

DEEP LEARNING OF QINLING FOREST FIRE ANOMALY DETECTION BASED ON GENETIC ALGORITHM OPTIMIZATION

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Located in the most famous part of the north-south boundary of China, Qinling Mountains boast dense forests and high vegetation coverage. In forest areas, effective monitoring and prevention of fires is an important issue demanding urgent solution. This is because fire prevention can not only effectively protect the surrounding environment, but also provide an important guarantee for living and personal safety of surrounding residents. To achieve rapid, effective and accurate analysis and prevention of forest fires, this paper proposes a deep learning time-series convolutional neural network (GA-CNN) optimized by genetic algorithm, which can detect fire occurrences with high accuracy in the environment. In different evaluation scenarios, it exhibits good performance in accuracy, true positivity, and false alarm rate. The optimized CNN is not only capable of global optimization, but also can judge convolutional neural network by time series. In this way, it can not only avoid the problem of convergence difficulty and improper model structure selection that are often encountered in convolutional neural networks, but also effectively reduce the allocation of human resources for forest protection. Experimental results show that the proposed forest fire image recognition method achieves higher recognition and false alarm rates than other algorithms (BP (Back Propagation) neural networks, namely the learning process of error inversion error backpropagation algorithm, SVM (Support Vector Machine) and genetic algorithm optimized BP neural network (GA-BP) and can be used to liberate manpower without requiring complex manual feature extraction to identify features of forest fire edges.

Keywords: forest fire, genetic algorithm, deep learning, time series, convolutional neural network, anomaly detection, global optimization

1. Introduction

Forest fires in the Qinling Mountains constitute one of the most harmful disasters affecting the ecological environment. Capable of rapid spread, it causes economic losses, environmental hazards and even threatens human lives. In fact,

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fire sensors, as a supplement to traditional point sensors (such as smoke and heat detectors), provide people with early warning against fire. However, cameras combined with image processing technology can detect fires more quickly than point sensors. In addition, it is easier for them to provide fire size, growth, and direction information than traditional detectors. At present, with the continuous advancement in digital image processing and the in-depth integration of machine learning pattern recognition algorithms, the recognition algorithms for forest fire detection are constantly updated and widely used. The images collected by forest fires generally consist of smoke images and flame images. Where, smoke image is of great significance in the early discrimination, while the flame image itself has the following characteristics such as infrared radiation, color, texture, etc. Traditional forest fire recognition methods are based on several artificially selected features in recognition of forest fire images, whose accuracy depends entirely on artificial selection of features [1]. Recognition must be performed under good visible light, without interference from factors like fog. However, in actual forest fire monitoring, a large forest area generally needs to be monitored, so more interference are likely, and the line of sight will be poor. In addition, forest area has high humidity and fog, which significantly reduces the visible transmittance. Flame combustion image features infrared radiation heat effect, continuous fire spread and texture. The recognition accuracy of the previous forest fire recognition algorithm based on pattern recognition depends on manual selection of features, thus merely applicable to specific data sets and with insufficient generalization ability. In view of this, some scholars have proposed a Convolutional Neural Network (short for CNN) fire image recognition method based on deep learning (short for DL). This method can avoid manual feature extraction and automatically extract forest fire image characteristics but cannot avoid falling into the local minimum. At the same time, some scholars have proposed to use adaptive CNN network and Faster R-CNN (Regions with CNN) network to increase training accuracy. Some researchers have proposed an image detection algorithm based on Principal Component Analysis Network (short for PCA-Net) [2]. PCA-net has the advantages of simple structure and fewer training parameters, which can effectively solve the gradient dispersion problem in backpropagation, avoid the explosion of its parameters in building models of various spatiotemporal features, such as color features, flicker features, and dynamic texture analysis features. Proven to be able to detect fires, it has the same effect as previous wavelet in detecting smoke and flames. The same is also true for support vector machines, Markov models, regional covariances, covariance matrices, etc.

However, when large-area flame is detectable, the fire is difficult to control, so we focus on not only fire flame detection, but also smoke detection. This is mainly because the smoke rises above the tree canopy, with more

possibility of falling into the observation range of the camera monitoring the forest [3]. Therefore, based on the basic characteristics of forest fire images mentioned earlier, we will propose a new forest fire image recognition method. In this method, first, based on the characteristics of forest fire images, a CNN classifier optimized by genetic algorithm is used to detect flames and smoke respectively, so that preliminary judgments can be made on anomaly detection of forest fires.

2. Method

Convolutional neural network [4] can process high-dimensional data and adapt to large-scale network environments. At the same time, it can fully perform nonlinear mapping of data features without manually extracting features to dig out the connections between features, which is thus one technology urgently needed for forest fire. However, in practical applications, convolutional neural networks often face various problems such as difficulty in convergence and improper model structure selection, resulting in its poor prediction performance in forest fire detection. Therefore, finding a globally optimized algorithm based on DL-CNN has become an urgent problem to be solved. In this paper, we combine the optimization algorithm GA genetic algorithm respectively and the time series-based convolutional neural network with the traditional BP neural networks to observe which algorithm combined is more advantageous. It is well known that traditional BP neural networks are a backpropagation algorithm, while time series-based convolutional neural networks have more advantages in images. To better explore its feasibility to solve this problem, as shown in Fig.1, this paper combines GA genetic algorithm and time series-based convolutional neural network.

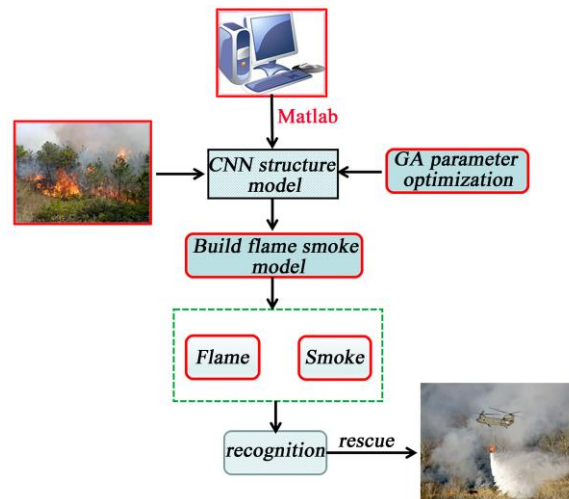


Fig. 1 Schematic diagram of forest fire detection

Considering that genetic algorithm itself has quite powerful global optimization capability, the two are combined to obtain a globally optimized deep learning [5] convolutional neural network. Subsequently, by detecting the fire part and smoke part in the image data set, the optimized time series convolutional neural network is analyzed and experimentally verified.

For CNN, it is a framework for deep learning, which is inspired by biological visual perception mechanisms. Widely used in image classification, it can achieve higher classification accuracy on large data sets compared with manual feature extraction, which is mainly composed of three continuous modules: convolutional layer, pooling layer and fully connected layer [6]. Convolutional layer operation is to apply several cores of different sizes on the input data to generate feature maps, and these feature maps are input to the next operation, becoming sub-sampling or pooling. The biggest activation item in the pooling layer is to select the nearest neighbors therefrom. These operations are quite important for reducing dimensionality of the feature vector and achieving a certain degree of translation invariance. Another important layer of the CNN model is the fully connected layer. Where, high-level abstraction is modeled from the input data. Among these three layer operations, the convolutional layer and the fully connected layer contain neurons, whose weights are learned and adjusted to better indicate the input data in the training process. The time series-based CNN model proposed here contains two consecutive convolutional layers behind the input layer. This structure supports extraction of higher-level features in a shallower network depth and also avoids feature information loss after pool layer processing. After the pooling operation, the feature is extended into one dimension, and then input to the fully connected layer to output the result.

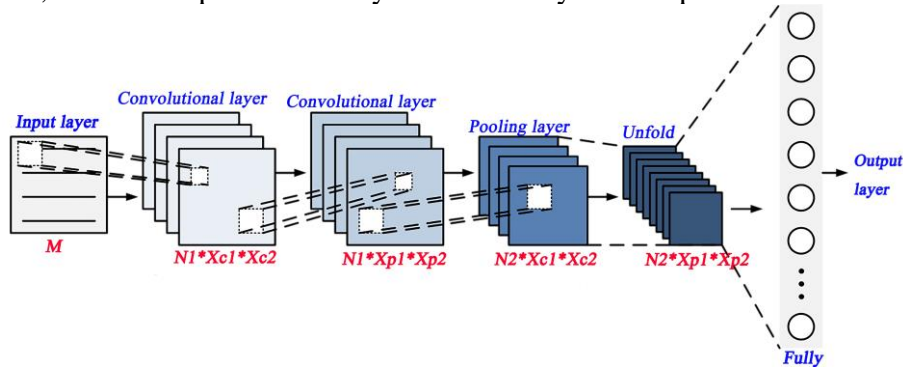


Fig. 2 Basic structure diagram of CNN based on time series model

As shown in Fig.2, CNN consists of a convolution layer, a pooling layer, and occasionally a full connection layer. CNN's performance relies heavily on its depth, and skipping connections can make depth a reality. We designed a new building block and directly used skip-layer to replace the convolution layer when forming CNN. Specifically, the skip layer consists of two convolution layers and a

skip connection. Skip connections connect the input of the first convolution layer to the output of the second convolution layer. As mentioned above, the parameters of the convolution layer are the number of feature maps, the filter size, the step size, and the type of convolution operation.

In the convolutional layer, the size of the output feature vector of the convolutional layer is affected by many parameters. These parameters are the key to determining the feature extraction effect of the CNN model. Choosing a good parameter combination can speed up the network learning effect.

$$m = \frac{i - k + 2l}{n} \quad (1)$$

In equation (1): m is the size of the output feature, i is the size of the input feature [7], k is the size of the convolution kernel, l is the moving step length, n is the number of fillers. These parameters need to be set in advance, which play a vital role in feature extraction.

The pooling layer is mainly to reduce the feature vectors output by the convolutional layer, further extract main features, retain important feature information, increase robustness of feature information extraction, thus effectively reducing model processing time and reducing overfitting. The size of the pooling layer output feature is determined by equation (2). Where, P_n is the sampled and l is the movement step size.

$$o = \frac{l - P_n}{n} \quad (2)$$

At the same time, the fully connected layer will flatten and filter the output parameters of the convolutional layer and the pooling layer, including: the number of neurons, dropout [8], the initial weight threshold, etc., thus avoiding impact of these parameters on features of convolutional layer and pooling layer.

Based on the above analysis, CNN learning effect is affected by many parameter factors, and unreasonable initial parameter setting may make the network unable to converge quickly, so that the network performance ultimately fails to achieve the expected effect. Therefore, CNN structure optimization is an urgent problem to be solved. In recent years, there are constantly emerging CNN optimization methods, but they are basically based on initial weights, fully connected weights and a small number of parameters. Many parameters still demand manual selection. On this basis, by selecting genetic algorithm, combining crossover and mutation operations, a GA-CNN algorithm [9] is proposed. This method makes the individual fitness value of the convolutional neural network with the smallest verification error as the basis for determining parameters such as number of convolution kernels, size of convolution kernels and pooling kernels in convolutional neural network, the maximum number of

iterations of training, and the regularization factor, thus deriving the optimal parameter combination.

3. Algorithm description

The genetic algorithm is applied to optimize the parameters of convolutional neural networks, including automatic selection of optimal initial weights, thresholds, network structure parameters, activation functions, optimizers and fully connected layer neurons. The specific operation process is as follows:

(1) Determine the size parameter of the population; equation (1) uses the set M to represent the primary population, and X_n is an individual of the population;

(2) Initialize the population and assign the network parameters in Fig. 2 to the individuals. The gene string of each individual is composed of the initial weight threshold, a set of network parameters and training parameters, and the loss function value and accuracy function value are set to 0; Equation (2) is a set to indicate individual gene sequences. Where, K represents the initial weight threshold, N_i represents the number of convolution kernels, X_{ci} and X_{pi} represents the size of the convolution kernel or pooling layer, λ represents the regularization factor, and η represents number of training iterations;

$$X_n = [K, N_1, X_{c1}, X_{p1}, N_2, X_{c2}, X_{p2}, \lambda, \eta] \quad (3)$$

(3) Optimize individual genetic operations and calculate the fitness value of chromosomes. The optimization criteria include methods to determine the crossover probability P_c and the mutation probability P_m [10]. The optimized parameter values conform to the following equations :

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{max} - f_{avg}} & f' > f_{avg} \\ P_{c1} & f' < f_{avg} \end{cases} \quad (4)$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(f_{max} - f)}{f_{max} - f} & f > f_{avg} \\ P_{m1} & f < f_{avg} \end{cases} \quad (5)$$

Where: f_{avg} is the average fitness of the target population, f_{max} is the maximum fitness of the target population, f' is the larger fitness individual in the calculation to be performed, and f is the individual fitness in the mutation [11].

(4) Check whether the generated new individual meets the optimal conditions. If so, continue to the next step; otherwise, return to step (3);

(5) Use the optimal initial weights, thresholds, network structure parameters, optimizer and the number of neurons in the fully connected layer

obtained by genetic algorithm to update the convolutional neural network [12] as a new network training model.

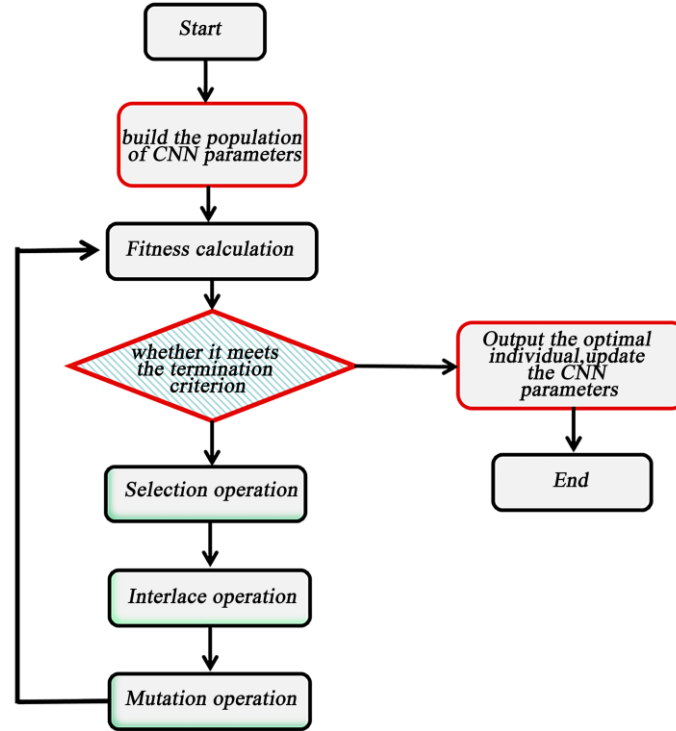


Fig. 3 Operation flow chart of optimized genetic algorithm

4. Experiment

Table 1 lists the data set of the forest fire detection experiment based on CNN, which is mainly derived from forest fire smoke videos [13] and pictures on the Internet to constitute a relatively complete forest fire smoke picture database. From the table, the data set is mainly composed of two parts: the training set and the test set, a total of 1900 images. The images are mainly composed of smoke images and flame images, and both include positive and negative samples. Based on the CNN algorithm[14], the BP neural network algorithm[15] and the SVM algorithm, the data in Table 1 are processed respectively, with the results shown in Table 2. From Table 2, it can be seen that the accuracy value of the optimized GA-CNN algorithm is 0.95, which is higher than that of unoptimized CNN algorithm (0.85), BP neural network algorithm (0.73) and the SVM algorithm; and its true positive rate is also higher than that of the unoptimized CNN and BP neural network algorithms. Fig. 4 shows the calculated forest fire results based on the optimized CNN algorithm. From this figure, it can be seen that Fig.4(a)-(e) are positive samples, and Fig.4(f) is a negative picture with misjudgment.

Table 1

Data set detection information of forest fire detection experiment

Classification		Training set	Test set	Total
Smoke image	positive	400	140	540
	Negative	350	60	410
Flame image	positive	400	110	510
	Negative	350	90	440
Total		1500	400	1900

Table 2

Comparison of results of different algorithms

Result	BP neural network	CNN	SVM	GA-BP	GA-CNN
Accuracy rate	0.73	0.85	0.82	0.83	0.95
True positive rate	0.75	0.81	0.79	0.8	0.92



Fig. 4 Forest fire detection results

5. Conclusion

This paper proposes a CNN model based on genetic algorithm optimization for forest smoke and flame detection. It uses crossover, mutation, and optimal evolution methods. The iterative genetic evolution method is used to model and train the individual that meets the fitness requirement as the target parameter. This greatly improves the accuracy of the model, improves its local optimization problems, and improves the recognition rate of images. Therefore, this model has important practical application value in forest fire prevention planning and forest management. Experiments show that the method proposed by GA-CNN on the basis of relatively limited samples, compared with purely using the CNN algorithm and the traditional BP neural network machine learning algorithm optimized using genetic algorithm and the algorithm of SVM, to detect forest fires, it improves the correctness and accuracy of detection. The accuracy rate reached 0.95, and the true positive rate reached 0.92. In addition, the method in this article proposes that smoke and flame can be detected at the same time, taking full account of the characteristics of forest fires in the early stage. Finally, the experimental results prove that this method is robust and effective.

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