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IoT-based cloud monitoring system for building fires

Guanhong Pan[1], Yanzhang Xie[1,2], and Qingping Yang[1,*]

[1] Department of Mechanical and Aerospace Engineering, Brunel University London, UK
[2] Key Laboratory of Instrumentation Science & Dynamic Measurement, Ministry of Education, North University of China, Taiyuan 030051, China

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Abstract. This paper presents an IoT (Internet of Things) based smart building fire cloud monitoring system to enhance fire safety in smart buildings. It integrates low-cost sensors and real-time video surveillance for real-time environmental data collection. Data are uploaded to the cloud for remote monitoring via a custom web interface. The system features an artificial neural network model that reduces computational complexity and response time, achieving >95% accuracy in fire prediction. It assists in planning evacuation routes based on fire location, enhancing safety and efficiency. Laboratory and field tests confirm reliable performance, and the novel system will find applications in smart fire detection and prevention.

Keywords: Smart buildings / low-cost sensors / real-time video monitoring / IoT / cloud / artificial neural networks

1 Introduction

With the intensification of urbanization globally, the fire safety of high-rise buildings has become increasingly critical. Structural fires accounted for a significant portion of global fire incidents between 2019 and 2020. In 2020, building fires constituted 32.2% of all building incidents in 34 countries, underscoring the necessity of accurate fire prediction, early detection, and effective evacuation planning. Despite the widespread installation of fire detectors, false alarms remain common [1]. In the UK, of the 555,795 fire service incidents in 2019, 67% were false alarms, which not only consumed substantial resources but also hindered rescue operations [1]. Detectors using optical or ionization smoke detection technologies often fail in challenging environmental conditions such as high humidity or dusty environments, exacerbating the problem of false alarms [2].

Fires are inherently unpredictable, necessitating continuous monitoring of environmental changes for early detection [3]. During a fire, parameters such as light, temperature, humidity, smoke density, and gas levels (such as carbon monoxide and carbon dioxide) undergo significant changes [3]. Effective sensors, including those monitoring changes in light, temperature, humidity, and gases like carbon monoxide and carbon dioxide, are crucial for early fire detection and prediction.

This study introduces an IoT-based smart building fire cloud monitoring system, integrated with artificial neural networks [4]. The system combines temperature, humidity, gas, and light sensors, along with real-time video monitoring, to achieve accurate fire detection. Data from sensors and video sources are uploaded to the cloud for storage, analysis, and display. Artificial neural networks enhance data analysis, predict fire likelihood, and devise early intervention measures and optimized evacuation routes based on real-time sensor data [4]. This approach reduces false alarms, enhances the accuracy of fire detection, and ensures safer and quicker evacuation guidance for building residents.

The rest of the paper is organized as follows: Section 2 discusses the related work on early fire detection based on sensors. Section 3 details the design of the smart fire monitoring system. Section 4 presents experiments on fire detection using the smart fire monitoring system design, and training and optimization of the AI model. Section 5 discusses the experimental results using our own dataset, system monitoring, and model prediction performance. Section 6 concludes and outlines future work.

2 Related work

Traditional building fire monitoring methods rely on single optical and ionization technologies, which, while effective under specific conditions, tend to produce higher false alarm rates in environments with high humidity or dust [3,5]. To overcome these limitations, fire monitoring

* Corresponding author: qingping.yang@brunel.ac.uk

systems based on the Internet of Things (IoT) have been widely studied. These systems connect various environmental sensors into a wireless network, continuously monitoring parameters such as temperature, humidity, and smoke, thereby significantly improving the accuracy and reliability of early fire detection.

The multi-sensor fire detection system developed by Minoli et al. [6] greatly enhanced the accuracy and efficiency of fire detection. Sarwar et al. [7] combined data from smoke, temperature, and humidity sensors with neuro-fuzzy logic to determine the occurrence of fires and sent fire alerts via the Global System for Mobile Communications (GSM). This method provides fire monitoring systems with a stronger emergency response capability. In comparison, Rachman et al. [8] processed sensor data using fuzzy logic and achieved a lower false alarm rate, while Sowah et al. [9] successfully designed a fire detection system combining multiple sensors by utilizing an Arduino microcontroller and fuzzy logic. Nevertheless, relying solely on physical sensors for fire monitoring remains limited in complex building environments. Video surveillance, as a complementary method, not only covers larger areas but also provides visual information about fire scale, fire spread, and smoke direction [10]. A system combining sensor data with real-time video analysis can significantly enhance situational awareness and provide better decision-making support for fire monitoring.

Additionally, the integration of IoT and cloud computing has greatly enhanced the capabilities of building fire monitoring systems. Du et al. [11] proposed a ZigBee-based fire detection system that uses wireless communication protocols to achieve real-time monitoring and response to fire events. In contrast, the study by Gangopadhyay et al. [12] demonstrated a cloud-based wireless framework that collects and analyzes data from various sensors in real-time through a cloud platform, enabling remote fire monitoring and alarm systems. Zhang et al. [13] developed a machine learning-based fire early warning system using TinyML and CloudML technologies, showcasing the potential for predicting and preventing fire hazards in buildings. Furthermore, the CloudFAS system [14], by integrating Building Information Modeling (BIM) with a cloud platform, achieved seamless integration of fire sensors and real-time data sharing, further enhancing the effectiveness of building fire monitoring.

At the same time, the introduction of machine learning technology has further optimized the intelligence level of fire monitoring systems. Machine learning not only processes data from multiple sensors but also reduces false alarm rates and predicts fire development trends. For example, Salhi et al. [15] used machine learning combined with multi-sensor data to detect gas leaks and fire hazards, although the low sampling frequency in their study may limit early fire detection performance. To address this issue, we optimized the sampling frequency during data collection, allowing for better tracking of fire characteristics and improved early fire detection efficiency. In studies [16] and [17], artificial neural networks (ANNs) were used to predict heat transfer during fires and classify risks.

In this paper we have further integrated IoT, cloud computing, and ANNs to develop a smart building fire monitoring system, significantly enhancing the system's intelligence and real-time response capabilities in fire detection.

3 System architecture and design

3.1 Overview of the system

This study addresses the challenge of false alarms in fire detection systems by developing a multi-parameter monitoring system leveraging IoT technology. Integrated with video stream data, this system employs heterogeneous data fusion to provide a comprehensive visual monitoring interface. Enhancing accuracy and reliability, a shallow neural network is incorporated to analyze data and predict fires efficiently, optimizing processing speed and reducing hardware requirements.

Specifically, the monitoring system is divided into following four main components:

Building State Information Collection: The system comprises two subsystems:

- Controlled by Arduino, a wireless sensor network collects environmental data (e.g. temperature, smoke density) processed at the edge before uploading to the cloud via a wireless network. Local indicators like buzzers and LEDs provide immediate alerts.
- Controlled by Raspberry Pi, a webcam facilitates real-time video monitoring, with processed video data also uploaded to the cloud.

Visualization Interface: Implemented using web technologies, the interface displays sensor readings and live video streams from the cloud. Users can interactively control the alarm system through the interface, adjusting settings in real-time.

Cloud: Central to system management, the cloud stores and preprocesses data from local sensors and video feeds. This preprocessing optimizes data for efficient analysis and real-time monitoring on the visualization interface.

Neural Network Data Analysis: In the cloud, a shallow neural network model is trained on the processed dataset, continuously adapting to changing environmental conditions to ensure accurate fire predictions.

The workflow of the system includes a parallel process of sensor data processing and real-time video monitoring. After edge processing, the data is transferred to the cloud for storage and further analysis. The video feed is streamed directly to the interface for instant observation by the user. Meanwhile, the sensor data is subjected to preliminary analysis and neural network modelling in the cloud to improve fire detection and response.

3.2 Building status information collection

3.2.1 Wireless sensor network

Domestic natural gas flames are clean, primarily emitting carbon dioxide and water vapor efficiently. Structural fires, characterized by yellow or orange flames and significant

Table 1. Sensor performance.

Sensor type	Factor	Measurement range	Precision
HTS221	Humidity	0 to 100(% RH)	±3.5, (20 to +80)(% RH)
	Temperature	−40 to 120(°C)	±0.5, (15 to +40) (°C)
LPS22HBTR	Pressure	260 to 1260 (hPa)	±0.1 (hPa)
APDS-9960	Light	0-65535(Lux)	±15%
MQ-2	Smoke	100–10,000 ppm	See Figure 2a
MQ-7	CO	10–2000 ppm	See Figure 2b
MQ-135	CO_2	10–1000 ppm	See Figure 2c

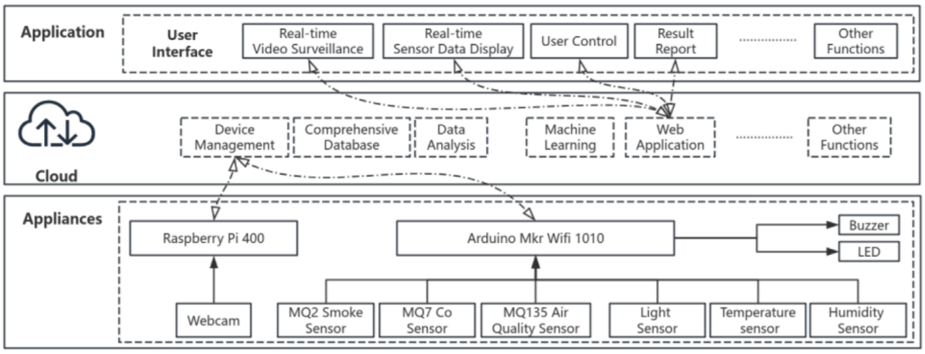
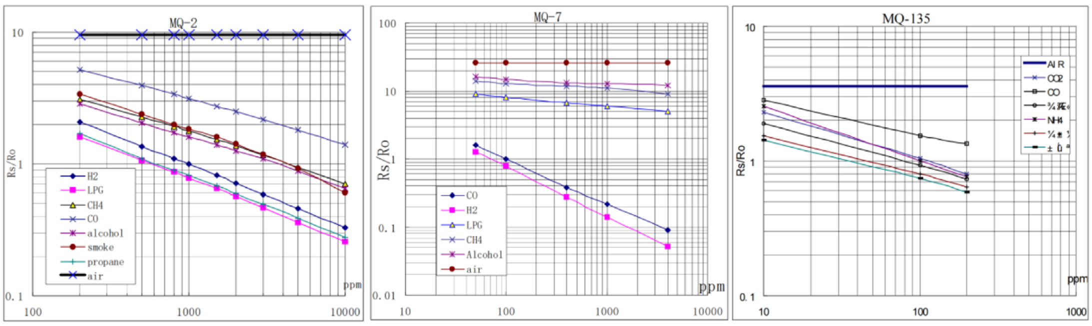


Fig. 1. Intelligent fire cloud monitoring system overall structure diagram.



(a) MQ-2 (b) MQ-7 (c) MQ-135

Fig. 2. (a) MQ-2 sensor sensitivity characteristics (b) MQ-7 sensor sensitivity characteristics (c) MQ-135 sensor sensitivity characteristics. (Fig. 2a) Hanwei Electronics Co. Ltd, Technical Data MQ-2 Gas Sensor. Available at: http://www.hwsensor.com (accessed: 21 March 2024). (Fig. 2b) Hanwei Electronics Co. Ltd, Technical Data MQ-7 Gas Sensor. Available at: http://www.hwsensor.com, (accessed: 21 March 2024). (Fig. 2c) Hanwei Electronics Co. Ltd, Technical Data MQ-135 Gas Sensor. Available at: http://www.hwsensor.com, (accessed: 21 March 2024).

black smoke, indicate incomplete combustion and release harmful gases like carbon monoxide, highlighting their rapid spread potential. Choosing appropriate sensors for early detection and fire type identification is crucial in structural fire monitoring. The following sections detail the low-cost sensor-based wireless network used to optimize data collection, enhancing fire monitoring accuracy and response speed.

We use the Arduino MKR WIFI 1010 with a Carrier expansion board and low cost MQ series sensors (MQ-2, MQ-7 and MQ-135 cost about £12.50 in total) for our wireless sensor network. The MQ-2 sensor detects smoke, alcohol, hydrogen, methane, and other gases with high sensitivity. The MQ-7 sensor is highly sensitive to carbon monoxide over a wide range, while the MQ-135 detects gases like carbon monoxide, carbon dioxide, and ammonia. The performance of the sensors used are shown in Table 1.

The Arduino reads data from Carrier board sensors via I2C for stability. MQ series sensors (MQ-2, MQ-7, MQ-135) connect to Arduino using Dupont wires (Fig. 3).

In the early stages of a fire, the temperature typically does not exceed 80 °C. Although MQ series sensors (such as MQ-2, MQ-7, and MQ-135) perform optimally at 20 °C and 65% humidity, their sensitivity may decrease by 20–30% in environments with temperatures around 50 °C. However, since the system is designed for early fire detection—when the temperature in the initial phase of a fire does not exceed 50 °C—the reduction in sensitivity will not significantly

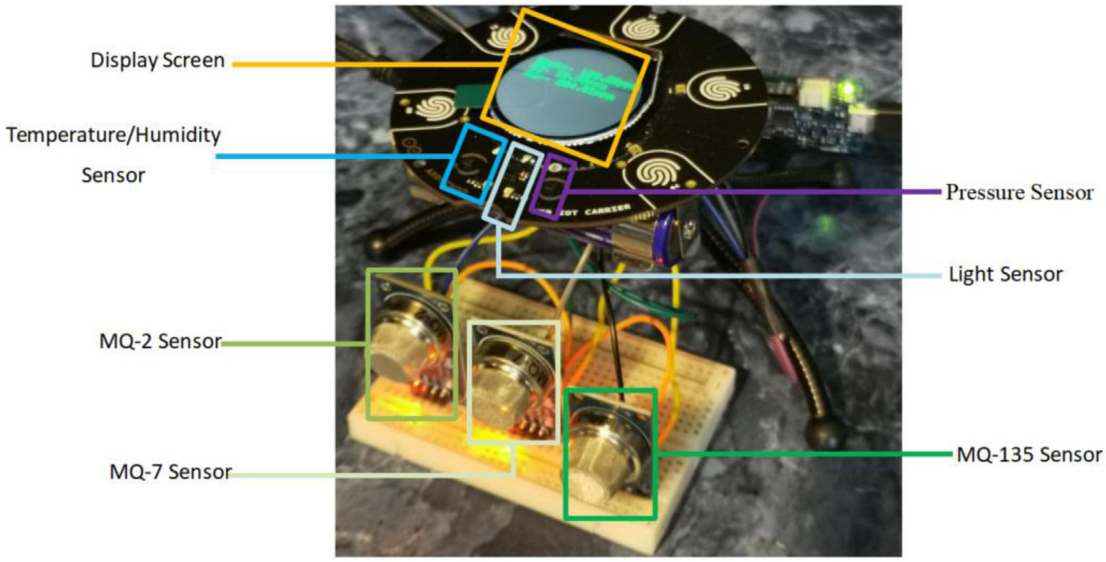


Fig. 3. Wireless sensor network hardware connections.

Fig. 4. Real-time video monitoring hardware connections.

impact the overall performance of the system. Additionally, the system employs a multi-sensor data fusion strategy, which enhances fire detection accuracy and reliability by evaluating multiple sensor outputs, such as gas concentration and carbon monoxide levels. Therefore, even though the ambient temperature may be slightly away from the sensors' ideal operating point, MQ series sensors can still effectively detect fires in the early stages of fire.

The system triggers alarms based on neural network analysis, activating local alerts via Arduino's buzzer and tri-color LED. It also sends text alerts to the interface and changes indicator lights accordingly, enhancing user interaction.

3.2.2 Real-time video monitoring

In addition to sensor data, video surveillance capabilities can further enhance users' understanding of the situation and their decision-making ability. The system utilizes a Raspberry Pi 400 and a USB camera, which offer excellent plug-and-play functionality without the need for additional drivers. The system supports dynamic adjustment of video resolution and frame rate based on specific needs, making it adaptable to various application scenarios and bandwidth conditions. Currently, the system enables one-way data transmission from the local devices to the cloud, processing video data in real-time while providing scalability for future upgrades to two-way communication systems (such as remote control and feedback). The network connection, based on Wi-Fi 6 technology, ensures high stability with a latency of less than 100 ms. During system testing, the overall response time was measured to be between 500 ms and 1 s, meeting the requirements for real-time monitoring applications.

3.3 Visualization interface

Efficient visual user interfaces (UI) are scarce in the current market, prompting our focus on developing a user-friendly UI that integrates clear monitoring data presentation with interactive controls for remote operations, including fire alarm activation. Accessible via cloud from any

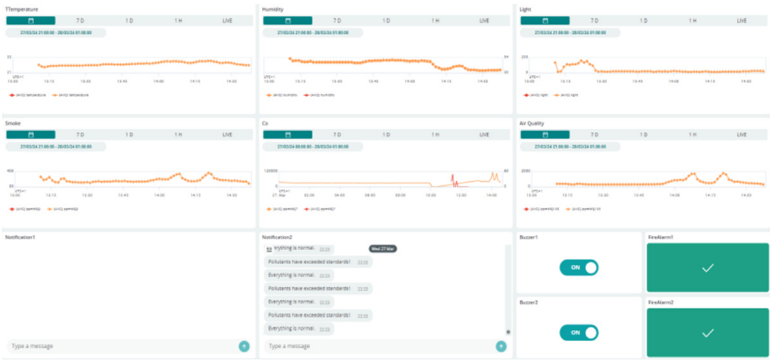


Fig. 5. Sensor visual interface.

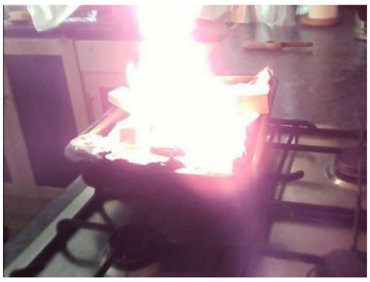


Fig. 6. Real-time video surveillance visual interface.

Internet-connected device, our UI features real-time line graphs, scatter plots, and numerical displays for monitoring parameters. Interactive buttons allow remote control of alarm status, while a real-time video interface enhances fault tolerance and monitoring capabilities (Figs. 5 and 6).

3.4 Cloud

The cloud manages authorization, configuration, and centralized management of all devices. Upon successful local device connection, it stores sensor data and uploaded video, preprocesses data for enhanced analysis efficiency, and provides processed data to the visualization interface for real-time system monitoring. Historical sensor data undergoes neural network analysis to derive insights for decision-making support.

3.5 Neural network model

This study utilizes an artificial neural network (ANN) model for fire monitoring and prediction. The model includes an input layer with five neurons for temperature, humidity, and gas concentrations. A hidden layer with 100 neurons employs the hyperbolic tangent activation function to handle nonlinearities effectively. The output layer features five neurons corresponding to distinct fire states, using the softmax activation function to estimate probabilities. The ANN aims to classify and predict various fire scenarios, optimizing monitoring by learning complex sensor-fire relationships.

4 Experiments

4.1 Experimental preparation

To simulate real-world building fire detection scenarios, we conducted indoor combustion experiments. We used an iron fire pan with a length of 40 cm and a width of 25 cm, with pieces of kiln dried kindling wood weighing approximately 150 grams each and having a moisture content of 15%, to simulate fire conditions inside a building. The fire intensity during the combustion process was controlled by adjusting the amount of combustible materials, ensuring the safety and repeatability of the experiments.

To collect accurate environmental data, a wireless sensor network consisting of temperature and humidity sensors, along with gas sensors (MQ-2, MQ-7 and MQ-135), was positioned 1 meter away from the fire source to monitor temperature changes and hazardous gas concentrations during the fire.

Figure 7 illustrates the experimental setup, including the positions of the fire pan, various sensors, and the overall environment. The sensor devices were connected to the cloud via a Wi-Fi 6 network, ensuring real-time data transmission and low-latency analysis.

4.2 Experimental design

The experimental setup includes using wood combustion to simulate fire scenarios, with household natural gas serving as a control group to evaluate the system's accuracy and predictive capabilities. The experiment involves five variable conditions: no fire, small and large household natural gas fires, as well as small and large wood fires. The monitored variables include temperature, humidity, smoke particle concentration, carbon monoxide levels, and air quality. The experimental design is shown in Table 2. Throughout the experiment, sensor data variations were monitored, and the combustion conditions were remotely controlled through a network interface.

4.3 Data processing

We clean data by replacing missing values with median sensor data and handling outliers with a Z-score cutoff (>3). For categorical fire conditions, one-hot encoding

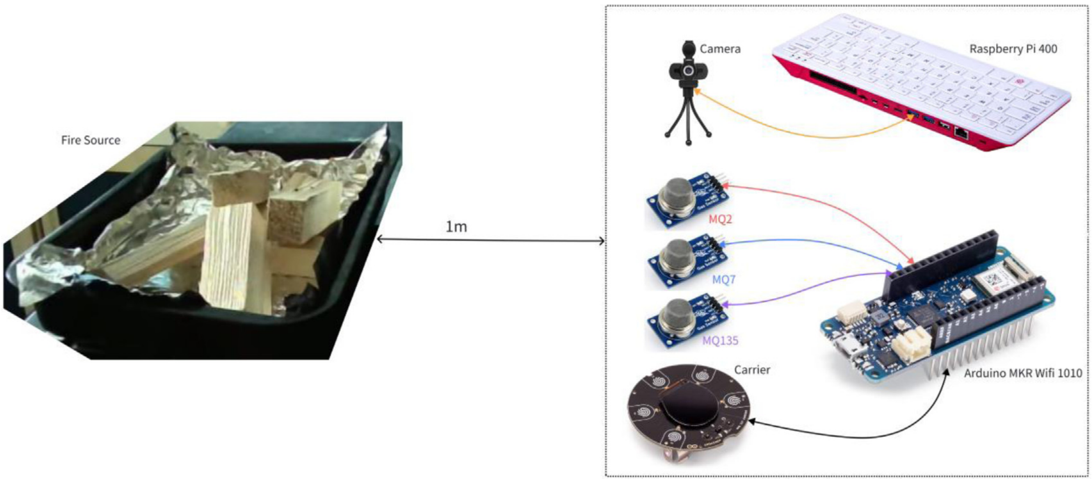


Fig. 7. Layout of the experimental site.

Table 2. Experimental factors and response variables.

Factor	Domestic gas fire		No fire	Simulated building fires	
	Big fire	Small fire		Big fire	Small fire
Factor Symbol	F1	F2	F3	F4	F5
Response			Humidity Smoke Temperature CO Level CO_2 Level		

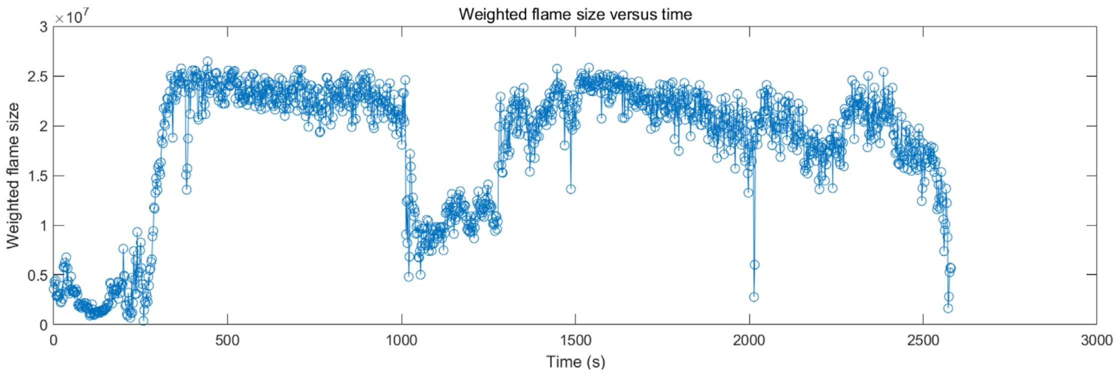


Fig. 8. Video data extraction frame sequence.

transforms labels into a binary matrix, essential for classification tasks. To maintain unbiased categories, sensor outputs avoid normalization; instead, continuous data undergo min-max scaling. The dataset (2000 points) is split 7:3 for training and testing, ensuring robust learning and validation for effective performance on new data.

Additionally, frames were extracted from the video data collected during the fire simulation process and converted into grayscale images to facilitate flame region extraction using an optimal grayscale threshold. The extracted frames from the video data are shown in Figure 8, and the corresponding grayscale images are displayed in Figure 9. The flame region extraction is based on a dynamically determined optimal grayscale value, which is calculated using the Otsu method.

Subsequently, the overall flame size is obtained by weighting the flame area (number of pixels) and flame intensity (average pixel grayscale value). To evaluate the effectiveness of the sensors, we conducted a correlation analysis and time response delay analysis by comparing the time series of flame size with the time series of sensor data. Image data were extracted at a sampling frequency of once every 2 s.

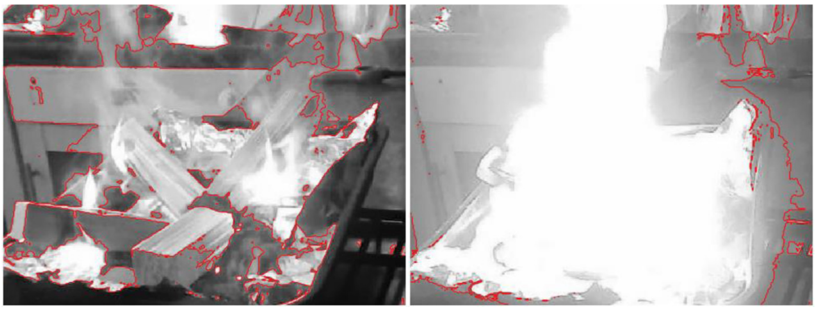


Fig. 9. Video data extraction frame to greyscale example.

Table 3. Correlation analysis of sensor data and response time lag.

	Temperature	Humidity	Smoke(MQ-2)	CO(MQ-7)	CO2 (MQ-135)
Correlation coefficient	0.3477	−0.1889	0.4199	0.4373	0.4842
Response time lag(s)	0	4	0	2	26

4.4 Model training and optimization process

To enhance our fire monitoring neural network model's performance, we utilized an ANN architecture with 100 hidden neurons in MATLAB. We implemented a training strategy spanning 136 epochs to prevent overfitting, employing a Stochastic Gradient Descent (SGD) optimizer with a learning rate set to 0.001 and a batch size of 136. The model's weights were initialized using a uniform distribution to expedite convergence. We limited the maximum number of failures to 12 to avoid overtraining. Post-training, the model evaluated classification scores to predict fire categories accurately. Accuracy assessments on training and test sets validated the model's robustness and generalization capabilities, crucial for practical deployment in fire monitoring systems.

5 Results and analysis

5.1 Performance evaluation of sensors

Based on the correlation bar chart in Figure 10a and the data in Table 3, there are noticeable differences in the correlation between various sensors and flame size. Temperature sensor shows a relatively high positive correlation, with a correlation coefficient of 0.3477. This is expected, as the presence of a flame leads to a significant temperature increase, and the temperature sensor is able to detect this change sensitively.

CO_2 sensor has the highest correlation (0.4842), indicating that the rise in CO_2 concentration during the combustion process is highly correlated with the flame size. The CO_2 sensor reacts prominently to flame changes, especially during wood combustion, where the production of CO_2 is higher, allowing the sensor to better capture changes in the fire scenarios.

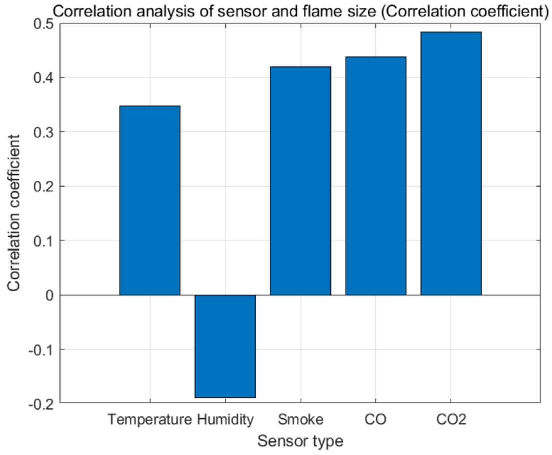
MQ-2 smoke sensor and MQ-7 carbon monoxide sensor have correlation coefficients of 0.4199 and 0.4373, respectively, showing that they can detect the smoke and carbon monoxide produced during the flame combustion. These sensors perform well in monitoring combustion by-products, particularly in wood fire scenarios.

In contrast, humidity sensor exhibits a negative correlation (−0.1889), suggesting that the presence of a flame leads to a decrease in ambient humidity. This is especially true in wood combustion, where the reduction in humidity reflects the flame's evaporation of moisture from the surrounding air. Although the humidity sensor has a lower correlation, it still provides valuable information about environmental changes following the onset of a fire. It is interesting to note that the humidity sensor can help distinguish between fire and boiling water steam since the latter will be positively correlated with humidity.

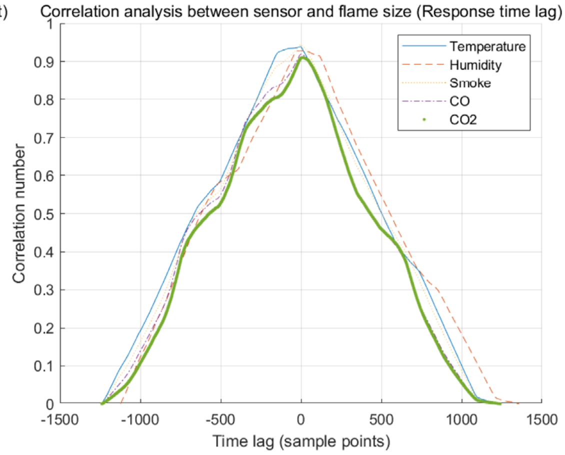
Based on the time delay analysis results shown in Figure 10b and Table 3, different sensors exhibit varying response times to the changes in flame size. Sensor 1 (temperature sensor) and Sensor 3 (MQ-2 smoke sensor) have almost no time delay, allowing them to quickly respond to changes in flame size. This indicates that temperature and smoke sensors can effectively detect the presence of flames in the early stages of a fire and react immediately.

In contrast, CO_2 sensor shows a more significant response delay, approximately 26 s. This suggests that the accumulation of CO_2 takes some time, resulting in a longer response delay for this sensor. Although the correlation between CO_2 concentration and flame size is high, this longer response time may affect its effectiveness for real-time fire detection in practical applications.

The time delay for humidity sensor is 4 s. While the delay is relatively short, due to its negative correlation with flame size, the humidity sensor mainly reflects



(a)



(b)

Fig. 10. Correlation analysis between sensor and flame size.

environmental changes after the fire has occurred, rather than the early stages of the fire. Therefore, its practical role in early fire detection is limited.

Overall, the experimental results show that the temperature sensor and the CO_2 sensor play key roles in fire detection. The temperature sensor responds to changes in flame size almost in real time, while the CO_2 sensor provides crucial information about combustion by-products, although its response has a certain delay. The combined use of these sensors helps achieve comprehensive fire monitoring, improving the overall reliability and accuracy of the detection system.

Additionally, the performance of the smoke sensor (MQ-2) and the carbon monoxide sensor (MQ-7) should not be overlooked. Particularly in wood fire scenarios, smoke and carbon monoxide are important combustion by-products. These sensors respond relatively quickly, with high correlations, making them suitable as complementary sensors in the fire detection system, further enhancing its detection capability.

In comparison, the negative correlation and delay exhibited by the humidity sensor suggest its primary role is in the later stages of a fire or in assessing the impact of the fire. While its direct response to flame changes is weaker, it can provide additional information about environmental changes.

These results align with the design expectations. By integrating the data from temperature, CO_2, smoke, and carbon monoxide sensors, the overall system performance is significantly improved. Data fusion not only compensates for potential response delays or accuracy limitations of individual sensors but also enhances the robustness of fire detection across various scenarios. This multi-sensor fusion strategy provides a more comprehensive and accurate fire monitoring solution, helping to reduce false alarms and missed detections, and improving the system's capabilities and reliability, especially in complex fire environments.

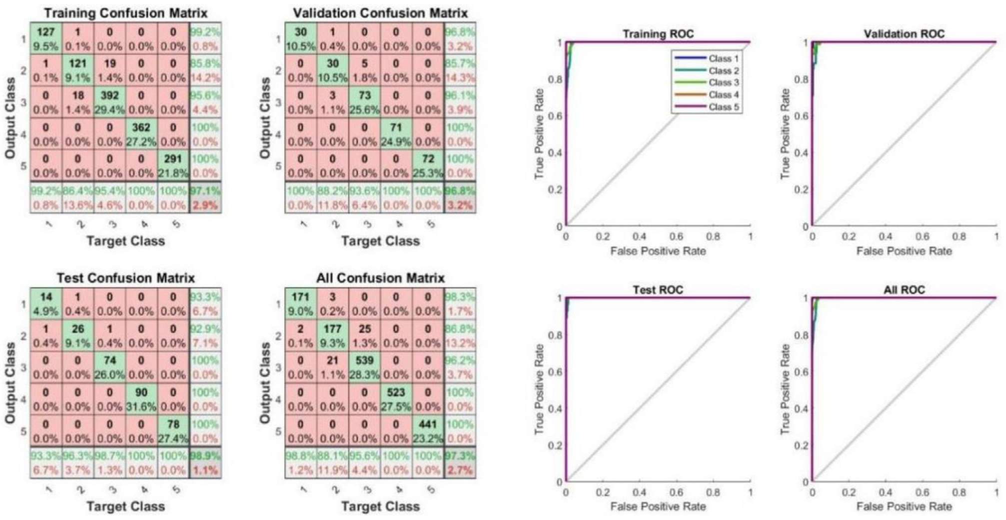
5.2 Model performance analysis and challenges in fire scenario detection

Figure 11a illustrates the model's strong performance in predicting fire scenarios, with an accuracy exceeding 95% on the test set. It shows high precision and recall in critical scenarios like residential gas and large wood fires. The confusion matrix confirms high true positive rates but reveals occasional false negatives in less frequent fires, guiding improvements to enhance sensitivity across varied conditions.

Upon reviewing the simulation experiment process, we found that the occurrence of false negatives is primarily caused by several factors. First, data imbalance is a key issue, with the quantity of natural gas fire data being only half that of wood fire data, leading to insufficient learning of natural gas fire characteristics by the model and increased classification errors. Additionally, the distance between the sensors and the fire source also affected detection performance. As the flames of natural gas tend to spread upwards with minimal horizontal dispersion, the sensors exhibited a certain response delay in capturing gas concentration changes, further exacerbating the occurrence of false negatives.

Figure 11b displays Receiver Operating Characteristic (ROC) curves for each fire scenario category, highlighting high Areas Under the Curve (AUC). These results demonstrate the model's strong capability in accurately distinguishing different fire types, ranging from minor domestic incidents to significant wood-induced fires.

The model exhibits high training efficiency, with each epoch completing in 1s, making it suitable for real-time fire detection applications. Optimizing the balance between model complexity and computational efficiency ensures swift response times, crucial for practical deployment where timely fire detection is critical.



(a) (b)

Fig. 11. Confusion matrix and ROC curves. (Class 1: F1; Class 2: F2; Class 3: F3; Class 4: F4; Class 5: F5).

Effective hyperparameter selection, including activation functions in hidden layers and output layer, significantly impacts the model performance. The choice of stochastic gradient descent as the optimizer proves adept at managing sensor data's non-linearities, enhancing the model's ability to generalize effectively in real-world settings.

6 Conclusions

This study developed an IOT-based smart building fire cloud monitoring system, addressing high costs, low sensitivity, and false alarms in traditional systems. Integrating cost-effective sensors and real-time video monitoring enhances real-time data collection and processing for faster fire detection. Key to the system is an efficient artificial neural network, reducing computational complexity with over 95% accuracy in fire prediction. It facilitate to decide the optimal evacuation routes based on fire location, improving safety and efficiency. The experimental tests confirmed quicker responses and reliability. Cloud integration optimized data storage and processing, with a user-friendly web interface enabling remote monitoring. The novel will find applications in future smart building fire safety management.

This study has the following limitations. Firstly, the size of the dataset is quite small, and small data samples may affect the generalization ability of the model. Secondly, the experiments mainly focus on wood and natural gas fire types, and have not yet covered comprehensive testing of complex fire scenarios such as electrical and chemical fires. Finally, the system relies on a stable network connection for real-time data uploads and remote monitoring, and any network interruption may affect the response time and effectiveness of the system.

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Conflicts of interest

The authors declare there is no conflict of interest.

Data availability statement

The dataset used in this paper is available at request.

Author contribution statement

Conceptualization, Q.Y., G.P., and Y.X.; Data collection, G.P., Y.X. and Q.Y., Methodology, Q.Y., G.P and Y.X.; Validation, Q. Y., Y.X.; Resources, Q.Y. and Y.X.; Writing—original draft, G. P., Y.X., Q.Y.; Writing—review & editing, Y.Q., Y.X.; Supervision, Q.Y.

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