

Article

Research on Highly Suspected True Alarm Model for Fire Alarm Data Based on Deep Learning Method

Xueming Shu ^{1,2,3}, Cheng Li ¹, Yixin Xu ⁴, Jingwu Wang ^{3,*}, YINUO Huo ^{3,*} and Juanxia He ⁵

¹ School of Safety Science and Engineering, Anhui University of Science and Technology, Huainan 232001, China

² School of Safety Sciences, Tsinghua University, Beijing 100084, China

³ Hefei Institute of Public Safety, Tsinghua University, Hefei 230061, China

⁴ Ansteel Group Mining Corporation Limited, Anshan 114001, China

⁵ College of Resources, Environment and Materials, Guangxi University, Nanning 530004, China

* Correspondence: wangjingwu@tsinghua-hf.edu.cn (J.W.); huoyinuo@tsinghua-hf.edu.cn (Y.H.)

Abstract

With the widespread application of automatic fire alarm systems in various types of buildings, the problem of fire false alarms has gradually become prominent, which not only causes resource waste, but also may reduce users' trust in the alarm system, thereby affecting the efficiency of emergency response in actual fires. According to data from a certain fire cloud platform, 99.85% of the suspected fires predicted by its system are false alarms. Although existing models can recognize most fire accidents, the accuracy of fire alarm recognition is only 0.15%, due to loose judgment logic, which still requires a large amount of manpower to verify alarms. This article analyzes a large amount of false alarm data and explores the main causes of false alarms, including environmental interference, equipment failure, and improper human operation. By using a fire dynamics simulator (FDS) to establish fire simulation models under different data settings, horizontal and vertical multi-scene fire simulation data are obtained. The study combines simulation and platform data to form a fire and false alarm dataset using a one-dimensional convolutional neural network (1D-CNN) and deep neural network (DNN) deep learning techniques to learn the deductive rules of the fire scene, establish a two-stage judgment model, and gradually, accurately, judge the results. By quantifying the precision, recall, and F1 score of the model, a deep learning model designed to accurately identify genuine fire alarms while filtering out false ones is proposed that can significantly reduce the false alarm rate. The results indicate that the model can identify 1705 false alarms out of 2255 highly suspected true alarms identified by existing systems in multiple practical scenarios and eliminate 75.61% of false positive alarms. On the premise of ensuring an authenticity recognition rate greater than 98%, the accuracy of fire alarm recognition increased from 0.15% to 28.85%, which will significantly reduce the workload of staff verifying alerts, and has good practical value.



Academic Editor: Ruiyu Chen

Received: 19 December 2025

Revised: 6 March 2026

Accepted: 9 March 2026

Published: 13 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: fire alarm system; false alarm; FDS; deep learning; two-stage judgement; alarm model

1. Introduction

In recent years, with rapid socioeconomic development and accelerated urbanization, high-rise buildings have proliferated, increasing construction density. Existing structures often utilize new insulation materials and feature complex interior finishes, leading to rapid

fire spread and extensive damage in the event of a fire, resulting in mass casualties [1]. Smoke detectors serve as a critical safeguard for fire monitoring. Despite their widespread installation, factors, such as detector aging, environmental interference, and improper installation, frequently cause false alarms. China's detector false alarm rate significantly exceeds that of developed countries [2].

Existing fire alarm systems can accurately monitor environmental anomalies, detect fires in their early stages, and trigger the fire control system for extinguishment [3]. This approach suppresses fires at their inception, minimizing property damage and reducing casualties. However, in practice, frequent false alarms caused by environmental interference and equipment failures lead to the 'the boy who cried wolf' phenomenon. Frontline firefighters gradually become less vigilant, growing complacent and eventually ignoring alarms. They may even disable alarm points to block signals [4]. This results in the inability to effectively identify real fires when they occur, preventing immediate response. Consequently, fires spread unchecked, causing casualties and property damage.

Data from a certain fire cloud platform indicate that, from August 2018 to the present, the system identified 265,749 suspected fire alarms. With only 409 being real fires, the false alarm rate exceeded 99.85%. While existing models detect most fires, their loose decision matrices result in a fire alarm accuracy rate of merely 0.15%. Therefore, reducing false alarms is a critical challenge in the field of fire safety. Currently, most networked fire monitoring systems merely transmit signals detected by fire alarm systems directly to monitoring platforms [5], without any information analysis or assessment. This approach fails to reduce false alarms to a level manageable by manual verification. Therefore, how to effectively identify real fire alarms from massive alarms and reduce the impact of false alarms on human beings is a core issue in improving the efficiency of fire safety management.

Regarding detector false alarms, scholars have conducted extensive research on reducing false alarm rates [6–8]; the research primarily focuses on detection technologies and detection algorithms.

Regarding detection technology research, the core of fire detection lies in identifying the characteristic hazard signals released by fires to achieve effective perception and rapid response to fire conditions. Various detection technologies, such as smoke detectors, heat detectors, flame detectors, and video-based fire detectors, have emerged and are widely applied in practice [9–11]. However, single-parameter detectors exhibit delayed responses to early-stage fires and are prone to false alarms due to environmental interference. Consequently, numerous scholars have investigated multi-sensor fusion detection technologies [12–14] and the integration of diverse fire detectors into collaborative detection systems via IoT technology, enabling information exchange and complementary performance among detectors [15,16]. For instance, Homeag et al. [17] developed a human experience-based fuzzy expert system fire detection algorithm using smoke, temperature, and gas characteristics derived from full-scale fire test data. Ding et al. [18] proposed a multi-sensor information fusion algorithm for detecting light, smoke, temperature, gas, and humidity based on D-S evidential theory. Currently, dual-sensor detection devices integrating temperature and smoke detection functions are being widely adopted [19]. The redundant information provided by multiple detectors enhances overall reliability, while complementary information compensates for the limitations and uncertainties inherent in single-type detectors, thereby effectively improving the comprehensive performance and judgment accuracy of fire detection systems [20,21]. However, due to the substantial hardware requirements for integrating multiple sensors, such systems are currently primarily used for research and have not been widely deployed.

Research on fire detection algorithms continues to advance, with scholars developing efficient, high-precision algorithms adaptable to diverse complex environments. These

algorithms can be broadly categorized into three types. The first type includes traditional image processing techniques relying on intuitive image analysis and feature extraction. Researchers have employed various methods to extract static flame characteristics. For instance, Horng et al. [22] established a color model for flames in the HIS space, utilizing differential methods to identify suspected flame regions and subsequently developing feature extractors. The second type includes machine learning-based approaches that automatically learn advanced patterns in flame images by training machine learning models. Researchers have employed various advanced algorithms to process complex datasets, addressing issues, such as low accuracy and poor generalization, in traditional fire detection methods [23]. The final type includes deep learning techniques, which represent the current frontier in flame detection and are capable of processing complex image data and generating highly accurate detection results. Classic object detection algorithms include CNN [24], RNN, Faster-RCNN [25], and YOLO [26,27]. These methods achieve rapid and accurate fire detection by automatically learning and extracting fire features from images. For instance, Chen Yanhong [28] developed the CNN-9 and CNN-17 models for concurrent smoke and flame detection, achieving high accuracy. Xu [29] proposed a lightweight YOLOv5 model to enhance accuracy and detection speed in complex fire scenarios. Continuously updated analysis algorithms not only facilitate rapid and accurate early fire warning but also reduce false and missed alarms.

However, current fire detection research worldwide, whether in innovative detection principles, recognition criteria development, or upgrades to basic components and discrimination algorithms, has not fundamentally resolved the inherent trade-off between sensitivity and false alarm rates. Current domestic fire detection systems still rely on single-point threshold alarm modes, lacking an interlinked analysis of the spatio-temporal relationships between detector alarms.

To address frequent false alarms, this study proposes a deep learning-based model for highly suspected true alarms. Grounded in simulation modeling and deep learning techniques, it investigates the spatio-temporal alarm correlations of smoke detectors during smoke diffusion. By learning from, and reasoning over, simulated data and false alarm data from a fire cloud platform, the model extracts useful patterns. It investigates the alarm linkage relationships between smoke detectors under real and false alarm conditions and predicts the likelihood of a fire in real time through a tiered alarm pattern. This approach reduces the cost of manual alarm verification while ensuring accurate fire feature recognition in existing fire protection systems, thereby advancing the development of smart fire protection.

2. Materials and Methods

2.1. Research Framework

As shown in Figure 1, the research framework of this paper is as follows. First, through simulation modeling, fire simulation data are obtained under various scenarios such as horizontal, vertical shafts, elevator shafts, and rooms with irregular ceilings. The data include room area, room type, spatial distance between detectors, spatial relationships, and detector response time differences. The concept of connectivity is introduced to characterize the proximity relationship between two detectors. Second, using the simulated data and real fire data from the fire cloud platform as real fire samples, and the false alarm data from the big data platform as false alarm samples, we generate fire and false alarm datasets. The raw data undergo preprocessing tailored to deep learning model training requirements, yielding training, validation, and test datasets. Subsequently, a 1D-CNN [30] combined with a DNN deep learning model trains the input data to generate a first-stage, highly probable true alarm model and return prediction values. Second-stage input data are

then merged with the first-stage predictions to form a new dataset for second-stage deep learning training, ultimately producing a second-stage, highly probable, true alarm model.

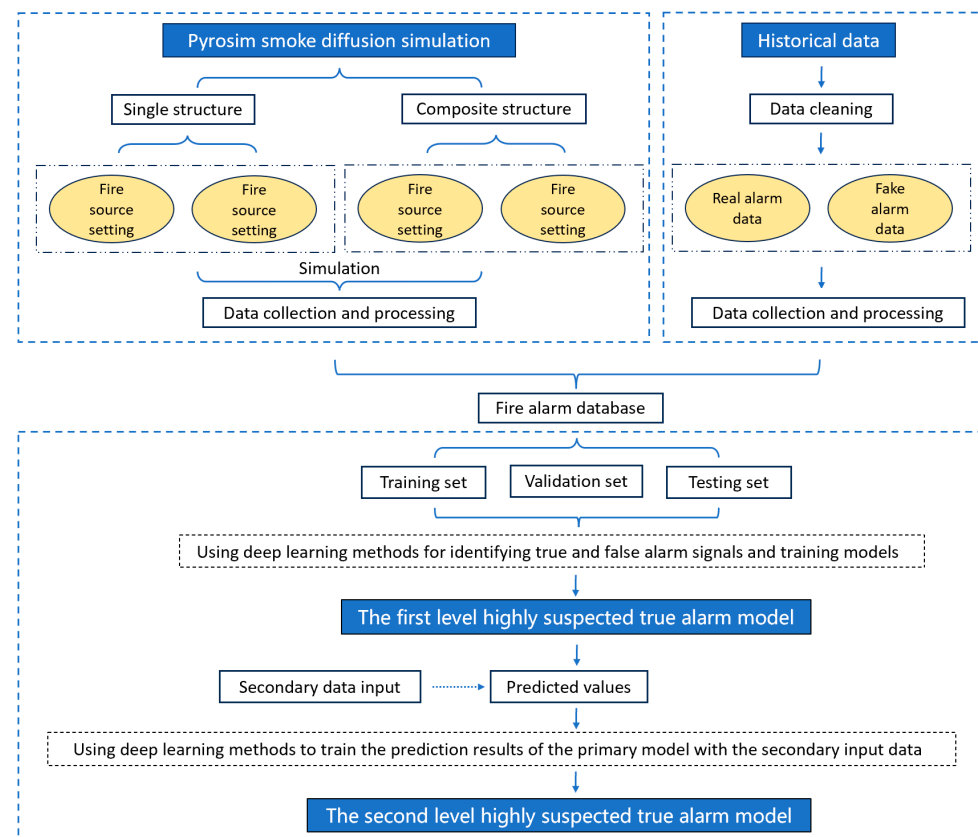


Figure 1. Research framework.

2.2. Fire Scenario Simulation

Due to the insufficient volume of real fire data available in the fire cloud platform to meet the sample requirements for deep learning, this study employs numerical simulation techniques to construct models of various building units. Following an orthogonal analysis of multiple fire-related factors, fire simulation experiments were conducted to replicate real fire scenarios. This approach aims to capture the spatio-temporal differences in smoke detector alarms and related data.

Given the random nature and complex conditions of fire incidents, it is extremely challenging to simulate and reproduce various fire scenarios to obtain smoke diffusion data. Therefore, to replicate real-world fire conditions as closely as possible, this study's simulation primarily controls the following six variables: fire source location; fire intensity; fuel type; ventilation conditions; room type; and the adjacency of smoke detectors (see Table 1).

Table 1. Variables and their corresponding values.

Fire Source Location	Maximum HRR (MW)	Fuel Type	Ventilation	Room Type	Adjacency Relationship
Corner	0~0.5	-	None	Chamber	Same Unit
Edge	0.5~1	Polyurethane Foam	Natural Ventilation	Corridor	Adjacent Unit
Center	1~1.5	-	-	Shafts	Non-Adjacent Unit

(1) Fire Source Location

The relative position of the fire source within the chamber significantly impacts the time difference in smoke detector alarms [31]. Simulation experiments indicate that the most unfavorable location is the wall corner. This study sets three positions as simulated fire sources: the chamber center, the chamber side wall, and the chamber wall corner;

(2) Maximum Heat Release Rate

The heat release rate (HRR) is a key parameter describing fire intensity. Considering that fire scenarios often occur in office environments, dormitories, and similar settings, relevant studies indicate that the peak maximum heat release rate for typical indoor fires generally remains below 1.5 MW [32]. To simulate most fire scenarios, this study established three intervals within the 0–1.5 MW HRR range: (0–0.5 MW), (0.5–1 MW), and (1–1.5 MW), for a cross-experimental design designed to cover scenarios ranging from small-scale smoldering fires to rapidly developing open flames. The fire type was rapid fire, with a medium-speed t^2 growth pattern. A planar fire source was employed;

(3) Fuel Type

The selection of polyurethane foam as the standard fuel was primarily based on two considerations. The first consideration was comparability. This material is a commonly used standard fuel in international fire research and FDS validation cases. Its combustion characteristics are well-documented, facilitating the comparison of results across different studies. The second consideration was representativeness. Furnishings and finishing materials in modern buildings extensively incorporate polyurethane components. Their combustion behavior combines significant heat release with substantial smoke production, effectively simulating the primary excitation sources for smoke detectors in real-world fire scenarios;

(4) Ventilation Conditions

The ventilation conditions were set as no ventilation and natural ventilation. In an enclosed space with simulated closed windows and doors lacking ventilation, fires are characterized primarily by oxygen-deficient combustion and smoke accumulation. Conversely, natural ventilation simulating open windows and doors typically involves air entrainment and smoke stratification. Together, these two scenarios broadly encompass the principal ventilation conditions prevailing during the initial stages of a fire;

(5) Room Type

Statistical analysis of fire false alarm data from a fire cloud platform indicates that over 90% of fires occur in chamber, corridors, and shafts. Therefore, this study incorporates these three elemental room types when defining fire locations;

(6) Adjacency Relationships

This study primarily investigates how smoke propagation under different building structures affects the spatio-temporal response of smoke detectors. In the FDS simulation, we uniformly configure detectors as photoelectric smoke detectors. This decision was based on historical data from a fire cloud platform, where photoelectric smoke detectors constitute over 85% of installations, representing the most widely deployed type currently. Regarding alarm thresholds, the smoke detectors in the simulation employed the Heskestad model, where the threshold was set to 3.24 and the detector activated when this threshold was exceeded. Detectors were simulated in three scenarios: within the same unit, in adjacent units, and in non-adjacent units on the same floor. The primary analysis focused on the relationship between the first, second, and third alarm points.

Given the numerous variables in fire simulations, conducting a full-factor simulation experiment would require 162 simulations per fire scenario, representing an enormous workload. Therefore, this study employs orthogonal experiments, requiring only 18 simulations per fire scenario. This approach enables efficient and systematic analysis of how various factors influence simulation results while reducing modeling efforts and lowering costs. Table 1 lists the variables and their corresponding values. This study established 14 fire simulation sites, including offices and dormitories. Each site contained 18 operating conditions, yielding a total of 252 simulated fires. A total of 1004 useful data points were extracted as positive samples for the dataset.

Given the extreme scarcity of real fire data, employing PyroSim 23.1 to generate simulated data constituted a necessary and reasonable research strategy. Data obtained from a certain fire cloud platform revealed that genuine fire incidents accounted for merely 1.5% of the total dataset, which was insufficient to support deep learning model training. Consequently, simulated fire data offer a viable solution for supplementing positive samples and constructing trainable datasets, thereby bridging the gap between simulation and reality.

However, fire simulation data may also exhibit the following biases and limitations. Simulated data may introduce systematic bias stemming from the inevitable simplifications inherent in model construction. Fire simulations primarily focus on key parameters, such as model structure, ignition source size, and location, often overlooking minor variables that could cause results to deviate from actual physical processes. Patterns derived from such biases represent projections of model assumptions rather than wholly objective reality. The deficiency in fire simulation data lies in the fact that simulations are typically built upon the perfect assumption that everything operates as designed. Crucial variables, such as the accidental failure of detectors or the unexpected reactions of building materials when heated, are often excluded from calculations. Fire simulation data frequently lack information on these potentially error-prone elements. The limitation of simulation is that it remains a computable approximation of reality, not reality itself. Its reliability is severely constrained by two major bottlenecks. The first is the difficulty of validation, as many complex fire scenarios lack sufficient high-precision experimental data to verify every detail of the model. The second bottleneck is resource constraints, where engineering applications are often forced to accept simplified results in the perpetual trade-off between computational accuracy and time-consuming costs. The value of the fire simulation in this study lies in helping us to explore smoke propagation patterns under controlled conditions and in providing quantified reference data for final decision-making.

To demonstrate the validity of this simulation design, Figure 2 illustrates a typical fire scenario where smoke propagates from a room into the corridor and lift lobby. Through time-sliced visualization, the smoke spread is analyzed from three perspectives: front view, vertical view, and side view. The findings align with the actual patterns of smoke diffusion observed in real-world scenarios.

During the initial phase of smoke propagation, driven by thermal buoyancy, the high-temperature smoke possesses lower density and accumulates vertically under buoyant forces. Subsequently, constrained by the ceiling, the smoke spreads horizontally in all directions while continuing to descend, forming a smoke layer that eventually fills the entire room, as depicted in the side view image at 120 s, shown above. As the room temperature rises, the pressure becomes higher than that of the exterior and adjacent areas. Consequently, the smoke flows towards the corridor, which is a lower-pressure zone, moving forward along the corridor. With the accumulation of smoke thickness in the corridor, the smoke then diffuses into the rooms adjacent to the corridor. During this process, the interaction between the leading edge of the smoke flow and the colder air ahead induces a 'hydraulic jump-like' phenomenon [33]. At this point, the smoke flow's

leading edge accumulates a greater volume of smoke, causing the smoke layer to thicken progressively while the flow velocity slows. Concurrently, intense entrainment occurs, as depicted in the front view image at 240 s. As the smoke continues to propagate forward into the lift lobby, it spreads into the lift shaft and stairwell via unsealed lift door gaps and fire doors that were either ineffectively closed or sealed. This triggered a rapid ‘chimney effect’ diffusion to other storeys, as depicted in the vertical view image at 300 s.

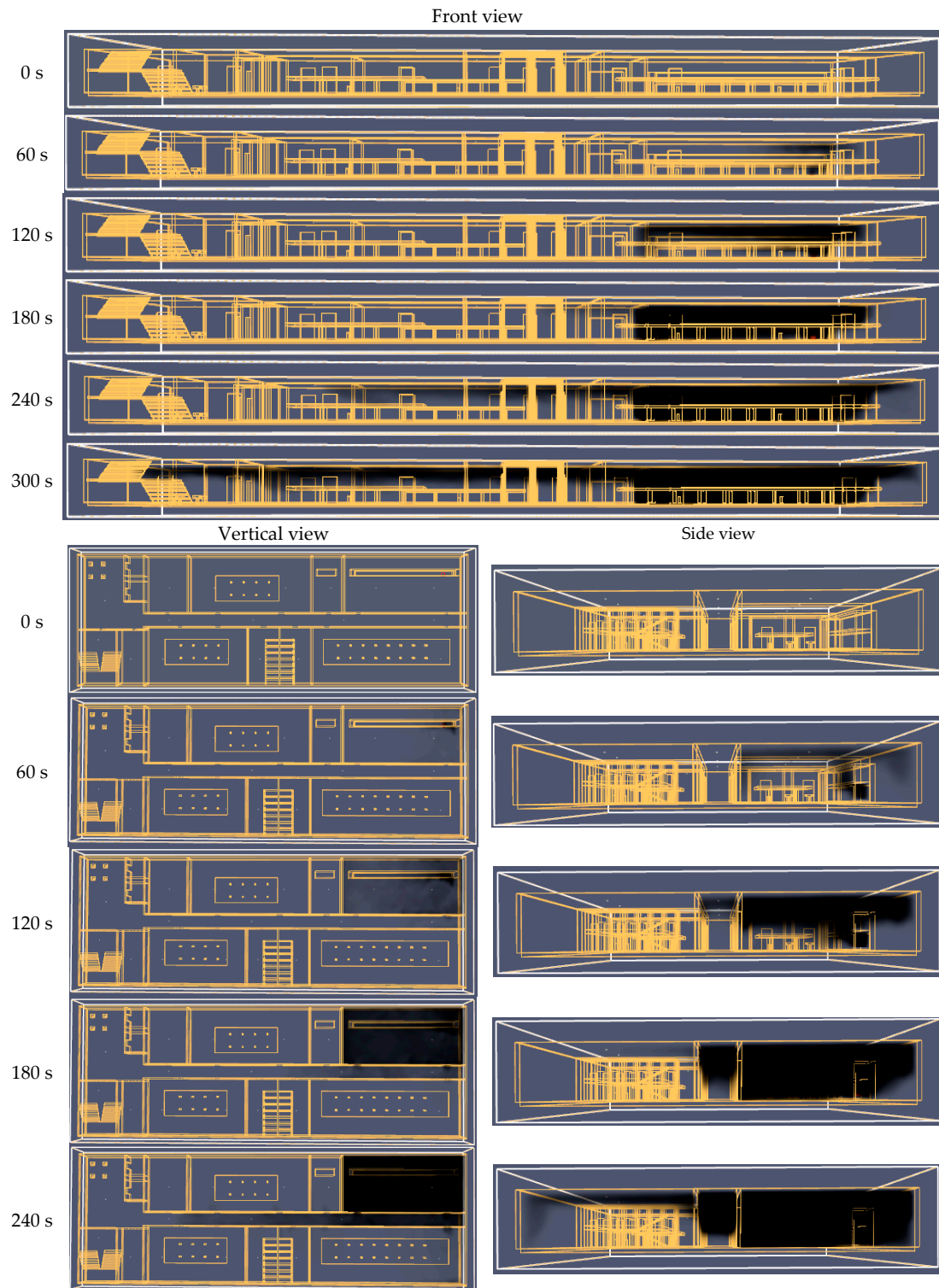


Figure 2. Cont.



Figure 2. Typical fire case of smoke spreading horizontally.

2.3. Establishment of Fire Database

To enhance the accuracy of fire alarms, this paper designs a two-stage decision model. The first-stage decision is based on the spatio-temporal relationship between the first and second alarm points of a smoke detector. The second-stage decision uses the prediction value from the first-stage decision and the spatio-temporal relationship between the first-third and second-third alarm points of the smoke detector as input to derive the second-stage decision result. The first-stage model dataset consists of data between detectors 1 and 2, including detector 1's floor area and room type, as well as the spatial distance, spatial relationship, time interval, floor difference, loop difference, and connectivity between detectors 1 and 2. The second-stage model dataset comprises data between detectors 1 and 3 and detectors 2 and 3, with the same data types as above, totaling 16 input values.

Consequently, the study's database comprises a first-stage judgment dataset and a second-stage judgment dataset. The first-stage dataset consists of a binary classification database with 8 input features and 1 output feature, while the second-stage dataset comprises a binary classification database with 16 input features and 1 output feature. Each data point in both datasets corresponds to the same fire event or false alarm. By organizing fire alarm data from a fire cloud platform and simulated data, the database comprises 1175 real fires and 11,236 highly suspected genuine alarms identified by the fire cloud platform (actually, false alarms misclassified as genuine by existing models). The database was randomly partitioned into a training set (70%), validation set (10%), and test set (20%). A sample of the training set data is shown in Table 2.

Table 2. Partial data of the training set.

Room Area (m ²)	Room Type	Spatial Distance (m)	Spatial Relationships	Time Interval (s)	Floor Difference	Loop Difference	Connectivity	Alarm Results
38.044	10,101	3.843	0	26	0	1	1.456	0
309.821	10,501	10.345	0	11	0	1	0.541	0
6.501	10,501	0	3	193	1	5	0	0
5.368	10,101	3.129	1	89	0	1	1.074	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
762.052	20,101	25.804	0	217	0	9	0.217	0
61.436	10,101	7.100	0	41	0	1	0.789	1
13.258	10,101	3.660	1	71	0	1	0.918	0
59.143	10,501	7.927	0	20	0	2	0.706	0

Combining simulated fire data with genuine false alarm data to construct datasets may introduce hybrid distribution bias, to some extent. This represents a deliberate and transparent trade-off under the current conditions of data scarcity. This bias primarily stems from the fundamental differences in the generation mechanisms of the two data types: simulated data are produced by controlled physical models, whose characteristics strictly adhere to predefined fire dynamics and ideal detector response models. Fire cloud platform data originate from complex and variable real-world environments, where characteristics are influenced by numerous uncontrollable factors such as equipment malfunctions, environmental interference, and installation practices. Simulated data may introduce systematic bias stemming from the inevitable simplifications inherent in model construction.

Fire simulations often prioritize key parameters, like model structure, fire source size, and location, frequently overlooking minor variables that could cause results to deviate from actual physical processes. The limitation of simulation lies in its nature as a computable approximation of reality, rather than reality itself.

The value of fire simulation in this study resides in its capacity to explore smoke propagation patterns under controlled conditions, thereby providing quantified reference points for final decision-making.

3. Results

3.1. Data Processing

To effectively enhance the model's ability to detect early-stage fires, this study employs a hierarchical judgment approach for the spatio-temporal relationships between the first, second, and third points of smoke detectors. This approach significantly improves the model's judgment capability. This database comprises eight distinct feature variables, as shown in Table 3.

Table 3. Feature vectors.

Number	1	2	3	4	5	6	7	8
Feature variable	Room Area (m ²)	Room Type	Spatial Distance (m)	Spatial Relationships	Time Interval (s)	Floor Difference	Loop Difference	Connectivity

The room area represents the area of the unit containing the first alarm. The room type is as follows: 10,101 denotes a room, 10,501 denotes a corridor, and 20,101 denotes a stairwell or shaft. Spatial distance indicates the spatial distance between two detectors. For the spatial relationship, 0 indicates that both detectors are in the same unit, 1 indicates adjacent units, 2 indicates non-adjacent units on the same floor, 3 indicates adjacent floors, and 4 indicates non-adjacent floors. The time interval indicates the time difference between the two detectors' alarms. The floor difference indicates the difference in floors occupied by the two detectors. The loop difference indicates the difference in fire protection point loop codes between the two detectors. Connectivity indicates the closeness of the relationship between the two detectors.

All the above alarm results were obtained through FDS numerical simulation. Data, such as detectors, room area, type, spatial positional difference, and connectivity within the alarm results, were derived from the modelling process, while the detector alarm time difference was obtained by processing detector data from the simulation results. We determined the time intervals between alarms by configuring smoke detector parameters, collecting the precise alarm times for the first three detectors, and applying the difference method. For instance, the time difference between detectors 1 and 2 was calculated by subtracting the alarm time of the first detector from that of the second detector. Similarly, the time differences between detectors 1 and 3, and 2 and 3, were derived.

3.1.1. Standardized Processing

To eliminate the impact of dimensional differences between features on model training, this study employs standardization for feature data preprocessing. The standardization process transforms raw features into a normal distribution with mean 0 and standard deviation 1, using the following formula:

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

In the formula, x is the original feature value, μ is the feature mean, σ is the feature standard deviation, and z is the standardized feature value. Separate standardizers were

constructed for two independent datasets. The fit_transform operation was performed on the training set to compute and apply the standardization parameters. The transform operation was executed on the test set using the parameters calculated from the training set, ensuring model training stability and evaluation fairness. This provided high-quality input features for the subsequent two-stage neural network model.

3.1.2. SMOTE Algorithm

Due to the limited number of real fire alarm samples in this study, the SMOTE algorithm method was employed to balance the training set. Its fundamental principle involves generating new synthetic samples through linear interpolation between minority class samples, thereby expanding categories with insufficient data and achieving balanced sample counts across different categories. The specific implementation steps are as follows:

- ① Initialize the minority class sample set as $S_{min} = \{x_1, x_2, \dots, x_n\}$;
- ② For each minority class sample x_n , use the k-nearest neighbors' algorithm to identify its k closest neighbors in the feature space, forming the neighborhood set $X_{nk} = \{x_{n1}, x_{n2}, \dots, x_{nk}\}$;
- ③ Randomly select m samples (where $m < k$) from the neighborhood set X_{nk} . Perform linear interpolation between each selected sample and the original sample x_n to synthesize new minority class samples. This oversampling process achieves class balance in the dataset.

The training dataset in this study contained 823 true alarms and 7865 false alarms. By applying the SMOTE algorithm, the number of true alarms was increased to 7865 for model training.

3.2. Construction of a Two-Stage Classification Model Using 1D-CNN + DNN

To achieve efficient fusion and classification of multi-source alarm information, this paper proposes a two-stage judgment model based on the combination of 1D-CNN and DNN. Through feature extraction and decision fusion across two stages, this model progressively enhances its capability to identify complex alarm information.

3.2.1. Network Architecture Design

This study adopts a two-stage architecture combining 1D-CNN and DNN, representing the optimal solution based on task characteristics and experimental validation. For sequence data derived from static features, the 1D-CNN efficiently slides convolutional kernels across feature dimensions, precisely capturing critical local correlation patterns such as the proximity of detectors and short alarm intervals. This aligns perfectly with the task's core requirements. Furthermore, ablation experiments conducted in this study confirmed the necessity of the two-stage design. While the first-stage model alone achieves a certain recall rate, its precision remains low. By integrating additional alarm point information and the first-stage prediction results through the second-stage model, precision improves by approximately 10%, while maintaining recall. This demonstrates the architecture's comprehensive superiority in false alarm identification.

This study employs a unified implementation framework and hyperparameter selection strategy for all baseline models. For hyperparameters that are well-validated and mature in application, standard default values from the relevant field were directly adopted to avoid subjective arbitrariness. For architectural parameters, such as the number of convolutional kernels, kernel size, and the number of hidden layer units, single-factor sensitivity analyses were conducted to comprehensively evaluate their impact on the performance of the 1D-CNN + DNN model in imbalanced binary classification tasks.

The analysis results are presented in Figure 3. The optimal number of convolutional kernels is 32; increasing this to 64 results in a decline in performance. The size of the convolutional kernel has a negligible impact on results, with 1×3 being optimal. The number of fully connected layer neurons peaks at 64; excessive width induces slight overfitting. Regarding the number of convolutional and fully connected layers, this model handles a relatively small dataset. Shallow convolutional layers suffice to extract effective features while avoiding overfitting and reducing computational overhead. Employing two fully connected layers enhances the model's nonlinear expressive capability, enabling it to fit more complex decision boundaries. This approach thus achieves favorable classification performance even when dealing with simple features. This architecture ensures efficient feature extraction while enhancing the classifier's discriminative power through the depth of the fully connected layers.

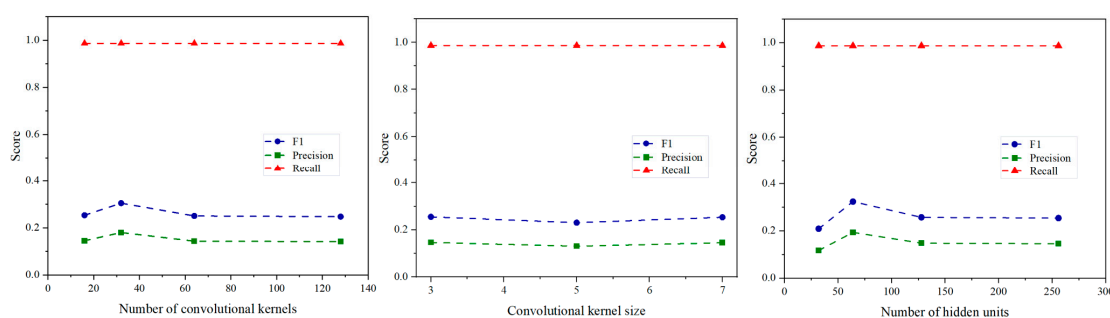


Figure 3. Sensitivity analysis of 1D-CNN + DNN model parameters.

This study proposes a two-stage processing architecture, with each stage comprising a combination of a 1D convolutional neural network and a fully connected network, as shown in Figure 4. The first-stage network structure is as follows. The input layer receives standardized 1–2 point alarm information difference data. The 1D convolutional layer utilizes 32 convolutional kernels with a size of 1×3 , padded with ones, and employs the ReLU activation function. The maximum pooling layer has 1×2 pooling kernel for dimension reduction and feature selection. The adaptive average pooling layer uniformly adjusts feature maps to a fixed length of 16. The fully connected network includes two hidden layers (64 and 32 neurons), each followed by a ReLU activation function and a dropout layer (dropout rate 0.2). The output layer has one neuron using a sigmoid activation function to output preliminary classification probabilities, the parameter settings are as shown in Table 4. The second-stage network structure mirrors the first-stage network; both employ a 1D-CNN + DNN architecture. The input layer receives 2–3 point- and 1–3 point-alarm information difference data alongside the first-stage prediction results for feature fusion, enabling deep feature extraction and final classification. The network model training employs a learning rate of 0.001 using the Adam optimizer. The above hyperparameters were obtained through hyperparameter sensitivity analysis.

Table 4. Key hyperparameters of the model.

Network Layer	Parameter Name	Parameter Value
Convolution Layer	Number of convolutional kernels	32
Convolution Layer	Convolutional kernel size	1×3
Pooling Layer	Pooling size	1×2
Adaptive Pooling	Output length	16
Fully Connected Layer	Number of hidden units	64 → 32
Regularization	Dropout rate	0.2
Activation Function	Hidden layer	ReLU
Activation Function	Output layer	Sigmoid

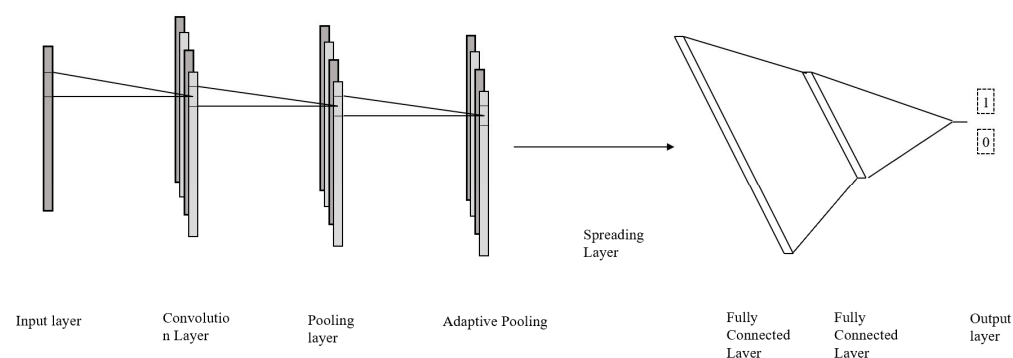


Figure 4. Network structure diagram of 1D-CNN + DNN.

3.2.2. Sample Balance

To address the issue of class imbalance, this study proposes a composite loss function CB_FocalLoss that combines focal loss with class-balanced weights.

First, based on the focal loss principle, the weight of easily classified samples is reduced by adjusting the factor $(1 - p_t)^\gamma$, enabling the model to focus more on difficult-to-classify samples. Here, p_t represents the model's predicted probability for the true class and γ is the focal parameter (set to 2) used to adjust the weighting between easy and difficult samples.

Second, a category balancing weight mechanism is introduced, calculating weights based on the number of valid samples in each category:

$$w_{cb} = \frac{1 - \beta}{1 - \beta^{n_y}} \quad (2)$$

In the formula, n_y is the number of samples in category y and β is the balancing hyper-parameter (set to 0.99). This weighting assigns a higher loss weight to the underrepresented category, effectively mitigating the class imbalance issue.

Ultimately, the composite loss function is expressed as:

$$\text{CB_FocalLoss} = w_{cb} \cdot \alpha (1 - p_t)^\gamma L_{\text{BCE}} \quad (3)$$

where α is the balancing factor (set to 0.25). This design enables the model to maintain focus on hard-to-classify samples while balancing the numerical disparities between different categories, thereby enhancing classification performance on imbalanced datasets.

3.3. Model Accuracy Analysis

Model Validity Analysis

To assess the robustness of model performance and mitigate the randomness inherent in single-run partitioning, this study employed a repeated, random subsampling validation method, conducting ten independent experiments. The results are summarized in Table 5 below. Through ten iterations of data-partitioning and training set evaluation, the following comparisons were obtained. Among these, Group 1 demonstrated superior F1 scores and precision in Stage 2 compared to other groups, while maintaining a recall threshold exceeding 98%. Although the fourth group exhibited the highest F1 score and precision, its recall fell below our minimum benchmark of 98%. Furthermore, as more alarm data were incorporated, Stage 2 recall decreased relative to Stage 1. This indicates that the model misclassified events initially correctly identified as true alarms as false alarms during the second assessment. This represents the most undesirable outcome in fire detection operations. Further calculation of the standard deviation across ten experimental runs revealed that a smaller standard deviation indicated minimal performance variation across different data partitions, signifying robust model stability. Consequently, by comparing experimental results obtained through multiple iterations using ten distinct

data-partitioning schemes, the robust performance of the model described in the paper was validated.

Table 5. Data-partitioning experiment results comparison table.

Experimental Batch Number	1	2	3	4	5	6	7	8	9	10	Average	Standard Deviation
stage1_test_f1 (%)	32.55	30.51	24.23	30.66	37.53	24.79	25.65	27.04	23.32	28.31	28.46	4.42
stage1_test_precision (%)	19.51	18.01	13.8	18.23	23.27	14.18	14.74	15.7	13.22	16.52	16.72	3.11
stage1_test_recall (%)	98.24	99.57	99.15	96.58	97.02	98.3	98.72	97.45	98.72	98.72	98.25	0.95
stage2_test_f1 (%)	44.60	26.4	32.61	50	21.67	34.8	36.90	25.84	32.95	23.73	32.95	9.14
stage2_test_precision (%)	28.85	15.21	19.5	33.84	12.16	21.08	22.71	14.86	19.84	13.47	20.15	6.93
stage2_test_recall (%)	98.24	99.57	99.57	95.73	99.57	99.57	98.3	98.72	97.02	99.57	98.59	1.32

To prevent model overfitting, we conducted validation set–test set consistency tests, diagnosing overfitting by comparing performance discrepancies between validation and test sets. As illustrated in Figure 5, the horizontal axis denotes experimental batches, while the vertical axis represents the overfitting gap in F1 scores for Stage 1 and Stage 2. A gap below 0.05 indicates excellent model generalization capability. All ten experimental groups exhibited gaps below 0.05. This minimal generalization gap indicates that the model has not overfitted to the validation set and generalizes well to unseen data, confirming that the second-order model developed in this study carries no risk of overfitting.

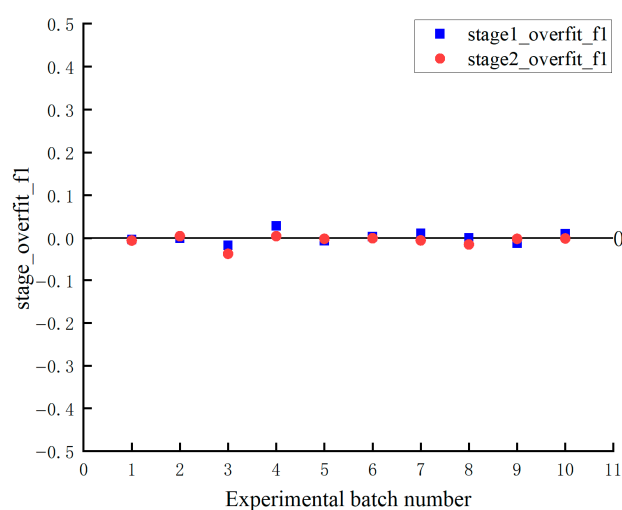


Figure 5. Validation set–test set consistency test chart.

To validate the effectiveness and diagnostic accuracy of the proposed model, evaluation metrics, including precision, recall, and F1 score, were employed. Figure 6 displays the confusion matrices for the first-stage model (left) and second-stage model (right) of the first experimental group.

In Figure 6, for the confusion matrix, the horizontal axis represents model predictions while the vertical axis denotes actual values. Taking the figure on the right as an example, the number 4 in the lower left corner indicates that the model predicted four false alarms; however, the actual number of true alarms was four (i.e., the number of true alarms missed). The upper-left corner shows 1705 instances where the model correctly predicted a false alarm and the actual outcome was, indeed, a false alarm (i.e., the number of correctly identified false alarms). The bottom-right corner value of 223 indicates 223 instances where the

model correctly predicted true alarms (i.e., the number of correctly identified true alarms). The top-right corner value of 550 indicates 550 instances where the model predicted true alarms that were actually false alarms (i.e., the number of incorrectly identified false alarms). The calculations yield is as follows: True Alarm Recognition Rate = $\frac{223}{4+223} = 98.24\%$, Accuracy of Identified True Alarms = $\frac{223}{550+223} = 28.85\%$. In the second stage, the metric for true negatives (i.e., the model correctly predicted the negative class) increased compared to the first stage's prediction values. This indicates that the model has improved with respect to reducing false positives.

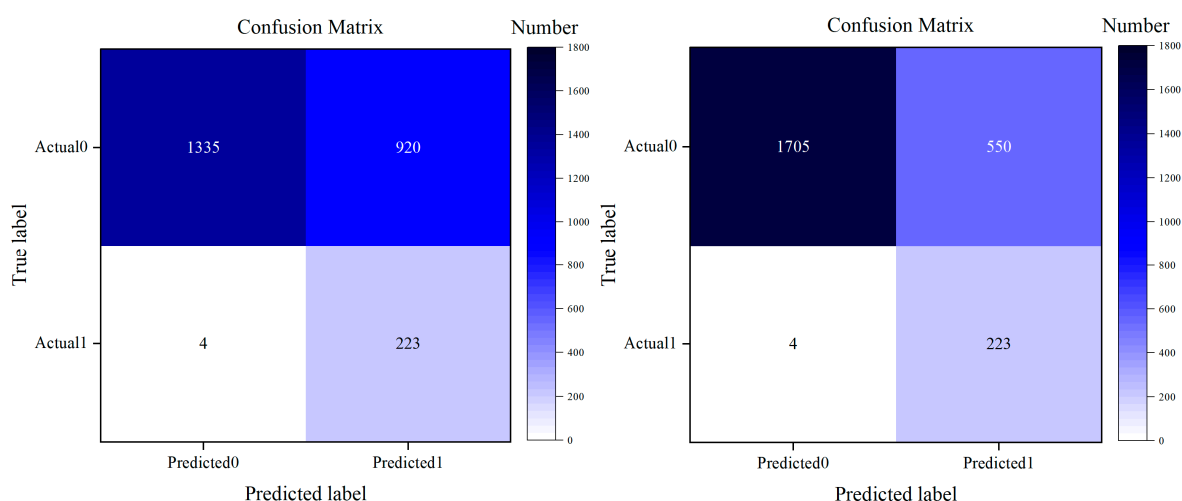


Figure 6. Confusion matrix for two-stage judgment evaluation.

The recall in Figure 7 represents the true alarm recognition rate, which indicates the proportion of predicted actual fires out of the total number of fires. It measures the percentage of true positives correctly predicted by the model. Precision represents the accuracy of identified true alarms, which indicates the ratio of actual fire alarms to fire alarms identified by the model, quantifying the proportion of samples correctly classified as positives by the model. Excessive false positives increase operational burden, while false negatives may create safety hazards.

The F1 score, as a core metric for evaluating classification model performance, derives its fundamental value from effectively reconciling precision and recall—two metrics that often constrain one another. This provides a more comprehensive and robust standard for measuring model performance. In practical applications, optimizing precision alone may lead to overly conservative models that classify numerous genuine fires as false alarms, resulting in significant underreporting of the true positives. Conversely, if recall is pursued unilaterally, the model may become overly aggressive, misclassifying numerous false positives as genuine alarms, resulting in an inundation of warning information and diminished credibility. By calculating the harmonic mean of precision and recall, the F1 score assigns equal importance to both metrics, compelling the model to seek an optimal balance between minimizing false positives and avoiding false negatives. This balancing mechanism holds critical guidance for real-world deployment scenarios.

We evaluated both the first-stage and second-stage models. The first-stage model was trained using the initial feature set, while the second-stage model incorporated the prediction probabilities from the first stage as additional features. Evaluation results (Figure 5) demonstrate that the two-stage approach progressively improves the accuracy of identified true alarms while maintaining a true alarm recognition rate exceeding 98%. The results indicate that the second-stage model maintains the comparable true alarm recognition rate to the first-stage model, likely due to fewer borderline cases processed in

the second stage—cases that are difficult to distinguish and represent a small minority of samples. Improvements in precision and F1 score metrics demonstrate the effectiveness of the two-stage judgment model. By incorporating alarm information from detector 1 and 3, as well as detector 2 and 3, into the second-stage judgement, the accuracy of identified true alarms improved by 9.34%. Similarly, continuously updating alarm information (e.g., the fourth alarm detector) can progressively enhance the accuracy of identified true alarms while ensuring that true alarms are identified. This approach effectively reduces false alarms and minimizes manual verification efforts.

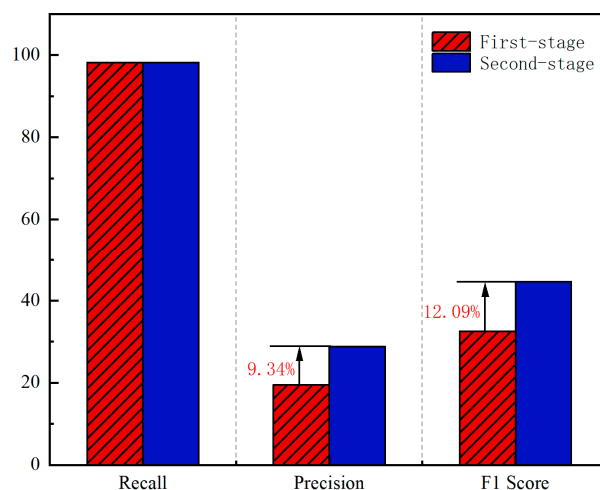


Figure 7. Two-stage judgment evaluation results.

4. Discussion

4.1. SMOTE Effectiveness Analysis

To validate the effectiveness of SMOTE, this study designed a comparative experiment. Based on the identical two-stage model architecture of 1D-CNN + DNN, the original imbalanced dataset and the balanced dataset processed by SMOTE oversampling were employed, respectively. By maintaining consistency in model structure and other hyperparameters, performance differences were directly attributed to the data distribution processing method. The evaluation results are presented in Table 6.

Table 6. Results of different dataset judgment.

Dataset	True Positive Rate	Recognition Accuracy	F1 Score
Unbalanced Dataset	97.80%	25.11%	39.96%
SMOTE Balanced Dataset	98.24%	28.85%	44.60%

Compared to the model trained on the original imbalanced dataset, the model trained on the SMOTE-balanced dataset demonstrated improved true alarm recognition rates. This indicates that SMOTE, by synthesizing minority class samples, assists the model in better learning the complete feature distribution of actual fires. This is particularly beneficial for fire pattern variants that were previously underrepresented due to sparse sampling, thereby reducing false negatives for genuine fire alarms. Significant gains were also observed in the accuracy of identified true alarms, indicating that the balancing process corrected prediction biases arising from the model's tendency towards the majority class. When learning from balanced data, the model's decisions no longer skew heavily towards the majority class, thereby generating alerts with higher confidence—that is, fewer false alarms.

The concurrent increase in F1 scores demonstrates that SMOTE processing does not sacrifice precision for recall. Instead, it facilitates a win–win outcome for both mutually constraining metrics, optimizing overall classification performance. For the highly imbalanced fire alarm data in this study, the SMOTE sample generation technique proves an effective preprocessing strategy. By actively mitigating class imbalance, it fundamentally enhances the model’s ability to distinguish highly suspected true alarms, particularly those with ambiguous features and challenging classifications. Consequently, the application of SMOTE provides an indispensable data foundation for constructing intelligent fire assessment systems characterized by high reliability.

4.2. CB_FocalLoss Effectiveness Analysis

To validate the effectiveness of the proposed composite loss function, CB_FocalLoss, comparative experiments were designed, the results are shown in Table 7. The experiments were conducted under identical conditions: a two-stage 1D-CNN + DNN model architecture and identical training and testing datasets (SMOTE-equalized). The sole variable was the loss function employed during training: one group utilized the standard binary cross-entropy loss function, while another employed the CB_FocalLoss loss function designed in this study. By comparing their performance on an independent test set, the efficacy of the CB_FocalLoss loss function can be evaluated.

Table 7. Determination results of different loss functions.

Loss Function	True Positive Rate	Recognition Accuracy	F1 Score
Standard Loss Function	86.78%	35.16%	50.04%
CB_FocalLoss Loss Function	98.24%	28.85%	44.60%

Compared to the standard binary cross-entropy loss function, CB_FocalLoss achieves a significant and clear improvement in the true alarm recognition rate metric. Standard cross-entropy treats all samples equally; in scenarios where the number of positive and negative samples is vastly different, its gradient updates are rapidly dominated by the large number of easily classifiable majority samples, leading to insufficient feature learning for the minority class. CB_FocalLoss, however, introduces a dual mechanism comprising category balancing w_{cb} and a focus modulation factor $(1 - p_t)^\gamma$. This actively assigns higher learning weights to minority class samples and compels the model to concentrate more attention on those difficult-to-classify instances. Consequently, the model demonstrates enhanced capability in capturing genuine fire signals, particularly those exhibiting atypical characteristics or occurring in the early stages of development, thereby effectively mitigating the risk of false negatives.

Meanwhile, CB_FocalLoss exhibits a decline in the accuracy of identified true alarms and F1 score compared to the baseline. This represents an anticipated trade-off in performance accompanying the shift in the loss function’s design objective. When the model is guided to more actively identify minority classes, its decision boundary shifts moderately towards the minority side. This inevitably leads to some majority samples with ambiguous features being classified as positive examples, resulting in a slight increase in false positives and a corresponding decrease in precision. The F1 score, as the harmonic mean of precision and recall, is equally sensitive to this shift. The efficacy of the CB_FocalLoss loss function is thoroughly validated. By integrating dual optimization mechanisms, category balancing, and sample difficulty focus, it directs the model’s learning emphasis towards the critical objective of reducing false negatives, significantly mitigating the adverse impact of category

imbalance on model performance. Although a reasonable trade-off in precision is made, the priority of avoiding false negatives far outweighs reducing false positives in fire alarm scenarios. Consequently, this loss function markedly enhances the system's capability to identify highly suspected true alarms, particularly early-stage and concealed fires.

4.3. Comparative Analysis of Different Model Accuracies Model Accuracy Analysis

The effectiveness of the model employed in this study was analyzed. The study employed LSTM, SVM, and residual DNN classical models to train and test identical training and testing datasets. As shown in Table 8, the proposed 1D-CNN + DNN two-stage architecture demonstrated significantly superior performance in fire alarm recognition accuracy metrics compared to other reference models: Its accuracy exceeded that of LSTM, SVM, and residual DNN by 8.14%, 8.26%, and 15.87%, respectively. This demonstrates the model's exceptional efficacy and superiority in handling complex fire alarm data, particularly in identifying and filtering false alarms.

Table 8. True positive rate and false positive rate under different models.

Models	True Positive Rate	Recognition Accuracy	F1 Score
Existing Models	-	0.15%	-
LSTM	97.80%	20.71%	34.18%
SVM	98.24%	20.59%	34.05%
Residual DNN	97.36%	12.98%	22.91%
1D-CNN + DNN	98.24%	28.85%	44.60%

The three model architectures compared in this study each comprise over 10 independent hyperparameters, encompassing both architectural and training parameters. Conducting a Cartesian product grid search across all parameters would yield over 10,000 possible combinations based on typical parameter ranges. This excessively large hyperparameter space renders a comprehensive grid search entirely impractical within the constraints of limited project timelines and computational resources. Therefore, during model construction, we adopted baseline configurations for selected hyperparameters, employing mainstream default values. The compared LSTM, residual DNN, and SVM models were all based on classical architectures from published studies in the literature, referencing common configurations within their respective fields. Systematic single-factor sensitivity analyses were conducted on architectural parameters such as the number of network layers and neurons per layer. This approach avoided subjective arbitrariness and ensured fair model comparison.

Traditional, deep, fully connected networks treat the feature vector of each alarm event as an independent, flat static input. While possessing strong nonlinear fitting capabilities, they struggle to explicitly capture the local spatio-temporal dependencies inherent in the alarm point sequences that are precisely crucial for judging the plausibility of smoke propagation. The 1D-CNN layer in this study enables local spatio-temporal feature extraction. Its convolutional kernels slide across temporal and spatial dimensions, automatically learning and extracting micro-correlated features. These refined, information-dense features are then fed into the subsequent DNN for global decision-making, achieving decoupling and synergy between feature extraction and classification. In contrast, residual DNN models, while supporting deep architectures through residual connections to mitigate gradient vanishing, suffer from parameter redundancy and overfitting in fire alarm scenarios due to low-dimensional input data and short sequences. Their deep abstraction capabilities also prove to be limited in capturing local spatio-temporal correlations.

Compared to LSTM models, while both excel at handling sequential data, LSTMs are primarily designed to model long-range temporal dependencies and memory. In the specific scenario of this study, critical judgment logic typically relies on short sequences formed by the earliest 2–3 triggered alarm points. The core information lies in the local spatio-temporal relationships between points, rather than long-term historical states requiring complex memory units. Furthermore, the two-stage cascaded architecture employed in this study, where the first stage makes preliminary judgments based on 1–2 points, and the second stage integrates the third point for verification, intrinsically incorporates a progressive reasoning and contextual memory mechanism. This partially achieves the strengths of LSTMs, striking a better balance between performance and efficiency. The 1D-CNNs are more specialized for capturing these short-range, local patterns and typically exhibit greater training stability and computational efficiency.

Compared to SVM models, the performance of SVMs heavily relies on complex and sophisticated manual feature engineering, requiring domain experts to predefine high-order features such as spatio-temporal association weight functions. The end-to-end learning paradigm of 1D-CNN + DNN enables direct, automatic learning of optimal, data-driven feature representations from raw spatial distances, temporal intervals, connectivity, and other fundamental data. This approach not only avoids the subjective biases and informational limitations inherent in manually designed features but also uncovers latent discriminative patterns unnoticed by human experts, the fundamental reason for its substantial performance advantage over SVM.

The 1D-CNN + DNN model demonstrated excellent performance in distinguishing genuine from false fire alarms in this study. Leveraging its architectural advantage of combining local feature extraction with global synthesis, along with its end-to-end adaptive learning capability, this model not only ensures high detection rates for genuine alarms but also significantly reduces false alarm burdens by enhancing overall recognition accuracy. This achieves higher precision in the intelligent assessment of fire alarm authenticity.

5. Conclusions

For distinguishing between genuine and false alarms, a two-stage, high-probability genuine alarm prediction model was constructed and validated based on fire simulation and engineering data. This model combines 1D-CNN and DNN techniques to address the classification task of multi-source alarm information. The analysis yielded the following results:

- (1) To address the imbalanced sample distribution in the fire dataset, the designed SMOTE and CB_FocalLoss loss functions effectively mitigated the common class imbalance in alarm data through sample generation techniques combined with focal loss and category balancing methods, thereby improving the recognition accuracy of minority class samples. In addition, through its hierarchical cascading architecture design, this model achieves effective recognition and decision fusion of complex alarm information. By continuously updating alarm information, the model progressively improves its accuracy in identifying fire false alarms. Future researchers can further enhance false alarm accuracy by iteratively refining alarm information;
- (2) The model achieved a true alarm recognition rate of 98.24%, increasing the current fire alarm recognition accuracy from 0.15% to 28.85%, outperforming classic models, like LSTM (8.14%), SVM (8.26%), and residual DNN (15.87%), in false alarm recognition. This demonstrates the model's superior false alarm discrimination capability and high accuracy in distinguishing genuine alarms from false positives, validating its effectiveness. Compared to existing models, this research model employs deep learning to identify alarm information, with its judgement accuracy improving as the number of genuine fire alarms increases. For the management of existing alarm systems, the

- quantity of alarm entries requiring urgent handling and assessment by fire control center personnel is correspondingly reduced. Staff can dedicate the substantial time saved to in-depth analysis of remaining higher-risk alarms, emergency drills, or facility inspections, thereby enhancing the overall precision of fire safety management;
- (3) This research model can be seamlessly integrated into existing smart fire protection platforms as an intelligent pre-processing and classification module for alarm information streams. The operational mode is as follows: “Detector alarm → Platform reception → Model real-time assessment and classification (high risk/low risk) → Manual prioritization of high-risk alarms”. However, transitioning from laboratory research to large-scale deployment presents a series of challenges. First, in terms of computational resources and real-time performance, the concurrent processing demands during alarm peaks impose heightened requirements on server computing power and latency, potentially necessitating additional hardware investment. Second, data interface and quality consistency are paramount. The model relies on accurate, timely device metadata to generate features. Incomplete or delayed ledger updates will directly compromise assessment accuracy. Finally, the model may encounter blind spots in extreme scenarios not covered by training data, necessitating continuous monitoring and iterative refinement mechanisms;
 - (4) The objective of this model is to minimize false fire alarms whilst ensuring that the majority of genuine fire alerts are identified. However, the model possesses certain limitations requiring further refinement by subsequent researchers. First, its effectiveness is highly contingent upon the premise of multi-detector correlated alarms. Should a fire trigger only a single-point alarm, or should network delays cause alarm sequences to become disordered or lost, the model will be unable to function effectively due to missing or distorted features. Second, its positive samples primarily derive from idealized physical simulation data, introducing uncertainty regarding its ability to recognize rare fire scenarios beyond simulated parameters or complex building structures not covered in training data (such as large atriums or tunnels). Furthermore, the model extracts correlation features based on static events, making it difficult to effectively distinguish persistent environmental disturbances from genuine fire incidents. Consequently, the model may prove ineffective or unsuitable in scenarios featuring sparse detector placement, incomplete alarm information, extremely rapid-fire development (e.g., flash fires), or environmental disturbances exhibiting persistent temporal characteristics. This model is positioned as an intelligent enhancement module for conventional fire alarm systems, requiring coordination with mechanisms, such as detector self-diagnostics and manual inspections, to collectively form a comprehensive fire warning system.

Author Contributions: Conceptualization, X.S., C.L., J.W. and Y.H.; Methodology, X.S., C.L., J.W. and Y.H.; Writing—original draft, C.L.; Writing—review & editing, X.S., J.W. and Y.H.; Supervision, Y.X. and J.H.; Funding acquisition, J.W. and J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Key R&D Program of China (Grant No. 2024YFC3014703), Key R&D Program of Guangxi Zhuang Autonomous Region (Grant No. Guike AB23026055), and Anhui Provincial Natural Science Foundation (Grant No. 2208085UD13).

Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: Author Yixin Xu was employed by the company Ansteel Group Mining Corporation. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Zhao, W.X. Analysis of current status and development trends in fire protection technology for building exterior wall insulation systems. *Bulk Cem.* **2025**, *3*, 61–63+66.
2. Xu, X.B.; Miao, X.P.; Jiang, F.; Tian, Y.L. Analysis and countermeasures of false alarm causes in automatic fire alarm system. *Contam. Control Air-Cond. Technol.* **2011**, *3*, 28–32.
3. Hong, B. Working principle and linkage application analysis of automatic fire alarm system. *Fire Prot. Ind.* **2023**, *9*, 46–48.
4. Zhou, X.J. Investigation into problems and countermeasures in the interlocking control of fire alarm systems. *China Plant Eng.* **2024**, *22*, 245–247.
5. Yang, L.; Feng, J.; Lu, X.L.; Liu, Q. Design of an IoT-Based smart home security monitoring system. *Mod. Electron. Tech.* **2019**, *42*, 55–58.
6. Liu, Z.G.; Andrew, K.K. Review of recent developments in fire detection technologies. *J. Fire Prot. Eng.* **2003**, *13*, 129–151. [[CrossRef](#)]
7. James, A.M.; Matthe, E.H.; Clarenc, L.W. Investigation of multi-sensor algorithms for fire detection. *Fire Technol.* **2003**, *39*, 363–382. [[CrossRef](#)]
8. Milke, J.; Zevotek, R. Analysis of the response of smoke detectors to smoldering fires and nuisance sources. *Fire Technol.* **2016**, *52*, 1235–1253. [[CrossRef](#)]
9. Du, J.H.; Zhang, R.C. Current status and development trends in fire detector research. *Fire Tech. Prod. Inf.* **2004**, *7*, 10–15.
10. Chen, T.; Yuan, H.Y.; Fan, W.C. The developing fire detection technology. *Fire Saf. Sci.* **2001**, *10*, 108–112.
11. Guo, T.N. Fire situation of China and the development of fire science and technology. *Fire Sci. Technol.* **2005**, *24*, 663–673.
12. Fu, T.; Wang, J.S.; Cheng, Y.Y.; Wang, Y.Z. Advances in fire detection technology: From traditional detection and alarm to latent period monitoring and early warning. *Fire Sci. Technol.* **2025**, *44*, 1176–1183+1189.
13. Lei, H.X. Smart firefighting application design based on multi-fusion detection technology. *Build. Electr.* **2025**, *44*, 43–47.
14. He, Y.B.; Dong, Y.S.; Lei, J. Research on multi-sensor method for detecting aircraft cargo fire. *China Saf. Sci. J.* **2018**, *28*, 74–79.
15. Zhao, W.Q. Design of Fire Detection System Based on Multi-Sensor Composite. Master's Thesis, Nanjing University of Science and Technology, Nanjing, China, 2023.
16. Wang, Q.W. Research on Multi-Sensor Composite Fire Detection Information Fusion Alarm Method. Master's Thesis, Shenyang University of Aeronautics and Astronautics, Shenyang, China, 2019.
17. Homeag, I.; Pärlog-Cristian, R.; Covrig, M. Efficiency increase for electrical fire detection and alarm systems through implementation of fuzzy expert systems. *Elect. Eng* **2013**, *75*, 251–266.
18. Ding, Q.; Peng, Z.; Liu, T. Multi-sensor building fire alarm system with information fusion technology based on DS evidence theory. *Algorithms* **2014**, *7*, 523–537. [[CrossRef](#)]
19. Xu, C.; Li, X.C.; Zhang, L.; Yang, H. Multi-sensor fire early-warming system based on ZigBee. *J. Xihua Univ.* **2012**, *31*, 73–76+80.
20. Wang, S.P.; Wang, H.C.; Fan, M.H.; Zhang, J.Q. Research on comprehensive detection technology for electrical fires based on multi-information fusion. *Fire Sci. Technol.* **2017**, *36*, 213–217.
21. He, Z.X.; Wang, L.G.; Meng, C.; Qian, W. Design of a multi-data fusion-based composite fire detection system. *Fire Sci. Technol.* **2019**, *38*, 977–980.
22. Horng, W.B.; Peng, J.W. Image-based fire detection using neural networks. In Proceedings of the 9th Joint Conference on Information Sciences, JCIS-06, Kaohsiung City, Taiwan, 8–11 October 2006. [[CrossRef](#)]
23. He, N.L.; Zhang, J.S.; Lin, W.S. Forest fire image recognition based on deep learning multi-target detection technology. *J. Nanjing For. Univ.* **2024**, *48*, 207–218.
24. Kanagaraj, S.; Moroz, I.; Durairaj, P.; Karthikeyan, A.; Rajagopal, K. Imperfect chimera and synchronization in a hybrid adaptive conductance based exponential integrate and fire neuron model. *Cogn. Neurodyn.* **2024**, *18*, 473–484. [[CrossRef](#)]
25. Chao, X.C.; Shang, W.; Zhang, F. Information-guided flame detection based on faster R-CNN. *IEEE Access* **2020**, *8*, 58923–58932. [[CrossRef](#)]
26. Tang, W.; Zhang, W.D.; Yuan, H.; Jie, C.; Ren, J.H. Improvement of infrared smoldering fire detection algorithm based on YOLOv7. *J. Combust. Sci. Technol.* **2024**, *30*, 532–538.
27. Deng, L.; Zhou, J.; Liu, Q.Y. Fire detection algorithm based on an improved YOLOv8 model. *J. Saf. Environ.* **2025**, *25*, 888–897.
28. Chen, Y.H. Research on Forest Fire Detection Using Unmanned Aerial Vehicles Based on Convolutional Neural Network. Master's Thesis, Xi'an University of Technology, Xi'an, China, 2019.
29. Xu, H.; Li, B.; Zhong, F. Light-YOLOv5: A lightweight algorithm for improved YOLOv5 in complex fire scenarios. *Appl. Sci.* **2022**, *12*, 12312. [[CrossRef](#)]
30. Chen, S.H.; Zhang, M.; Liu, H. A method for diagnosing faults of hydraulic pump and accumulator with 1D-CNN and multi-sensor information fusion. *Mech. Sci. Technol. Aerosp. Eng.* **2023**, *4*, 715–723.
31. Zhan, N.Y.; Jiang, Z.X.; Yi, H.Y.; Zhang, X.H.; Miao, P. Influence of fire source location on smoke spreading characteristics of underground garage based on FDS. *J. Hunan Univ. Sci. Technol.* **2024**, *39*, 22–29.

32. Drysdale, D. *An Introduction to Fire Dynamics (Third Edition) States That Small Fires Typically Correspond to Low HRR (<1 MW)*; Wiley: Hoboken, NJ, USA, 2011.
33. Hurley, M.J.; Gottuk, D.T.; Hall, J.R.; Harada, K.; Kuligowski, E.D.; Puchovsky, M.; Torero, J.; Watts, J.M. Wieczorek CJSFPE *Handbook of Fire Protection Engineering*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 429–454.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.