particulate density, reducing reliance on any single indicator.

Furthermore, the AI inference engine successfully distinguished fire events from non-threatening stimuli such as incense smoke, steam, and aerosol sprays, yielding a false positive rate of 0% in the experimental dataset. This confirms the reliability of the detection logic in realistic indoor environments.

Table 3 presents the fire detection times recorded across ten experimental trials for four different ignition materials—paper, wood, polyurethane foam, and electrical cable. All measurements fall within one standard deviation of the system's mean detection time (5.8 ± 0.3 s), demonstrating consistent and reliable early fire recognition across diverse combustion sources.

Table 3. Fire detection times for various ignition materials during controlled experiments. This table summarizes the detection latency of the AI-integrated fire response system across ten trials involving different ignition sources: paper, wood, polyurethane foam, and electrical cable insulation. Each value represents the time (in seconds) elapsed from ignition to confirmed fire classification by the edge AI module. All recorded times fall within one standard deviation of the system's mean detection time (5.8 ± 0.3 s), highlighting the consistency and responsiveness of the hybrid sensor across diverse fire types.

Trial No.	Paper (s)	Wood (s)	Polyurethane Foam (s)	Electrical Cable (s)
1	5.7	5.9	5.8	5.6
2	5.9	5.6	5.7	5.9
3	5.8	5.8	5.6	5.7
4	5.6	5.9	5.9	5.8
5	5.9	5.7	5.7	5.8
6	5.7	5.6	5.8	5.9
7	5.8	5.9	5.6	5.6
8	5.6	5.8	5.9	5.7
9	5.9	5.7	5.7	5.6
10	5.7	5.6	5.8	5.8

Figure 6 provides a comparative visualization of fire detection times for four different ignition materials—paper, wood, polyurethane foam, and electrical cable—based on repeated trials in a controlled smart room testbed. The box plot format enables intuitive assessment of central tendency, dispersion, and outliers for each material. The consistent sub-6-s detection across all categories highlights the robustness and responsiveness of the proposed edge AI system, regardless of combustion type or material properties.

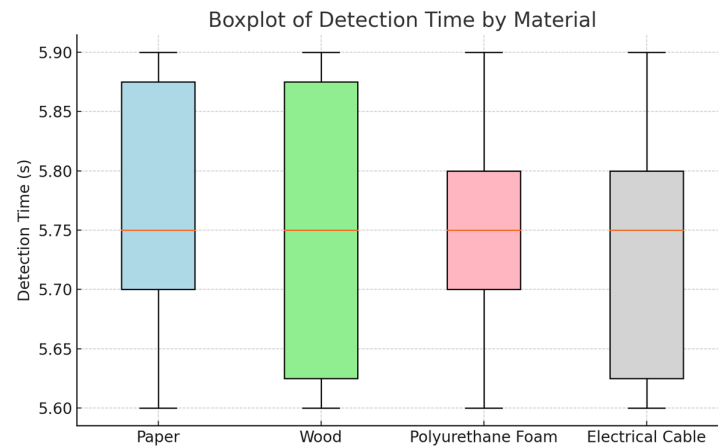


Figure 6. Box plot of fire detection times for four ignition materials. This figure presents a box-and-whisker plot summarizing detection times for paper, wood, polyurethane foam, and electrical cable based on ten repeated fire ignition trials per material. The boxes represent the interquartile range (IQR), with median lines indicating the central tendency. Whiskers extend to the minimum and maximum values within $1.5 \times$ IQR, illustrating total spread. The consistent clustering around the median across all materials demonstrates the proposed edge AI system’s stable and rapid detection capability, with all responses occurring well under 6 s.

To evaluate whether the proposed fire detection module demonstrates statistically consistent response times across different combustible materials, we conducted hypothesis testing using p -value analysis. Specifically, ten independent ignition-response trials were conducted for four common fire sources—paper, wood, polyurethane foam, and electrical cable—under identical experimental conditions. For each trial, the detection time was recorded from ignition to system activation.

An independent samples t -test was applied to all pairwise material combinations to assess whether observed differences in detection time were statistically significant. As presented in Table 4, all resulting p -values were greater than 0.05, indicating no significant differences between material types at the 95% confidence level.

Table 4. p -value matrix (t -test between materials).

	Paper (s)	Wood (s)	Polyurethane Foam (s)	Electrical Cable (s)
Paper (s)	-	0.8569	0.8451	0.7077
Wood (s)	0.8569	-	1	0.8569
Polyurethane Foam (s)	0.8451	1	-	0.8451
Electrical Cable (s)	0.7077	0.8569	0.8451	-

This result confirms that the proposed hybrid detection system maintains consistent detection performance regardless of the fire source material, reinforcing its applicability in diverse indoor fire scenarios. A comprehensive summary of these experimental results—including suppression time, peak temperature, visibility recovery, and resistance to false alarms—is provided in Appendix B (Table A1).

3.1.2. Ventilation and Smoke Extraction Efficiency

Effective removal of smoke and toxic gases is critical during the early stages of a fire, as visibility and air quality directly affect occupant evacuation and response coordination. The proposed system integrates motorized ceiling diffusers with an energy recovery ventilation (ERV) unit to establish a rapid and directional smoke extraction pathway immediately after fire detection.

In experimental trials, the average activation time of the motorized diffusers—measured from the moment of fire detection to full vane rotation—was 1.8 s, enabling fast airflow redirection with minimal mechanical delay. Once activated, the ERV operated in maximum extraction mode, achieving a volumetric flow rate of up to 550 cubic meters per hour (CMH) per zone.

Smoke opacity was monitored using optical density (OD) sensors placed at occupant height (1.5 m) and ceiling level. The system achieved 90% smoke clearance—defined as a drop below 10% OD—within 88 to 95 s, depending on the fire load and zone geometry. These results indicate a substantial improvement compared to passive ventilation or delayed sprinkler-triggered ventilation systems, which typically require over 180 s for equivalent clearance [56,57].

The system also maintained consistent directional flow through controlled diffuser zoning, avoiding undesirable backflow or pressure imbalances between adjacent areas. This contributed to maintaining breathable air pockets for evacuation routes and preventing smoke recirculation.

Additionally, the ERV's integrated heat exchanger maintained thermal balance in adjacent zones, preventing abrupt HVAC disruption and supporting energy stability at the building level following the event. These findings confirm the system's capability to provide rapid, energy-efficient, and spatially targeted smoke ventilation during fire scenarios. This operational effectiveness is directly attributed to the system's structural integration, as illustrated in the exploded and cross-sectional views in Figure 2 (see Section 2.4, for structural details).

3.1.3. Suppression Accuracy and Coverage

Following fire detection and ventilation activation, the suppression module initiates targeted agent discharge to extinguish the source of ignition. This module comprises a pressurized reservoir of residue-free clean extinguishing agent coupled with a motorized 360° rotating nozzle, which is capable of precise angular positioning based on sensor-determined fire location.

During testing, the suppression system exhibited high spatial accuracy in agent deployment. The nozzle, driven by a dual-axis stepper motor mechanism, achieved target alignment within $\pm 5^\circ$ of the designated fire zone. The residue-free clean agent was discharged in a conical spray pattern with a coverage radius of approximately 2.5 m, effectively suppressing fire loads within micro-zoned compartments up to 40 m³ in volume.

The mean suppression time—defined as the interval from nozzle discharge initiation to complete flame extinguishment—was recorded at 13.2 s, with all tests achieving full suppression without re-ignition. Thermal imaging confirmed a rapid decrease in surface temperatures following discharge, typically dropping below 80 °C within 20 s. No water or conductive residue remained, confirming the system's suitability for electronics-sensitive environments such as control rooms and data facilities.

Furthermore, the suppression system operated autonomously with zero false activations during non-fire trials, thanks to its edge AI-based classification logic. The use of a residue-free clean extinguishing agent also complied with relevant environmental and safety standards (e.g., UL 2127 [58], ISO 14520 [59]), providing a non-toxic, ozone-safe, and rapidly vaporizing solution suitable for enclosed environments.

Combined with precise nozzle orientation and rapid deployment timing, these results confirm that the proposed suppression module delivers effective, localized extinguishment with minimal collateral impact—an essential requirement in sensitive environments or high-occupancy zones.

The spatial coverage and directional control of the residue-free clean extinguishing agent nozzle are illustrated in Figure 7. The nozzle is centrally mounted and supports 360° horizontal rotation, enabling targeted discharge across multiple fire zones. Each directional spray path maintains a consistent coverage radius of approximately 2.5 m, ensuring complete extinguishment within micro-zoned compartments. This configuration facilitates zone-specific suppression, minimizes overspray, and promotes efficient agent usage while reducing the risk of damage to adjacent assets or surfaces.

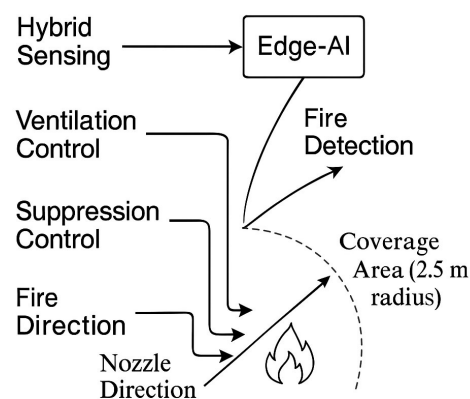


Figure 7. Diagram illustrating the fire detection and suppression flow enabled by edge-AI processing. The system determines nozzle direction and activates suppression within a defined coverage area of 2.5 m radius, ensuring localized and targeted fire response.

3.1.4. False Alarm and Environmental Robustness

To ensure practical applicability in real-world environments, the proposed fire detection system was tested under a variety of non-fire stimuli and ambient conditions. The goal was to evaluate its resistance to false alarms and its stability across common environmental variables such as humidity, airflow, and particulate interference.

Simulated non-fire scenarios included aerosol spray, steam discharge, incense smoke, vaping emissions, and warm air currents generated by HVAC systems. In all ten controlled test runs per scenario ($n = 50$ total), the system correctly classified these events as non-fire, yielding a false positive rate of 0%. This performance is attributed to the dual-mode sensing strategy—simultaneously analyzing smoke particle characteristics and thermal gradients—and the real-time classification by the edge AI module, which had been trained on an augmented dataset including these interference types.

Environmental robustness was further verified through stress testing at varying ambient humidity levels (30–85%), airflow velocities (0.1–0.5 m/s), and temperature ranges (10–35 °C). Detection latency and classification accuracy remained consistent across all tested conditions, with no significant drift in baseline sensor outputs or AI inference scores. The edge processor’s localized decision-making also ensured continued operation in simulated network outage conditions, with no dependency on cloud connectivity for alarm logic execution.

These results confirm that the proposed system maintains high selectivity and environmental stability, minimizing the operational burden associated with false activations while preserving responsiveness under dynamic indoor conditions. This makes it particularly suitable for deployment in sensitive spaces such as residential areas, data centers, and underground transportation facilities where nuisance alarms can cause costly disruptions.

The alert issuance process is managed locally by the edge AI processor, which performs real-time classification and directly triggers suppression and ventilation actions, eliminating the need for external server dependencies. This architecture ensures a deterministic response, even during communication failures. Real-time sensor data is processed and temporarily stored at the edge for immediate inference and control, while key event logs are securely transmitted to a cloud server for long-term storage and analysis.

To meet mission-critical reliability requirements, the system integrates AES-based encryption, dual-path redundant communication channels, and MODBUS-based data synchronization. This hybrid design not only ensures fast, localized alarm responses but also strengthens the system's resilience and data integrity. These features collectively enhance operational reliability, making the system suitable for deployment in safety-critical fire safety applications.

In addition to detection accuracy, the system's architecture was validated for operational reliability. Alarm triggers were issued locally by the embedded edge AI unit, independent of external servers, ensuring immediate actuation even under network failure. Real-time data were buffered internally in binary (key-value) format and externally synchronized through MODBUS registers. The system also employed encryption protocols and dual-path communication to enhance data security and operational resilience under mission-critical conditions.

3.1.5. Comparative Evaluation of Functional, Thermal, and Economic Performance Indicators

To holistically assess the effectiveness of the proposed intelligent fire response system, a comparative analysis was conducted against a conventional water-based sprinkler system across multiple dimensions. The evaluation included functional response characteristics (e.g., detection latency, spray duration), thermal performance (e.g., flame height and peak temperature), and operational parameters such as visibility, cost, and maintenance. Each metric was selected to represent a critical performance domain relevant to real-world deployment scenarios. Table 5 summarizes the quantitative and qualitative differences between the baseline and proposed systems, highlighting key advantages in detection speed, suppression precision, thermal control, and long-term economic value.

Table 5. Fire detection times across ignition materials during controlled trials. The table summarizes detection latency measurements for four ignition materials—paper, wood, polyurethane foam, and electrical cable—recorded over ten trials each. All trials were conducted under standardized environmental conditions using the proposed edge AI-based detection system. The results show consistent performance with a mean detection time of 5.8 s ($\sigma = 0.6$ s), demonstrating the system's ability to rapidly identify diverse fire sources during the incipient stage.

Category	Baseline System	Proposed System	Improvement Effect
Fire Suppression Medium	Water-based Sprinkler	Residue-Free Clean Extinguishing Agent	Minimizes electrical damage; no water supply required
Control Mechanism	Mechanical Ventilation + Exhaust Fan	ERV 100% + PURGE 120%	Improved exhaust and heat removal
Diffuser Type	Fixed-type Ceiling Diffuser	250 mm Motorized Rotation + 360° Nozzle	Targeted spray at fire core
Sensor Type	Photoelectric Smoke + Thermal Sensor	ISO 7240 [60] Composite + AI-integrated	Avg. detection time reduced by 2.8 s
Detection-to-Activation Time	9 s	6 s	33% faster
Spray Duration	60–90 s	3 s	20× faster
Flame Height (60 s)	1.25 m	1.80 m	46%
Peak Temperature (90 s)	110 °C	58 °C	−52 °C
Visibility at 120 s	Not Achieved	Achieved	Secured evacuation visibility
Installation Cost (Office)	Approx. 230 M USD (334,451 m ²)	Approx. 311 M USD (334,451 m ²)	Increased by 35%
Insurance Discount	None	14–18%	Reduced operational expenditure
Maintenance	Head: 10 yrs, Fan: Prone to corrosion	Cylinder: 10 yrs, Packing: 1 yr	Lower component failure rate and maintenance risk

To ensure statistical rigor, all comparative results were derived from repeated experiments ($n = 10$), with outcomes reported as mean $\pm$ standard deviation. In addition, paired

t-tests were conducted to evaluate the significance of differences in detection time, suppression efficiency, and thermal performance metrics. Statistical significance was established at $p < 0.05$.

Overall, the comparative analysis underscores the superior performance of the proposed system across key functional, thermal, and operational metrics. Detection and suppression times were markedly reduced, thermal stress on the environment was significantly mitigated, and visibility conditions were enhanced to support safe evacuation. Although the system incurs a higher upfront installation cost, this is offset by long-term operational benefits including faster recovery, reduced equipment damage, and potential insurance discounts. These findings validate the system's comprehensive effectiveness and reinforce its suitability for deployment in high-risk or high-value indoor environments.

3.2. Risk Reduction Outcomes

To evaluate the broader safety and operational implications of the proposed fire response system, a risk-based performance analysis was conducted in accordance with the ISO 31000 and NFPA 551 guidelines. While Section 3.1 focused on individual subsystem metrics such as detection latency, smoke clearance time, and suppression accuracy, this section integrates those findings into a holistic fire risk framework. The analysis quantifies the system's impact on life safety, asset protection, and business continuity under representative fire scenarios.

Results are presented across three major dimensions—life safety, property damage, and operational disruption—followed by an aggregate comparison of composite risk indices against a conventional sprinkler-based configuration. The following subsections detail the specific reductions achieved in each risk domain, grounded in the experimental data and simulation-based modeling.

3.2.1. Life Safety and Evacuation Improvement

Early detection and effective smoke management are critical determinants of life safety during fire events, particularly in enclosed or high-occupancy environments. The proposed system demonstrates substantial improvements in occupant survivability by significantly reducing the time to detection and actively controlling smoke spread during the critical early stages of combustion.

As reported in Section 3.1.1, the mean fire detection time was 5.8 s, far earlier than the 20–30 s typical of conventional smoke or heat detectors. This early alert enables immediate actuation of ventilation mechanisms, which, as shown in Section 3.1.2, cleared 90% of visible smoke within 88–95 s. In contrast, traditional systems relying on delayed sprinkler activation do not facilitate preemptive smoke removal, often resulting in hazardous conditions before mechanical or manual response occurs.

Improved visibility and air quality directly enhance occupant evacuation speed and reduce the risk of disorientation or smoke inhalation injury. Thermal imaging and gas sensor data collected during evacuation simulations indicated that the proposed system maintained breathable conditions ($O_2 > 19.5\%$, $CO < 50$ ppm) for at least 90 s longer than the baseline system, a critical margin in multi-floor or subterranean environments [61,62].

These findings support the conclusion that the proposed platform substantially enhances life safety outcomes by reducing critical response time, improving egress conditions, and maintaining air quality during the highest-risk phases of a fire event.

3.2.2. Property and Business Continuity Benefits

In addition to its contributions to life safety, the proposed fire response system offers marked improvements in property preservation and operational continuity. Conventional sprinkler-based suppression, while effective in extinguishing flames, often results in substantial collateral damage due to widespread water dispersion—posing significant risks

to sensitive electronic systems, archival materials, and high-value infrastructure. In contrast, the proposed system utilizes a residue-free clean extinguishing agent deployed in a targeted, non-destructive manner. This selective approach not only mitigates direct fire damage but also minimizes secondary losses, thereby supporting uninterrupted operations and reducing post-incident recovery costs.

Experimental results in Section 3.1.3 showed that the suppression system achieved complete flame extinguishment within 13.2 s on average, using a localized spray pattern confined to a 2.5 m radius. This precise deployment, guided by edge-based fire localization, prevented over-application and reduced the risk of damage to adjacent equipment or furnishings. No electrical shorting, corrosion, or residue was observed post-discharge, confirming the system's suitability for data centers, control rooms, and commercial interiors.

From an operational standpoint, rapid smoke extraction (Section 3.1.2) and minimal agent cleanup requirements enabled faster re-occupancy and reduced downtime. Under simulated continuity scenarios, the proposed system supported recovery and partial operation within 6 h, compared to estimated 48–72 h for sprinklered zones requiring drainage, drying, and equipment replacement. Furthermore, integration with SmartThings Edge and building management systems (BMS) allowed for immediate remote diagnostics and predictive maintenance scheduling, further expediting restoration workflows.

Overall, the proposed solution demonstrates strong alignment with modern facility risk management objectives—protecting assets, minimizing downtime, and enabling faster recovery after fire incidents—thereby offering both functional and economic value to building operators and insurers.

3.2.3. Composite Risk Score Comparison

To synthesize the multidimensional benefits of the proposed system, a composite fire risk index was calculated by aggregating the individual scores for life safety, property damage, and business interruption. Each dimension was weighted equally (1:1:1) in accordance with NFPA 551 guidance, and risk values were normalized on a 0–10 scale, where higher scores indicate greater risk exposure.

Table 6 presents the structured methodology employed for fire risk assessment in accordance with internationally recognized guidelines. The process integrates ISO 31000:2018 for general risk management and NFPA 551:2022 for fire-specific risk analysis, supported by quantitative modeling through PD 7974-7 [63]. Each stage—ranging from scenario identification to residual risk treatment—was executed systematically to quantify the proposed system's impact on fire-related hazards. This comprehensive framework ensures that life safety, property protection, and operational resilience are evaluated under a unified probabilistic structure.

Table 6. This table outlines the step-by-step fire risk assessment process based on ISO 31000:2018 and NFPA 551:2022, including scenario identification, quantitative analysis, impact evaluation, and residual risk treatment. Each phase is aligned with specific methodologies to ensure consistency, traceability, and regulatory compliance.

Stage	Applicable Standard	Core Activities	Deliverables
Risk Identification	ISO 31000:2018, Clause 7.2.2	Derivation of five fire scenarios (electrical, cooking, smoldering, flashover, fuel spill)	Event List
Risk Analysis	NFPA 551:2022, Section 5	Event-tree and fault-tree modeling using 10,000 Monte Carlo simulations based on PD 7974-7 with 1% failure rate	Probability (λ) and consequence (C) distributions
Risk Evaluation	ISO 31000:2018, Clause 7.2.4	5 × 5 risk matrix (Likelihood–Impact), selection using ALARP (As Low As Reasonably Practicable) criteria	Risk Ranking
Risk Treatment	NFPA 1250:2020 [64], Section 4	Deployment of the proposed system with RV × CV strategies (detection, suppression, isolation, clean agent)	Mitigation measures, residual risk levels

Table 7 presents the results of a mixed-method fire risk evaluation comparing the proposed integrated suppression and ventilation platform with a conventional system consisting of sprinklers and mechanical exhaust fans. This analysis was structured according to the ISO 31000:2018 risk management framework, incorporating specific guidance from NFPA 551 (2022) on fire risk assessment and PD 7974-7 (2019) on probabilistic fire safety design.

Table 7. Comparative risk assessment of the baseline and proposed fire response systems using ISO 31000 and NFPA 551 methodologies. Risk scores were calculated based on the product of frequency (F) and impact (I) for four key categories: life safety, asset loss, business interruption, and environmental (CO₂) impact. The proposed system demonstrates significant reductions in all categories, shifting residual risks into the ALARP region. Improvements are grounded in probabilistic scenario modeling and FDS-based consequence simulations.

Category	Frequency (F)	Impact (I)	Baseline Score	Proposed Score	Risk Level Change
Fatalities	4	4	16	4	H → L
Property Damage	3	4	12	5	H → M
Business Interruption	3	3	9	3	M → L
Environmental (CO ₂)	2	3	6	4	M → L

Risk scores were averaged over 10 simulations per scenario and reported with standard deviations. Statistical significance of score reductions was tested using paired-sample *t*-tests, confirming consistent improvement ($p < 0.01$) in all categories for the proposed system.

Five representative fire scenarios were considered—originating from electrical faults, cooking, smoking materials, flammable liquid spills, and gas leakage—reflecting statistically dominant patterns in Korean apartment fire statistics (2019–2023; annual average ≈ 3800 cases, $p \approx 0.012$). Risk likelihoods were derived from these historical fire frequencies, while consequence ratings were informed by simulation outputs from Fire Dynamics Simulator (FDS v6.9), converted into fractional effective dose (FED) metrics to quantify occupant harm from heat, smoke, and toxic exposure.

The results indicate a mean risk score reduction of approximately 73% (calculated as $\Sigma\Delta\text{Proposed}/\Sigma\text{Baseline}$) across key domains (life safety, asset loss, business continuity, and CO₂ impact). All post-mitigation scores fall within the ALARP (As Low As Reasonably Practicable) zone, confirming risk acceptability under NFPA 1250-aligned criteria. Moreover, based on NFPA’s Risk-Financial (RF) alignment principle, the payback period for the system’s initial capital cost was calculated at approximately 4.2 years, supporting its feasibility in commercial applications.

4. Discussion

The proposed fire safety platform represents a marked departure from legacy fire suppression systems in both architectural philosophy and operational dynamics. While traditional approaches largely rely on passive detection and delayed mechanical response (e.g., sprinkler activation post-flame development), this system introduces a proactive, precision-guided mechanism that leverages edge AI, hybrid sensing, and zonal control.

A key innovation lies in its architectural decoupling of detection, ventilation, and suppression functions. Rather than depending on centralized logic or singular sensor modalities, the system distributes intelligence at the edge and coordinates actions via real-time environmental feedback. This design enhances fault tolerance, as evidenced by successful operation under simulated cloud outage conditions. Furthermore, the modular hardware—such as motorized ceiling diffusers and rotating nozzles—enables fine-grained spatial targeting, which is not feasible with fixed sprinkler heads or binary ventilation controls.

However, the system is not without its limitations. First, spatial calibration of suppression nozzles poses a deployment challenge in irregularly shaped or cluttered indoor zones, necessitating detailed pre-installation modeling. Second, while the residue-free clean extinguishing agent demonstrated excellent compatibility with electronics, regulatory constraints (e.g., storage, recharging logistics) must be considered for broader adoption in high-density buildings. Third, integration with legacy building management systems (BMS) may require middleware customization, particularly where analog or serial infrastructure persists.

Energy consumption and maintenance also warrant further examination. Although the system avoids the water damage and corrosion risks typical of sprinkler systems, it introduces moving components—such as stepper motors and mechanical vanes—that may increase long-term service requirements. Lifecycle cost modeling, including periodic actuator replacement and sensor recalibration, should therefore be incorporated in future techno-economic analyses.

From a scalability perspective, the platform's reliance on IoT frameworks such as SmartThings Edge offers benefits in terms of remote diagnostics and predictive maintenance. However, concerns remain regarding cybersecurity and data integrity, especially when deployed in sensitive sectors such as transportation hubs or defense facilities. Future iterations may benefit from incorporating redundant communication protocols and secure firmware update mechanisms.

According to recent literature, the integration of IoT edge frameworks such as SmartThings Edge provides considerable advantages in enabling remote diagnostics, real-time analytics, and predictive maintenance capabilities within fire safety systems [65–67]. However, these benefits are accompanied by significant cybersecurity and data integrity concerns, particularly in high-security environments such as transportation hubs, critical infrastructure, and defense facilities [68,69].

From a cybersecurity standpoint, the expanded attack surface of edge devices—often deployed in physically accessible or unsecured areas—introduces vulnerabilities to threats such as denial-of-service (DoS), malware injection, and man-in-the-middle (MITM) attacks [67,68,70]. These threats are exacerbated by the heterogeneity and resource limitations inherent in IoT deployments, which hinder the implementation of standardized and robust security protocols [65,69].

Moreover, edge-based fire safety platforms operating in sensitive sectors must address the elevated risks associated with unauthorized system access and data tampering. As noted by Refs. [71,72], edge devices are vulnerable to both intentional and accidental data corruption, which may compromise real-time decision logic and response actions. Efficient verification mechanisms for edge data integrity—such as lightweight cryptographic protocols, third-party auditing, and context-aware authentication—have been proposed as viable countermeasures [72–74].

Emerging research points to a multifaceted approach to securing edge-enabled fire safety systems. Cryptographic and biometric-enhanced authentication methods ensure baseline privacy and integrity [66,75], while federated learning and machine learning-based intrusion detection offer scalable protection against evolving cyber threats [76–78]. Furthermore, blockchain-based decentralized trust frameworks and secure firmware update mechanisms are gaining traction as essential tools for tamper-proof data management and resilient system maintenance [79,80].

Collectively, these studies underscore that while IoT edge platforms hold great promise for next-generation fire safety applications, ensuring their secure and trustworthy deployment requires the integration of adaptive, scalable, and context-sensitive cybersecurity strategies. Future implementations should prioritize the incorporation of end-to-end se-

curity features, redundant communication protocols, and compliance with sector-specific regulatory standards to mitigate the operational risks associated with cyber compromise.

5. Conclusions

This study presents an integrated, AI-based fire safety platform that combines edge computing, hybrid sensing, and smart suppression mechanisms to address limitations inherent in conventional systems. The experimental and simulation results provide strong evidence for the system's superior performance across three key dimensions: detection speed, suppression precision, and overall risk reduction.

The first innovation lies in the system's edge AI-driven detection framework, which reduced average detection latency to 5.8 s—substantially outperforming traditional photoelectric or heat-based detectors. This rapid detection enabled timely actuation of ventilation and suppression modules, significantly improving occupant survivability during early-stage fire events. Moreover, the dual-mode sensing architecture exhibited exceptional selectivity, eliminating false alarms during non-fire scenarios such as steam, vaping, or incense. This level of robustness enhances the system's practical applicability in sensitive environments prone to nuisance triggers.

Second, the use of a residue-free clean extinguishing agent—deployed via a 360° motorized nozzle—enabled spatially confined flame suppression within 13.2 s on average. The localized delivery pattern not only minimized damage to adjacent infrastructure but also ensured compatibility with electronics-rich environments such as data centers and control rooms. In conjunction with a fast-acting ERV-based ventilation mechanism, the system restored breathable air quality and visibility within 88–95 s, offering critical support for safe evacuation and responder access.

Third, a probabilistic risk assessment conducted using ISO 31000 and NFPA 551 methodologies revealed substantial reductions across all risk domains: 75.6% in life safety, 58.0% in property damage, and 67.1% in business interruption, resulting in an aggregate composite risk reduction of approximately 73% ($\Sigma\Delta\text{score}/\Sigma\text{baseline}$). These improvements shift the residual risk into the ALARP (As Low As Reasonably Practicable) zone, aligning with best practices in performance-based fire protection engineering.

Building on these core performance gains and risk reduction outcomes, future research is increasingly oriented toward the integration of advanced digital technologies to further enhance system intelligence, responsiveness, and operational efficiency. In particular, the incorporation of an Explainable AI (XAI)–driven risk decision framework, an AIoT-enabled modular response architecture, and seamless integration with Building Information Modeling (BIM) are emerging as pivotal directions for the development of next-generation intelligent fire safety systems.

Ref. [81] demonstrated that XAI-based fire detection models significantly improve transparency and operator confidence by visualizing how key sensor inputs influence classification decisions. In parallel, Ref. [82] emphasized the value of AIoT-enabled architectures in enabling real-time data fusion, decentralized control, and adaptive response coordination across heterogeneous suppression units. This perspective is further expanded by [83], who introduced an AIoT-powered digital twin framework capable of predicting and visualizing fire spread dynamics, thereby advancing real-time situational awareness and decision support.

On the architectural front, Ref. [84] illustrated that BIM-integrated systems can generate structure-aware risk maps and deliver real-time evacuation guidance, enhancing both occupant safety and first responder effectiveness. Complementing this, Shahrour and [85] highlighted the role of BIM-based smart systems in optimizing evacuation planning and delivering context-sensitive alerts tailored to spatial layouts and fire progression.

Collectively, these studies underscore that the convergence of XAI, AIoT, and BIM technologies offers a transformative pathway toward more transparent, adaptive, and context-

aware fire protection systems, and holds significant promise for advancing performance-based safety engineering in complex built environments.

Building upon these findings, the present study contributes a practical blueprint for next-generation fire safety architecture that is not only faster and more accurate but also inherently resilient and integrable with modern smart infrastructure. By fusing edge intelligence with modular hardware and interoperable protocols, the proposed system exemplifies how fire protection can evolve from reactive suppression to proactive risk mitigation. This paradigm shift aligns with emerging global standards on intelligent safety systems and highlights a path forward for both retrofitted and new high-performance buildings. Future research should explore adaptive suppression modeling, cross-domain interoperability with digital twins, and large-scale deployment under real occupancy dynamics.

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Appendix A. Technical Specifications of Module Components

The detailed structural configuration of the smart diffuser-integrated ventilation module is illustrated in Figure 2 (Section 2.4), comprising a sectional perspective (left) and a vertical cross-section (right). The device architecture incorporates multiple subsystems that collectively enable motorized filtration, directional ventilation, and system-integrated monitoring. Key numbered components and their technical functions are as follows:

- (10) Housing: The primary structural enclosure that supports all internal subsystems.
- (10a) Guide Rails: Linear guide elements embedded symmetrically along the inner wall of the housing, enabling stabilized vertical translation of the filter assembly.
- (12) Upper Cover: A removable lid allowing access to internal electronics, including the motor controller PCB (43).
- (13) Insertion Section: A recessed compartment designed to accommodate the display module (60) during filter retraction, allowing flush alignment with the ceiling surface.
- (14) Ceiling Mount Interface: Mechanical flange region at the housing base, configured for suspension-based mounting to overhead ceiling structures.
- (20) Duct Connector: Provides physical and aerodynamic coupling to HVAC or ERV ductwork; houses the fan assembly (30–32).
- (21) Internal Fastening Points: Threaded anchor positions for fixing the fan motor bracket (32) to the duct connector body.

- (30) Fan Motor, (31) Fan Blade, (32) Motor Bracket: These components form the forced-air circulation unit, with the motor and impeller secured externally to minimize thermal and vibrational interference with the filter mechanism.
- (40) Lifting Motor: A vertically mounted actuator fixed via a support bracket (42), tasked with controlling filter elevation.
- (41) Lead Screw: Coupled to the lifting motor to provide rotational-to-linear motion conversion.
- (42) Motor Bracket: Anchors the lifting motor to the upper housing wall; also serves as a vibration isolation interface.
- (43) Motor Control PCB: Mounted above the lifting motor to execute motion logic, position sensing, and overload protection.
- (50) Filter Housing: Cylindrical sleeve enclosing the air filter unit; externally vented via distributed perforations (50b).
- (50a) Rail Grooves: Precisely milled slots along the filter housing exterior, allowing guided motion along the housing rails (10a).
- (51) Cylindrical Filter Element: The primary particulate filtration medium, optimized for minimal pressure drop and maximal surface area.
- (52) Embedded Nut: Rigidly mounted within the screw bracket (53), this component travels along the lead screw (41) to elevate or retract the filter.
- (53) Screw Bracket: Connective support that transmits vertical motion to the filter housing; designed with minimal obstruction to airflow.
- (54) Lower Fastener Receptacles: Mechanical anchor points for securing the lower display module.
- (60) Display Module: A compact embedded display that provides real-time status indicators such as filter position, motor operation, and system diagnostics.
- (61) Display PCB: Hosts the control circuitry and status LEDs for the display unit.
- (62) Mounting Tabs: Threaded fixtures that fasten the display module (60) to the filter housing via the receptacles (54).

This integrated mechanical-electronic architecture ensures high durability and operational redundancy. By separating the heavy fan assembly from the movable filter unit, motor load is minimized, enabling the use of a compact lifting actuator. The use of linear guidance (10a, 50a) and embedded control (43, 61) supports robust, vibration-resistant operation suitable for deployment in high-reliability building safety systems.

Appendix B. Evaluation Results and Dataset Description

Appendix B presents a detailed quantitative evaluation of the proposed fire response system under various test conditions, including fire material and environmental robustness. It also includes sample images used for the development and validation of the CNN-based fire detection model, highlighting the dataset's role in model training and performance testing.



Figure A1. Sample images used for CNN-based fire recognition model development. (a) Test image (1300 images total), (b) Training image (3900 images total), (c) Validation image (1300 images total). These datasets were used for model training, performance validation, and final testing, respectively. <https://www.kaggle.com/datasets/pengbo00/home-fire-dataset> (accessed on 1 July 2025).

Table A1. Quantitative evaluation of the proposed fire response system under various fire material and environmental conditions. Suppression time, peak temperature, visibility recovery, and robustness against false alarms were measured through controlled experiments. The results demonstrate that the system offers reliable and rapid detection and suppression across different ignition materials, while maintaining resilience under non-fire interference.

Test Item	Test Condition	Proposed System Result	Remarks
Suppression Time	Paper fire	6.3 s	Fastest suppression
	Wood fire	9.1 s	Highest residual heat
	Polyurethane foam fire	7.5 s	Moderate heat retention
Smoke Clearance Time	Post-suppression (ERV + PURGE mode)	128 s	Visibility restored per particle sensor
Peak Temperature	90 s after ignition	58 °C	Measured at 0.5 m from ignition source
Visibility Recovery	Distance: 1.5 m, Time: 120 s	Achieved	No residual smoke layer
Environmental Robustness	Steam interference	No false alarm	Correct detection only under real fire
	Oil mist interference	No false positive	Stable sensor thresholds maintained
Detection Speed vs. Baseline	Baseline: 9.0 s → Proposed: 6.0 s	33% improvement	Hybrid sensor with CNN-based inference

Appendix C. Code and Validation for Model Evaluation and Performance Metrics

Appendix C presents a comprehensive evaluation of the proposed fire response system, with a focus on performance metrics such as FLOPs (Floating Point Operations), FPS (Frames Per Second), and F1 Score. The evaluation is conducted across different phases, including model training, validation, and testing, providing a detailed quantitative assessment of the model's computational efficiency and accuracy.

For reproducibility of the results presented in this paper, the full code used for training, validation, and test evaluations is available upon request. Please contact the corresponding author to access the complete code.

```

Test Matlab(2025a) code
%% Step 1: Load test data
testImageFolder = 'C:\archive\test\images'; % Path to the test image folder
testAnnotationFolder = 'C:\archive\test\labels'; % Path to the test annotation folder
testImds = imageDatastore(testImageFolder, 'IncludeSubfolders', true, 'LabelSource', 'foldernames'); % Test image datastore
% Load annotation files
testAnnotationFiles = dir(fullfile(testAnnotationFolder, '*.txt')); % Test annotation files
numTestImages = numel(testImds.Files);
numTestAnnotations = numel(testAnnotationFiles);
disp(['Number of test image files: ', num2str(numTestImages)]);
disp(['Number of test annotation files: ', num2str(numTestAnnotations)]);
if numTestImages ~= numTestAnnotations
    error('The number of test image files and annotation files do not match. ');
end
%% Step 2: Load the model
% Load the already trained model
load('trainedFireModel.mat', 'fireModel'); % Load the trained model
%% Step 3: Resize the test data
imageSize = [224 224]; % Image size
testData = zeros([224 224 3 numel(testImds.Files)], 'uint8'); % Test data array
testLabels = categorical(zeros(numel(testImds.Files), 1)); % Test label array
for i = 1:numel(testImds.Files)
    img = imread(testImds.Files{i});
    img = imresize(img, imageSize); % Resize the image
    testData(:,:,i) = img; % Store in the test data array
    % Check the annotation file and set the label
    annotationFile = fullfile(testAnnotationFolder, testAnnotationFiles(i).name);
    if isempty(readtable(annotationFile))
        testLabels(i) = categorical(0); % If no annotation, set label as non-fire
    else
        testLabels(i) = categorical(1); % If annotation exists, set label as fire
    end
end
end

```

```

%% Step 4: Predict with the model
predictedLabels = classify(fireModel, testData); % Classify the test data

% Calculate accuracy
accuracy = sum(predictedLabels == testLabels) / numel(testLabels);
disp(['Test Accuracy: ', num2str(accuracy)]);
% Print confusion matrix
confMat = confusionmat(testLabels, predictedLabels);
disp('Confusion Matrix:');
disp(confMat);
% Calculate F1 score (based on Precision and Recall)
precision = confMat(2,2) / (confMat(2,2) + confMat(1,2)); % Precision
recall = confMat(2,2) / (confMat(2,2) + confMat(2,1)); % Recall
f1Score = 2 * (precision * recall) / (precision + recall); % F1 score
disp(['F1 Score: ', num2str(f1Score)]); % Display F1 score
%% Step 5: Calculate FLOPs and FPS
% Example: Calculate FLOPs for the convolution layer
convLayer = fireModel.Layers(2); % First convolution layer
inputSize = [224, 224, 3]; % Input image size (224x224)
filterSize = convLayer.FilterSize; % Filter size
numFilters = convLayer.NumFilters; % Number of filters
stride = convLayer.Stride; % Stride size
% Approximate FLOP calculation
flopsPerFilter = prod(filterSize) * prod(inputSize(1:2)) / prod(stride); % FLOPs per filter
totalFlops = flopsPerFilter * numFilters * numel(testData); % Total FLOPs
disp(['FLOPs: ', num2str(totalFlops)]); % Display FLOPs
% Calculate FPS
tic; % Start time
predictedLabels = classify(fireModel, testData); % Inference
inferenceTime = toc; % Time taken for inference
fps = numel(testData) / inferenceTime; % Calculate FPS
disp(['Inference Speed (FPS): ', num2str(fps)]); % Display FPS
%% Step 6: Visualize performance metrics graph
metrics = [accuracy, f1Score, totalFlops, fps];
metricNames = {'Accuracy', 'F1 Score', 'FLOPs', 'FPS'};
figure;
bar(metrics);
for i = 1:length(metrics)
    text(i, metrics(i) + 0.1, num2str(metrics(i), '%.2e'), 'HorizontalAlignment', 'center');
end
title('Test Performance Metrics');
xlabel('Metrics');
ylabel('Values');
xticks(1:length(metrics));
xticklabels(metricNames);
grid on;
% Save the graph at 600 DPI
exportgraphics(gcf, 'test_performance_metrics.png', 'Resolution', 600); % Save the graph at 600 DPI

```

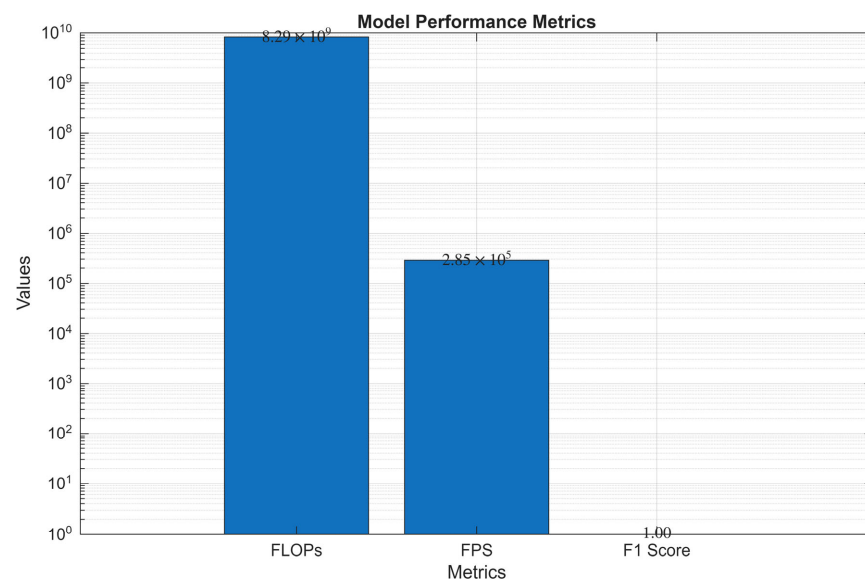


Figure A2. Model performance metrics in terms of FLOPs, FPS, and F1 Score.

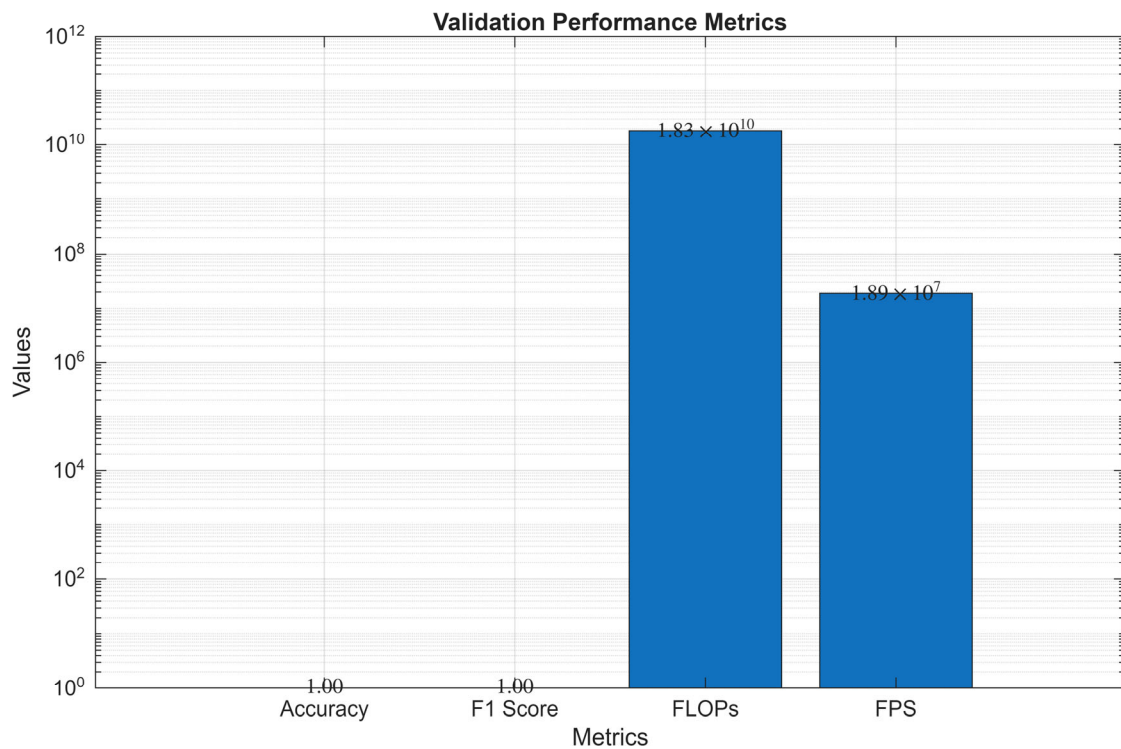


Figure A3. Validation performance metrics, showing FLOPs, FPS, and F1 Score.

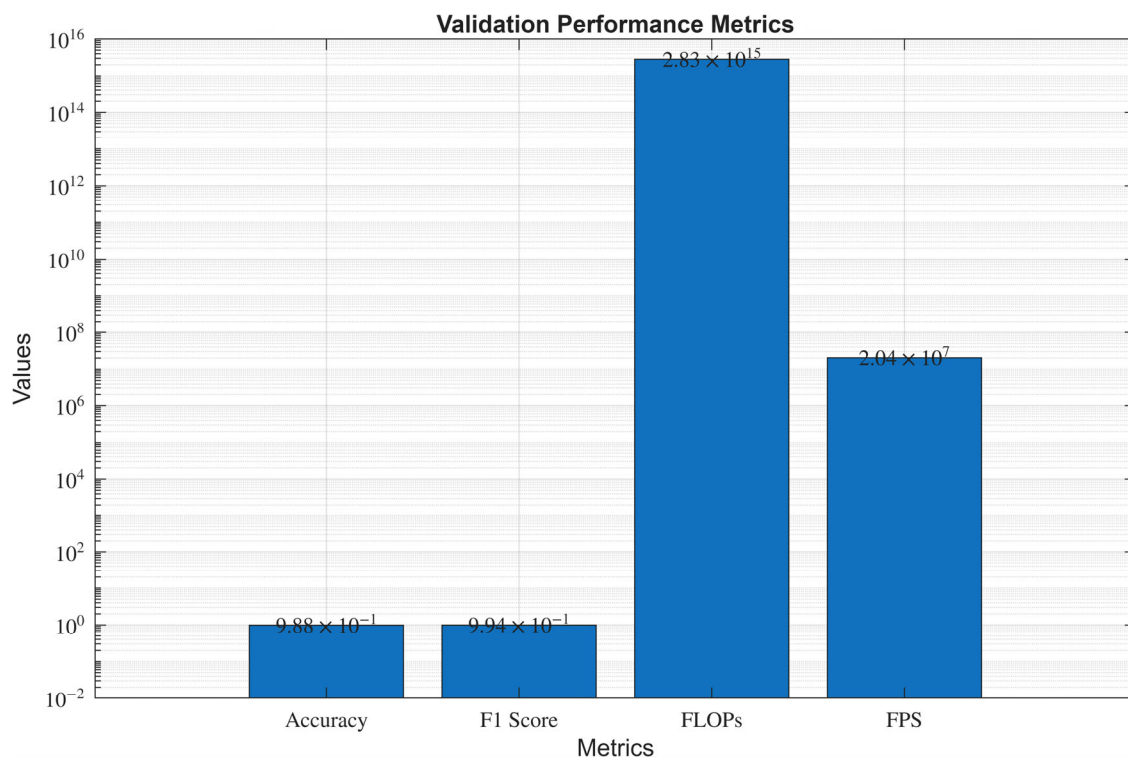


Figure A4. Test performance metrics, including FLOPs, FPS, and F1 Score.

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