Intelligent Fire Risk Comprehensive Assessment Model Construction Using Deep Learning

Zhixian Su*, Haihang Li

Abstract—**With the development of Internet technology, the concept of intelligent fire protection has been proposed. To achieve intelligent fire protection, it is necessary to conduct accurate research and real-time monitoring of fire risk. Based on the above requirements, an artificial neural network fire risk assessment model based on stochastic gradient descent optimization is proposed. It can solve the problem of basic information acquisition and timeliness of basic fire risk information. The experimental results showed that the average absolute error between the prediction results of the stochastic gradient descent artificial neural network model and the actual value was only 47.458 million yuan, and the average relative error was only 15.7%, which was far lower than the principal component regression model and vector autoregressive model. The average relative error of the stochastic gradient descent artificial neural network model in predicting fire accidents was about 14.2%, which was also lower than that of the principal component regression model and the vector autoregressive model. The average accuracy of the stochastic gradient descent artificial neural network model, principal component regression model, and vector autoregression model was 70.9%, 72.7%, and 79.9%, respectively, of which the stochastic gradient descent artificial neural network model had the highest accuracy. The average accuracy, F1-measure, and fit of the stochastic gradient descent artificial neural network model were about 81.2%, 0.8, and 0.94 respectively, which were higher than the other two models. The above results show that the stochastic gradient descent artificial neural network model has the highest accuracy in fire risk assessment and stronger generalization ability.**

Index Term—**Intelligent firefighting; Search data; Neural network; Stochastic gradient descent; Fire risk assessment**

I. Introduction

As the economy develops, the city scale continues to expand, and the population continues to concentrate, leading to a high concentration of VARious fire risks, which poses a great threat to people's safety. Meanwhile, the difficulty of urban fire protection work has increased significantly. The traditional fire management mode and management mechanism make it difficult to ensure the efficiency of fire protection work. Through the latest technologies such as the Internet of Things, artificial intelligence, and virtual reality, and combined with professional applications such as big data and intelligent research and judgement, intelligent fire protection can achieve intelligence, improve efficiency, ensure integrity, improve law enforcement, enhance rescue capability, and reduce fire occurrence and loss [1-2]. Intelligent fire protection is mainly divided into four aspects, namely, intelligent prevention and control, intelligent management, intelligent operation, and intelligent command [3]. To achieve intelligent fire protection, it is necessary to establish a remote monitoring system for urban IOT fire protection and a combat command platform based on big data with strong big data application capabilities. The main way of fire protection big data construction is to mine various types of data, integrate various types of data resources, and realize the rapid transformation and association of information. The use of Internet search data for fire risk assessment will help fire managers make more accurate and timely fire risk assessment conclusions, and provide more timely and effective data support for fire managers' decision-making. However, due to the characteristics of firefighting work, how to obtain firefighting information in the construction of firefighting big data has become a major problem. The network search data has the characteristics of information timeliness, large scale and strong availability, and reflects the actual information needs of users, reflecting the characteristics of human social activities. In recent years, research on web search data has included cancer monitoring, stock investment, macroeconomic activities, influenza monitoring, and other areas. Therefore, by processing relevant network data, fire information can be obtained in time, which provides a new idea for fire risk assessment. However, due to the huge size of network search data and the variety of information contained in it, it is difficult to use the data. The appropriate keyword index system can effectively reduce irrelevant data. Therefore, the study proposes to establish the fire keyword index system based on the Heinrich accident causal chain theory and Marlowe's hierarchy of needs theory. Considering the non-linear relationship between search keywords and fire, the artificial neural network (ANN) is used to evaluate the correlation between keywords and fire risk. The stochastic gradient descent (SGD) algorithm can optimize the neural network and realize the accurate prediction of fire risk. The research proposes a complete set of network search data application processes, including the construction of a theoretical framework, the establishment of a keyword index system, the construction of a fire risk assessment mathematical model, and the example verification and comparative analysis between models. By utilizing network search data, the fire risk assessment model is established to address two key challenges. First, it solves the problem of obtaining essential information by ensuring comprehensive data collection. Second, it solves the problem of timely updating of basic fire risk information,

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Zhixian Su is an associate professor of the Zhejiang College of Security Technology, Wenzhou, 325200, China (e-mail: aaffxzs@163.com).

Haihang Li is an associate professor of the China Jiliang University, Hangzhou, 310018, China (e-mail: lihaihang@cjlu.edu.cn).

thereby improving the accuracy of assessment results. This approach enables real-time monitoring and control of regional fire risks, meeting the demands for "precision", "automation" and "intelligence" in firefighting operations. Moreover, this framework serves as a fundamental step towards future fire risk assessment based on deep learning techniques. The application of network search data not only opens up a new area of fire risk assessment, but also provides a new idea for the application of fire big data.

The article includes four sections. The first section briefly describes the current research status of intelligent fire protection and ANN. The second section will study the fire risk assessment model based on SGD-ANN. The third section will test the performance of the SGD-ANN model and analyze its test results. The fourth section will summarize the research of the full text.

II. RELATED WORKS

Fire is a disaster caused by uncontrolled combustion in time or space, which is a major hazard to human life and property. Hashemzadeh M et al. proposed a smoke detection model based on a convolutional neural network and efficient spatiotemporal features for the problem of fire detection. The model extracted motion pixels from the input image using an effective motion detection scheme, and extracted the motion regions using a customized convolutional neural network to realize the identification of candidate smoke regions [4]. Hosseini A et al. addressed the problem of how to detect flame and smoke simultaneously and proposed a detection model based on the UFS network. The model detected fire and smoke in videos using a convolutional neural network and identified fire hazards by classifying video frames into eight categories [5]. Hashemzadeh M and Zademehdi A proposed a flame detection algorithm based on the ICAK-medoid color model for the automatic flame detection problem in video. The algorithm extracted the area of motion intensity through the motion detection technology, which was then used to analyze the characteristics of the fire and classify the fire-fire and non-fire areas using SVM [6]. Chen J et al. proposed a dynamic fire risk assessment model based on the Bayesian network to solve the problem that cotton storage is prone to fire. The model was divided into three parts: fire cause, fire detection, and fire control, and the accident risk was given in the form of economic loss. At the same time, the risk could be updated quickly by providing new evidence to the model node of Bayesian network [7]. Erdin C and Alar M proposed a fire risk prediction method based on an analytical hierarchy process and fuzzy logic to solve the problem of how to predict fire risk in rural areas. This method combined a geographic information system with analytic hierarchy process and fuzzy logic, and fully considered the characteristics of rural environments in different regions. The results showed an accurate prediction of fire risk in rural areas [8].

ANN is widely used in various fields because of its self-learning function and associative storage function. Bi H et al. proposed a combustion characteristics analysis method using ANN to analyze the combustion characteristics of sludge and peanut shells. Results showed that the fitting degree between the predicted and actual experimental results was high. This analysis method based on ANN could provide strong support for the large-scale application of mixed combustion of sludge and peanut shells [9]. Nagarajan D et al. proposed a prediction model for the strength prediction of sintered fly ash lightweight aggregate concrete. The model used a forward neural network and Levenberg Marquardt back propagation algorithm. After testing, the prediction result of the model highly fit the actual result [10]. Kalesse Los H et al. proposed a cloud liquid detection method based on ANN and cloud radar Doppler spectrum for the problem of how to evaluate the cloud liquid in the cloud network. In this method, the morphological features of cloud penetrating radar Doppler spectrum measurement were extracted from the ANN. Moreover, the liquids that exceeded the attenuation of all lidar signals were classified by using the particle backscattering coefficient and the particle depolarization ratio. The experimental results showed that it could effectively detect and classify cloud liquids [11]. Butola R et al. proposed a model for predicting tensile properties of friction stir processed materials. The results showed that the absolute error percentages of the model for ultimate tensile strength and total elongation were 2.788 and 2.578, respectively, which were lower than those of the response surface method [12]. Kumari J S and Nelakuditi U R proposed a gestational age estimation method based on ANN to evaluate pregnancy risk. In this method, the expected parameters were identified by probabilistic lifting tree classification and the fetal status was evaluated by ANN according to the gestational age. The results showed accurate measurement of fetal growth with small errors and short time [13].

In summary, the advent of information technology has led to advancements in the field of fire risk prediction. However, the majority of research in this area has focused on smoke and flame detection in specific scenarios or fires. This narrow focus hinders the ability to meet the demands of intelligent firefighting and limits the utilization of network search data. ANN technology exhibits distinct advantages in handling fuzzy, stochastic, and nonlinear data. It is particularly suitable for managing large, complex, structured, and ambiguous information systems, and it is very suitable for dealing with the nonlinear relationship between search data and fire risk. Therefore, a fire risk assessment model using ANN is proposed. This model first establishes the establishment of a keyword index system and evaluates the relationship between pipe detection and fire through the system, and then optimizes ANN by the SGD algorithm, and builds a fire risk assessment model based on search data.

III. FIRE RISK ASSESSMENT MODEL USING ARTIFICIAL NEURAL NETWORK

With the continuous increase of urban population density, various fire risks are highly concentrated, which leads to difficulties in fire protection work. Intelligent firefighting can improve the awareness, early warning ability, and intelligent ability by connecting various systems. It can realize the earlier detection and faster treatment of fire, and reduce the fire risk and impact to the minimum.

A. Network search data analysis based on artificial neural network

Intelligent fire protection refers to the use of the Internet of Things, artificial intelligence, "Internet+" and other technologies,

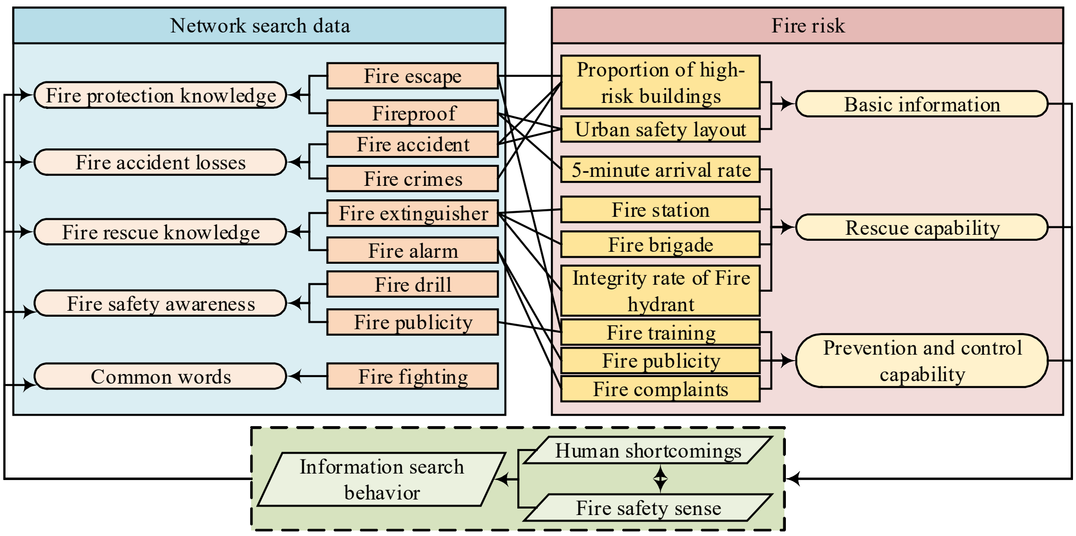

Fig. 1. Correlation framework between search data and fire risk

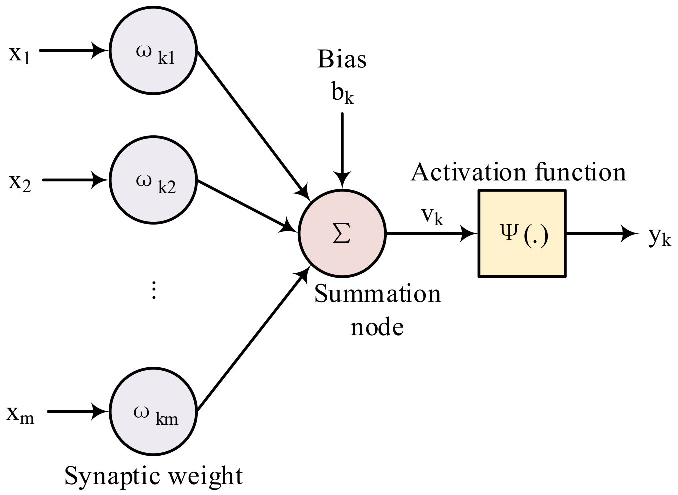

Fig. 2. Structure of perception

combined with big data cloud computing platforms, intelligent fire alarm research and judgment, and other professional applications, to achieve intelligent urban fire protection. However, due to insufficient accumulation of basic fire information and poor timeliness, it is difficult to make progress in intelligent fire protection. By analyzing network search information, the accurate prediction of fire risk can be realized and the timeliness of information can be ensured. To ensure a high correlation between network search information and fire risk, a reasonable correlation framework must be established, and search keywords can provide strong support for establishing the correlation framework. At different stages of fire development, there will be different information needs. In the early stages of a fire, firefighters tend to be trying to extinguish the fire or escape the scene. At this time, their information needs tend to be firefighting methods and self-rescue escape methods, and the corresponding search content is “fire safety common sense”. In the stage of fire spread, people inevitably have fear due to the rapid expansion of the fire scope. At this stage, the information needs of witnesses tend to be in the aspect of fire damage. In the fire rescue stage, the on-site experience or witnesses often call the fire alarm number, evacuate the crowd, and organize firefighting. At this time, their information needs are more inclined to fire rescue. In the post-disaster management stage, the causes of the fire will be analyzed, and the information demand will turn to fire safety awareness. By analyzing the behavior at each stage, the search terms with different information needs can be obtained, and the correlation framework between search data and fire risk can be established. The structure of the association framework between search data and fire risk is shown in Fig. 1.

After establishing the correlation framework between search data and fire risk, the appropriate keywords can be selected and a keyword selection database can be created. When selecting keywords, the study should not only include as many fire risk-related words as possible, but also avoid overlap between indicators and reduce redundancy of information. The selection of keywords is calculated by the Pearson correlation coefficient in formula (1).

$$\rho_{s,x} = \frac{\operatorname{cov}(s,x)}{\sigma_s \sigma_x} = \frac{E\left[(S-\mu_x)(X-\mu_s)\right]}{\sigma_s \sigma_x} \tag{1}$$

In formula (1), S means search keyword data. X indicates fire damage. After selecting the appropriate keywords, it is necessary to analyze the keywords to accurately express the relationship between keyword search volume and fire risk. Because of the non-linear relationship between search keywords

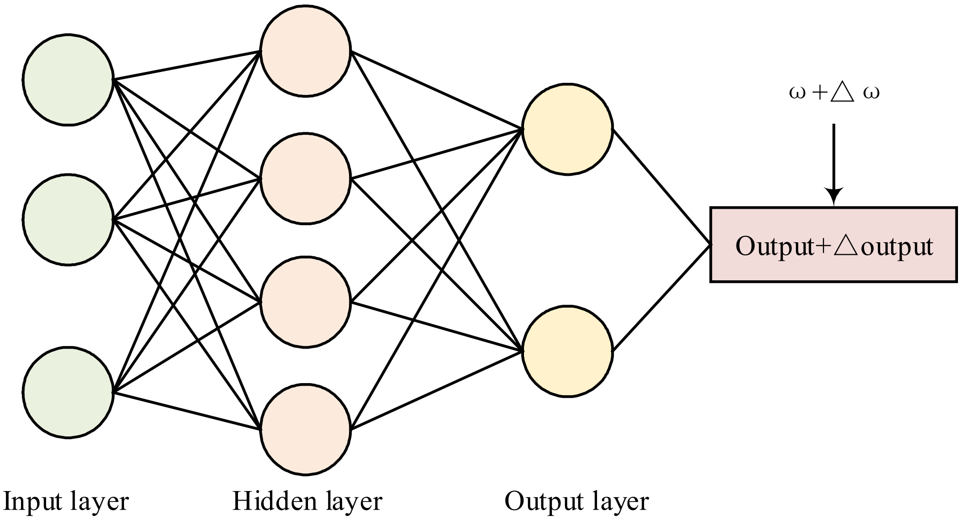

Fig. 3. Neural network structure

and fire, the analysis algorithm is required to have good non-linear processing ability. ANN can fit the nonlinear relationship. ANN is based on perceptron, and the structure of perceptron is shown in Fig. 2.

In Fig. 2, the perceptron has three binary inputs, and the importance of each input is adjusted by weight. Then the adjusted input is summed and offset. Finally, the output is calculated by the activation function. The output result is 1 or 0, which is determined by the sum of the assigned weights and the threshold [14-15]. Formula (2) is the output expression.

$$output = \begin{cases} 0 & if \sum_j \omega_i x_i \le threshold \\ 1 & if \sum_j \omega_i x_i > threshold \end{cases} \tag{2}$$

In formula (2), ω_i is the weight of the input i . x_i is the input i . Different decision models can be obtained by adjusting weights and thresholds. The ANN structure is shown in Fig. 3.

In Fig. 3, alterations in weight will consequently result in modifications to the output. Consequently, the desired output can be achieved by modifying the weight or threshold. However, since the change in weight or threshold of a single sensor will cause the complete reversal of the output, it is necessary to introduce an S-type nerve to overcome this problem [16-17]. Meanwhile, the output of the sensor will be rewritten as formula (3).

$$output = \begin{cases} 0 & if \sum_j \omega_i x_i + b \le 0 \\ 1 & if \sum_j \omega_i x_i + b > 0 \end{cases} \tag{3}$$

In formula (3), b means offset. The output of the S-type primitive is an S-type function, and its calculation formula is shown in formula (4).

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{4}$$

In formula (4), z represents the input of S-type neurons. To find the appropriate weight and threshold, a cost function is defined in formula (5).

$$C(\omega,b) = \frac{1}{2n} \sum_x \left\| y(x) - a \right\|^2 \tag{5}$$

In formula (5), W represents the collection of all weights. B represents the aggregate of all offsets. n indicates the quantity of input data. a represents the output vector. The change of the independent VARiable in C is shown in formula (6).

$$\Delta v = \left(\Delta v_1, \Delta v_2, \cdots, \Delta v_m\right)^T \tag{6}$$

In formula (6), v represents the independent VARiable. Formula (7) is the change of cost function at this time.

$$\Delta C \approx \nabla C \cdot \Delta v \tag{7}$$

In formula (7), ∇C refers to gradient shown in formula (8).

$$\nabla C = \left(\frac{\partial C}{\partial v_1}, \cdots, \frac{\partial C}{\partial v_m}\right) \tag{8}$$

At this time, independent variable change calculation is shown in formula (9).

$$\Delta v = -\eta \nabla C \tag{9}$$

Through repeated v changes, the minimum value of the cost function can be found, to determine the learning rules of ANN.

B. Fire risk assessment based on SGD-ANN

Before building the model, it is necessary to collect fire-related data and network search data. The fire-related data is taken from “China Fire Yearbook”, and the network search data is taken from Baidu index of Baidu search. After collecting the data, a keyword candidate database is established. First, the initial keywords are determined according to the primary selection and expansion rules of keywords and expanded through the demand map of Baidu Index. After collecting the initial keywords, the text related to fire is retrieved from the Internet again, and all candidate words are obtained through the keyword mining tool. At this point, it should be noted that some professional words not included by Baidu and words with low search frequency are invalid words, which need to be kicked out of the keyword alternative library. The remaining candidate words are combined to form the initial keyword vocabulary. Finally, according to the search data and fire risk correlation framework, a keyword candidate database is built. The keyword alternative library is shown in Table 1.

In Table 1, different fire stages have different keywords. For example, in the stage of fire, keywords such as fire safety knowledge, fire escape, fire prevention, alarm, and so on are

TABLE 1
KEYWORD ALTERNATIVE LIBRARY

Fire stage	Classification	Keyword
Fire occurs	Fire protection knowledge	Fire safety knowledge, fireproof, fire escape, alarm
Fire spread and smoke spread	Accident losses	Crime of negligently causing a fire, fire accident
Fire rescue	Rescue system	Fire emergency plan, firefighting demonstration, fire code, safety management
	Rescue resources	Automatic fire alarm system, fire bride, fire fighter, fire extinguisher, firefighting equipment, fire facilities, fire engine, fire water tank
Post disaster handling	Safety awareness	Fire drill, fire publicity, fire engineer, fire collection, fire safety training
Daily status	Common words	firefighting, fire, fire alarm, fire safety

TABLE 2
CORRELATION COEFFICIENT AND SIGNIFICANCE LEVEL OF KEYWORD INDICATORS

Corresponding VARiable	Keyword	Correlation coefficient	Significance level
X1	Fire	0.59	0
X2	Fire bride	0.55	0
X3	Fire engineer	0.59	0
X4	Fire accident	0.65	0
X5	Fire facilities	0.58	0
X6	Fire emergency plan	-0.66	0
X7	Fire extinguisher	0.56	0
X8	Fire engine	0.56	0

more relevant to this stage. After creating the database of candidate keywords, the correlation coefficient of each keyword is calculated, and the keywords with the absolute value of the correlation coefficient greater than or equal to 0.5 are selected, and the significance test is performed to eliminate the words with high significance levels. Finally, the cointegration test is performed on the remaining words. If they can obtain a stable sequence after linear combination, it indicates that the corresponding keywords have a long-term stable relationship. The correlation coefficient and significance level of keyword indicators are shown in Table 2.

In Table 2, the coefficient absolute value of the selected keyword indicators is more than 0.5, and the significance level is 0, which is not a low probability event. After the keyword index system is selected, the fire risk assessment model can be established. Considering the non-linear relationship between keywords and fire loss, ANN is selected to build the fire risk assessment model. In the modeling process, first the environment variables are cleared and the data is imported. Then the data is divided into training data and validation data, and the data is standardized. Then, the ANN parameters are determined. The number of nodes in the input layer of ANN is 8. However, as the iteration of ANN increases, abnormal sample information is added to the model, resulting in over-fitting of the model. Therefore, the ANN needs to be optimized [18-19]. In the traditional neural network-free model, the gradient descent algorithm calculates the gradient of the objective function through all the training data. Its parameter update calculation formula is shown in formula (10).

$$\theta = \theta_0 - \eta * \nabla_\theta J\left(\theta\right) \tag{10}$$

In formula (10), θ represents the updated parameters. θ_0 indicates the parameters before updating. η represents the step size. $J\left(\theta\right)$ represents the function associated with θ. However, each time the parameters are updated, the gradient of similar samples will be repeatedly calculated due to the decline of batch gradient, resulting in computational redundancy. Therefore, the study selects SGD to optimize ANN and construct SGD-ANN. Formula (11) expresses the calculation formula of SGD.

$$\frac{\partial J\left(\Theta\right)}{\partial \theta_j} = \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right) x_j^{(i)} \tag{11}$$

In formula (11), $x^{(i)}$ and $y^{(i)}$ represent the sample and i output respectively. At this time, the parameter update calculation is shown in formula (12).

$$\theta = \theta_0 - \eta * \nabla_\theta J\left(\theta; x^{(i)}; y^{(i)}\right) \tag{12}$$

The SDG algorithm updates the parameters using a training sample and a label. When the batch gradient drops to the minimum, the SDG algorithm can make the loss function jump to a better local minimum through its fluctuation, effectively avoiding the problem of computational redundancy [20]. The commonly used transfer functions of ANN include logsig function, tansig function, and softmax function. The formula of logsig function is shown in formula (13).

$$\log sig = \frac{1}{1+e^{-n}} \tag{13}$$

The formula of tansig function, namely the hyperbolic tangent function, is shown in formula (14).

$$\tan sig\left(n\right) = \frac{2}{1+e^{-2n}} - 1 \tag{14}$$

The formula of softmax function, i.e. flexible maximum transfer function, is shown in formula (15).

$$f\left(x\right) = \frac{e^x}{\sum e^x} \tag{15}$$

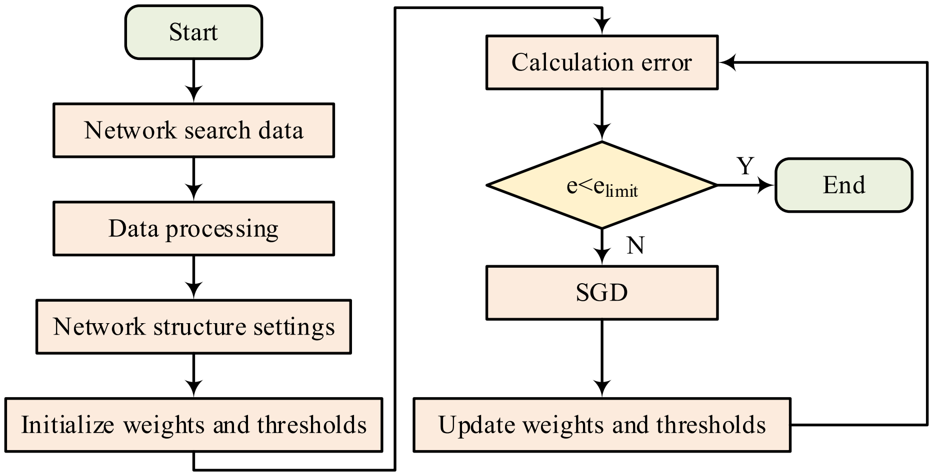

Fig. 4. The flow of the fire risk assessment model based on SGD-ANN

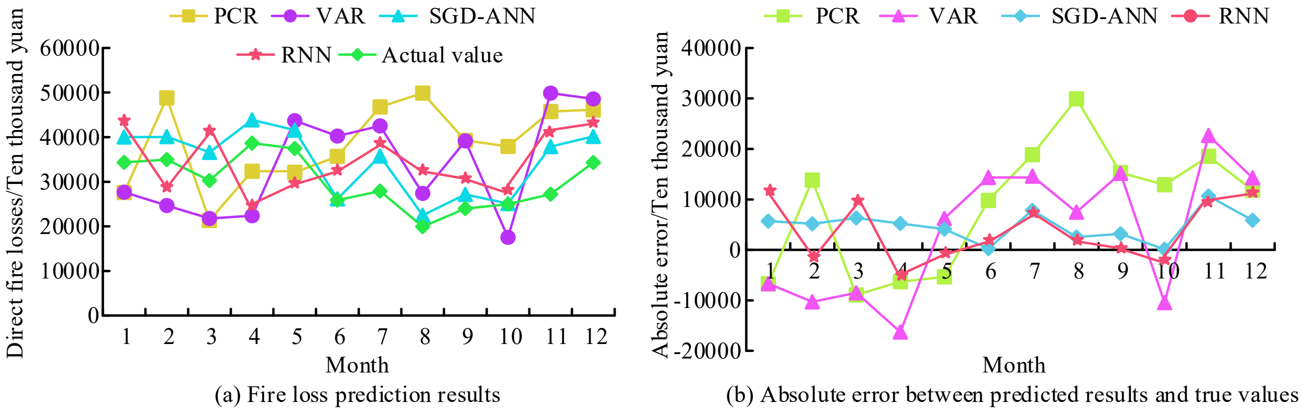

Fig. 5. Fire loss prediction results and absolute errors of SGD-ANN model, PCR model, and VAR model

The above transfer functions have their advantages and disadvantages, but considering the problem of reducing the fitting error of the model, the tansig function is selected as the ANN transfer function. Meanwhile, to obtain sufficient information and avoid over fitting problems, 7 hidden layer neurons are selected in this study. The flow of the fire risk assessment model based on SGD-ANN is shown in Fig. 4.

From Fig. 4, first, the network search data is processed, then the network structure is set, and the weight and threshold are initialized. If the error is less than the threshold, the algorithm ends, otherwise the weight and threshold are updated by SGD and the error is recalculated.

IV. FIRE RISK INTELLIGENT ASSESSMENT TEST

SGD-ANN was tested to verify its performance. It was compared with the principal component regression model, vector autoregressive model, and RNN. In the experiment, the number of nodes in the input layer of SGD-ANN was 8, the maximum number of iterations was 1000, and the training accuracy was 0.01. The data of the test set was the fire-related data of a certain year in China. The fire loss prediction results and absolute errors of the SGD-ANN model, PCR model, VAR model, and RNN are shown in Fig. 5.

According to Fig. 5(a), the maximum direct fire loss predicted by the PCR model was 487.86 million yuan, and the minimum was 213.46 million yuan. The maximum fire loss predicted by the VAR model was 498.78 million yuan, and the minimum was 175.27 million yuan. The maximum loss predicted by RNN was 476.85 million yuan, and the minimum was 225.14 million yuan. The maximum predicted loss of SGD-ANN was 438.71 million yuan, and the minimum was 224.86 million yuan. The prediction of SGD-ANN was consistent with the actual value. In Fig. 5 (b), the maximum absolute errors of PCR and VAR prediction results were 299.43 million yuan and 226.58 million yuan, respectively. The minimum absolute errors were 53.55 million yuan and 62.25 million yuan, respectively. The average absolute errors were 131.917 million yuan and 122.457 million yuan, respectively. The maximum, minimum, and average absolute error of SGD-ANN were about 106.67, 1.29, and 47.458 million yuan, the prediction error of RNN was not much different from that of SGD-ANN, but it was even higher than that of SGD-ANN. The above results showed that the proposed model predicted fire loss more accurately, because the search of multi-network data expanded the scope of data sources and provided more support for the prediction model. The error of the fire loss prediction results of SGD-ANN was smaller. The relative error of fire loss prediction is shown in Fig. 6.

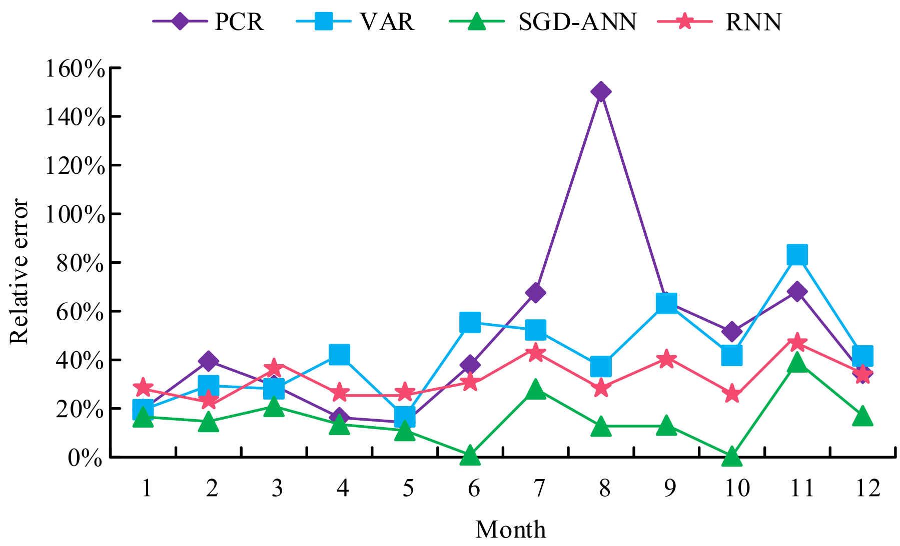

Fig. 6. Relative error of fire loss prediction

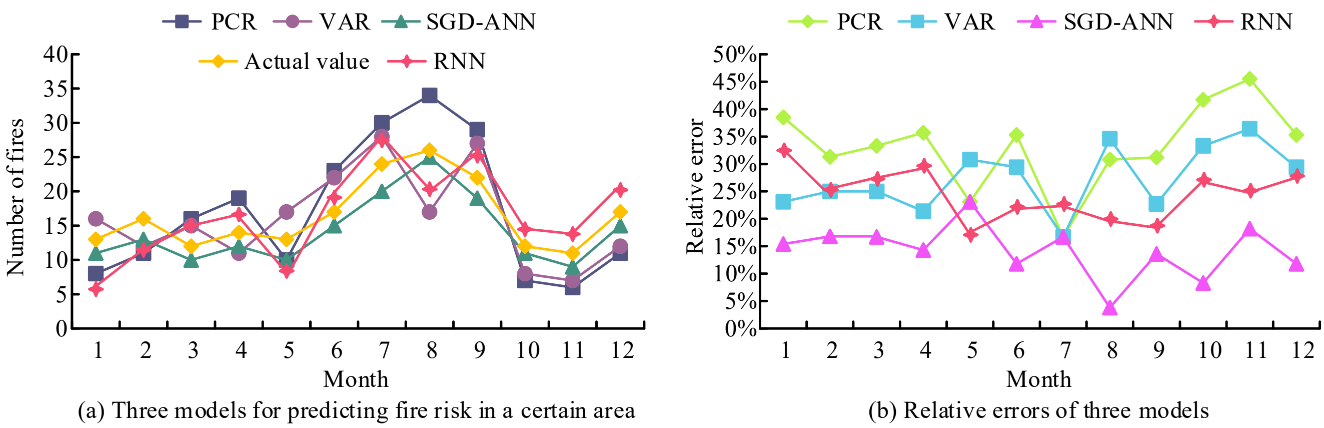

Fig. 7. Fire risk prediction results and relative errors of three models for a certain area

In Fig. 6, PCR and VAR maximum relative errors were about 150.2% and 83.2% respectively. The minimum relative errors were about 14.3% and 16.6% respectively. The average relative errors were 49.4% and 42.6% respectively. The maximum and minimum relative errors of RNN were 59.7% and 21.2%, respectively. The maximum, minimum, and average relative errors of SGD-ANN were about 39.2%, 0.5%, and 15.7%, respectively. SGD-ANN prediction results had a higher degree of fitting with the actual values. This was because by searching the network data, the research model had more sample data to predict the fire loss combined with the case data, and then improved the fit of the prediction results to the actual situation. The fire risk prediction results and relative errors of the four models for a certain place are shown in Fig. 7.

According to Fig. 7 (a), the maximum number of fires predicted by PCR, VAR, and RNN were 34, 28, and 27 respectively, which were different from the actual values by 8 and 4 respectively. The predicted minimum number of fires was 6 and 7, which differed from the actual by 5 and 4 times, respectively. The maximum and minimum number of fires predicted by SGD-ANN were 25 and 9, respectively, which were 1 and 2 times different from the actual value. According to Fig. 7 (b), PCR and VAR maximum relative errors were about 45.5% and 36.4%, respectively. The average relative errors were about 33.2% and 27.3%, respectively. The maximum and average relative error of SGD-ANN were about 23.1% and 14.2%, respectively. The outcomes revealed that the prediction result of SGD-ANN on fire risk was closer to the actual situation. Four models' accuracy is shown in Fig. 8.

In Fig. 8, the accuracy of PCR, VAR, and RNN was about 72.8%, 74.2%, and 78.3%, respectively. The lowest was about 68.5%, 71.8%, and 73.4%, respectively. The average accuracy was about 70.9%, 72.7%, and 75.5%, respectively. The accuracy of SGD-ANN was about 75.8% and 82.2%, respectively, and the average accuracy was about 79.9%. The above results showed that the fire prediction accuracy of SGD-ANN was higher. The precision and recall rates of the four models are shown in Fig. 9.

In Fig. 9 (a), the precision of PCR, RNN, and VAR was about 73.4%, 83.3%, and 74.9%, respectively. The lowest was about 69.7%, 75.4%, and 72.2%, respectively. The average accuracy was about 71.7%, 77.3%, and 73.9%, respectively. The highest precision, lowest precision, and average precision of SGD-ANN were 83.9%, 77.3%, and 81.2%, respectively. According to Fig. 9 (b), the highest recall rates of PCR, VAR, and SGD-ANN were about 76.7%, 77.5%, and 83.1%, respectively. The average recall rates were about 74.6%, 75.9%, and 81.9%, respectively. Among them, the accuracy and recall rate of SGD-ANN were higher than the other two models. The F1 measure of the four models is shown in Fig. 10.

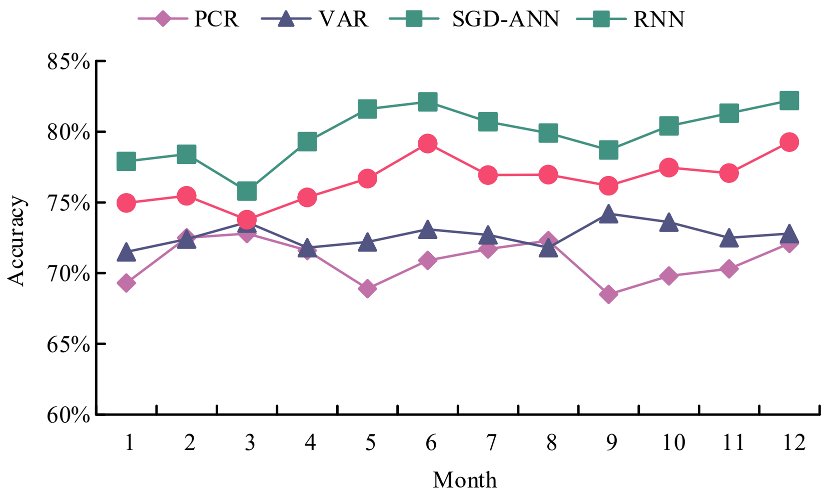

Fig. 8. Accuracy of three models

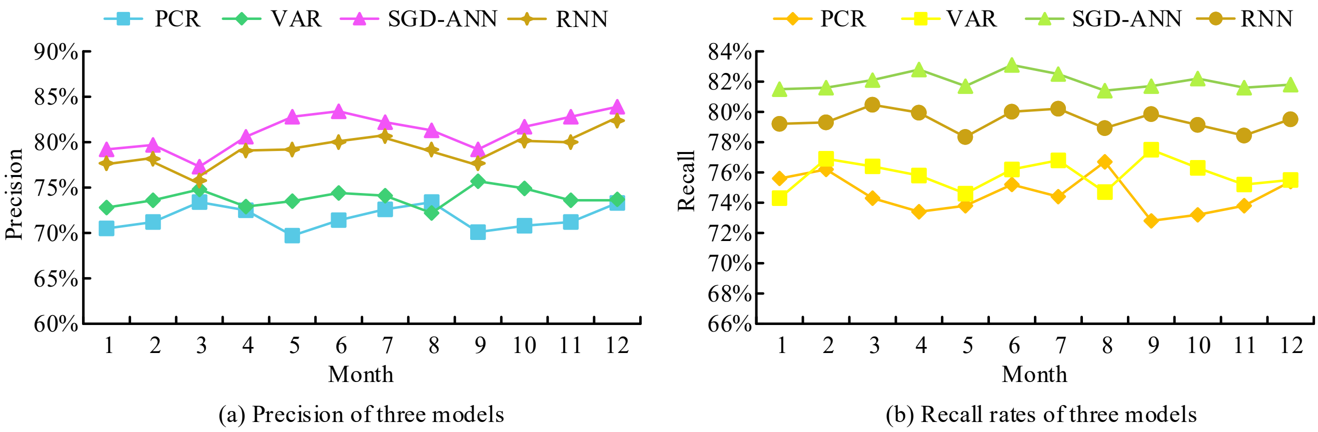

Fig. 9. Precision and recall of three models

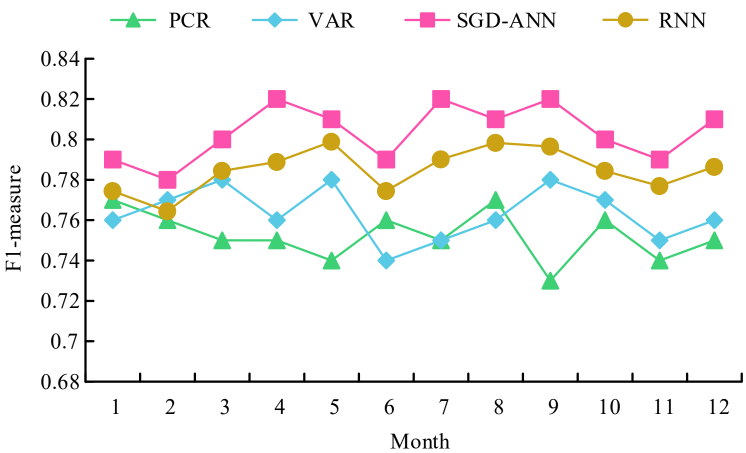

Fig. 10. The F1 measure of the four models

In Fig. 10, the F1 measure of PCR, VAR, RNN, and SGD-ANN was about 0.77, 0.78, 0.8, and 0.82 respectively. The lowest values were 0.73, 0.74, 0.76, and 0.78 respectively. The average F1 measure was about 0.75, 0.76, 0.77, and 0.8, respectively. The comprehensive performance of SGD-ANN outperformed the PCR model and VAR model. The fitting degree of the PCR, VAR, and SGD-ANN models is shown in Fig. 11.

In Fig. 11 (a), the difference between the output data of the SGD-ANN model and the average expected data was small, and its fitting degree was about 0.94. In Fig. 11(b), among the output data of the VAR model, three output data were very different from the expected data, and the rest were close to the expected data. Thus, the goodness of fit of the VAR model was about 0.83.

In Fig. 11 (c), in the output data of PCR, there was a large difference between the five and expected data.

The fitting degree of the model was about 0.61. The above results showed that the SGD-ANN model had good generalization ability. The time complexity of the algorithm is shown in Fig. 12.

In Fig. 12, the time consumption of the four algorithms increased with the data size. However, among the four algorithms, the RNN and SGD-ANN algorithms were always lower than the other two algorithms, which had a time consumption of about 2.9s at the data scale of 2600. To further analyze the performance of the proposed fire risk assessment model based on SGD-ANN, it was compared with the

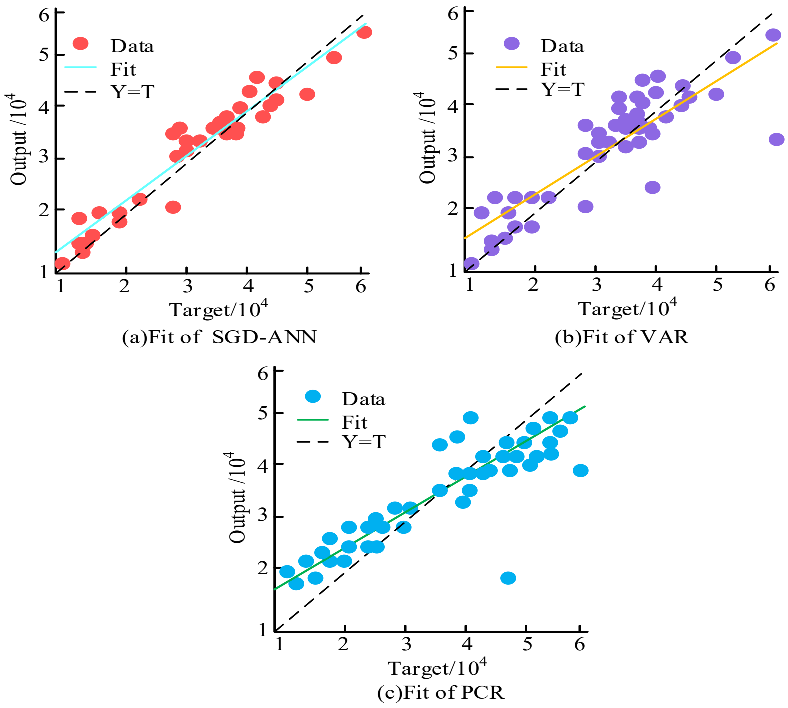

Fig. 11. Fit of three models

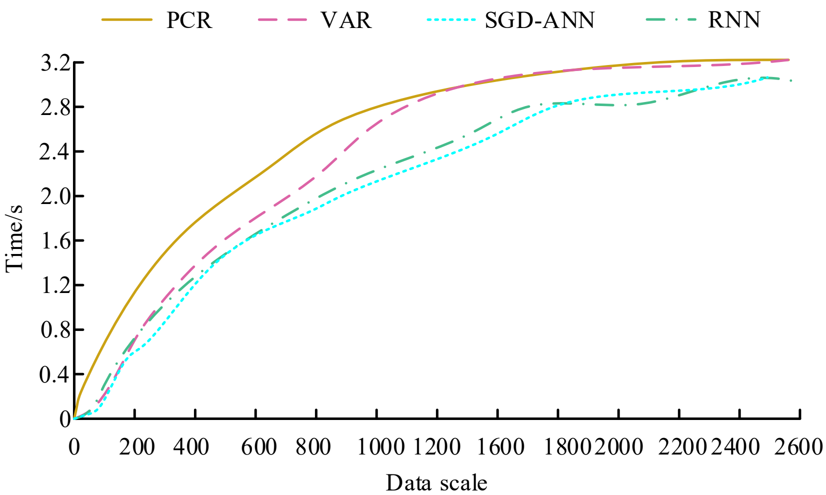

Fig. 12. of the time complexity of the algorithm

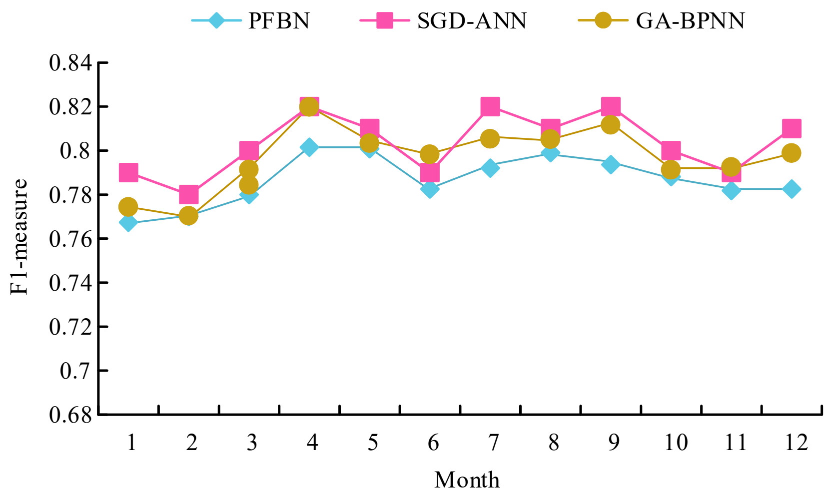

Fig. 13. performance of the fire risk assessment

polymorphic fuzzy Bayesian network (PFBN) and the genetic algorithm back propagation neural network (GA-BPNN). The results are shown in Fig. 13.

In Fig. 13, although the F1 measure of GA-BPNN is occasionally higher than that of SGD-ANN. However, overall, the F1 measure of SGD-ANN was still higher. The F1 measure of PFBN was consistently lower than that of SGD-ANN. The average F1 measures of PFBN, SGD-ANN, and GA-BPNN were 0.783, 0.800, and 0.792, respectively. The above results indicated that the proposed fire risk prediction model based on SGD-ANN had better performance.

V. Conclusion

As the population grows, the fire pressure of the city also increases. To alleviate this pressure and promote the development of intelligent fire protection, a fire risk assessment model based on SGD-ANN was proposed. This study established the theoretical framework of network search data applied to urban fire risk assessment through Heinrich's theory of needs, and used the SGD algorithm to optimize ANN to evaluate the correlation between search data and fire to realize the assessment of fire risk. The model was compared with the PCR model, VAR model, and RNN. The experimental results showed that the average absolute errors between the predicted results of the PCR model, VAR model, and SGD-ANN model and the actual values were 131.917 million yuan, 122.457 million yuan, and 47.458 million yuan, respectively. The relative errors were about 49.4%, 42.6%, and 15.7%, respectively. SGD-ANN was more accurate in predicting the direct loss of fire. In the prediction of fire accidents, the average absolute errors of the PCR model, VAR model, and SGD-ANN model with the actual value were 5.4, 4.4, and 2.3 respectively. The average relative errors were about 33.2%, 27.3%, and 14.2%, respectively. SGD-ANN prediction result was closer to the actual value. The average accuracy rates of the three models were about 70.9%, 72.7%, and 79.9%. The average accuracy rates were about 71.7%, 73.9%, and 81.2%. The average recall rates were about 74.6%, 75.9%, and 81.9%. The average F1 measure were 0.75, 0.76, and 0.8, respectively. It can be concluded that the SGD-ANN model had a stronger ability to assess fire risk. The fitting degrees of the SGD-ANN, PCR, and VAR models were 0.94, 0.61, and 0.83 respectively, which showed that the SGD-ANN model had stronger generalization ability. The above results showed that the fire prediction accuracy of SGD-ANN was not only high but also fitted the output results to the actual situation. The fire detection model proposed by Hashemzadeh M et al. could achieve early fire detection through smoke detection. The fire detection model based on the UFS network proposed by Hosseini A et al. could realize fire detection by simultaneously detecting flame and smoke. Hashemzadeh M and Zademehdi A proposed a flame detection algorithm based on the ICAK-color model to solve the problem of automatic flame detection in video. Although the above model could better detect the fire, it was difficult to assess the fire risk and give the loss of fire. The model proposed by the study could realize the fire risk prediction and give the possible fire loss situation, which was more suitable for intelligent firefighting than the above model. The fire risk assessment model based on network search data proposed in this article has high accuracy, but there are still some shortcomings. The research relies solely on ANN and does not incorporate other deep learning techniques such as CNN, DBN, and RNN. As a result, the proposed fire risk assessment model does not take full advantage of data exploration and lacks interpretability. Therefore, future research will focus on how to combine deep learning with fire risk assessment.

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