Forest fire monitoring system based on deep neural network

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Abstract. Forest fires not only damage properties, but also bring casualties to nearby residents. It becomes more and more important to monitor and even prevent forest fires at the beginning. With the development of various monitoring approaches, including remote sensing satellites, cameras, unmanned aerial vehicles, etc., we now possess more technical means to monitor the forest. Meanwhile, the collection of large amounts of data also puts a higher demand on the processing speed and accuracy. In recent years, with the rise of artificial intelligence technology represented by deep neural networks, researchers began to apply deep neural networks in forest fire monitoring systems and have achieved better classification and prediction results than traditional methods. In this paper, we review the deep neural network-based forest fire monitoring system, from the perspectives of input data types, methods, and effects. Based on the review, we will point out some further research directions.

Introduction

Forest fires refer to the fires that have lost human's control and freely spread and expand in forests, causing damage and loss to forests, forest ecosystems and human beings. Forest fire is unexpected, destructive and difficult to extinguish. Once a forest fire occurs, it will cause a series of damages, including burning down trees, endangering wild animals[1], causing soil erosion[2] and air pollution[3], lowering water quality of downstream rivers[4], and threatening people's lives and properties[5]. Forest is a renewable resource with a long growth cycle, which takes a long time to recover after suffering from fire. Especially after high-intensity large-area forest fires, the forest is difficult to restore its original appearance and is often replaced by lower trees or shrubs. If the forest suffers fire hazards many times, it will become barren grass, or even bare land. Forests are home to precious wild plants and animals, which means if the environment is destroyed by forest fires, these plants and animals would lose their habitat and become difficult to survive. In addition, forest burning produces a large amount of smoke, in which carbon monoxide, hydrocarbons, carbides, and nitrogen oxides account for about 5% to 10%, causing air pollution and endangering human beings and wild animals.

According to the statistics of National Bureau of Statistics of China from 2004 to 2017, there are thousands of fires in China every year (Figure 1), causing losses valued more than ten million RMB (Figure 3). The good news is that as shown in Figure 1 and Figure 2, the total number of area of forest fires are decreasing year by year.

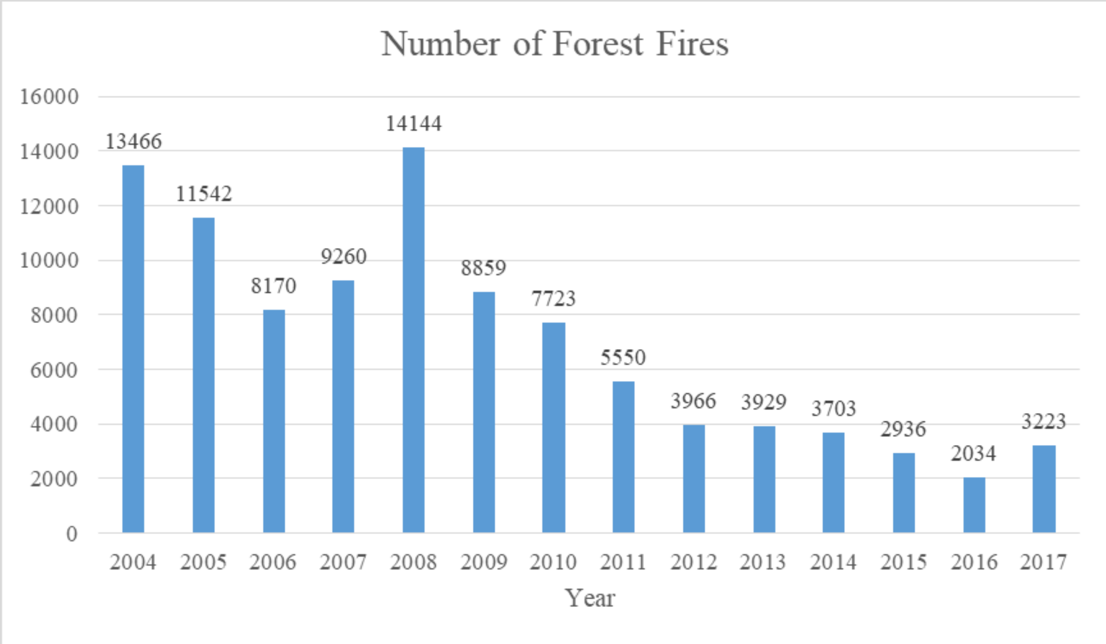

Figure 1. Number of forest fires in China from 2004 to 2017.

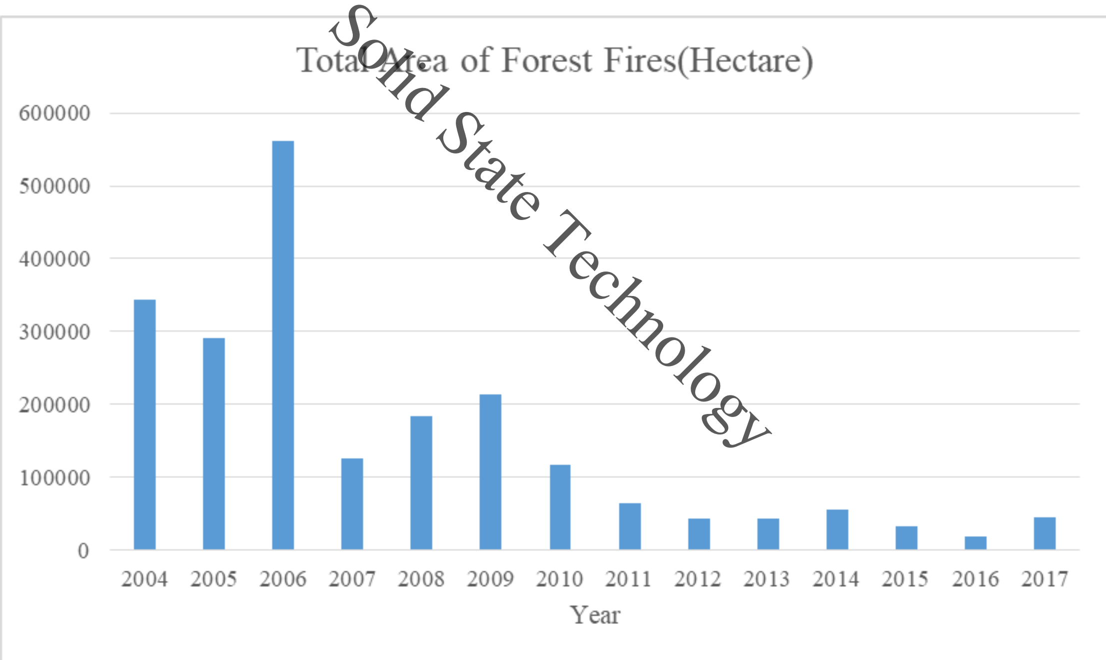

Figure 2. Total area of forest fires in China from 2004 to 2017.

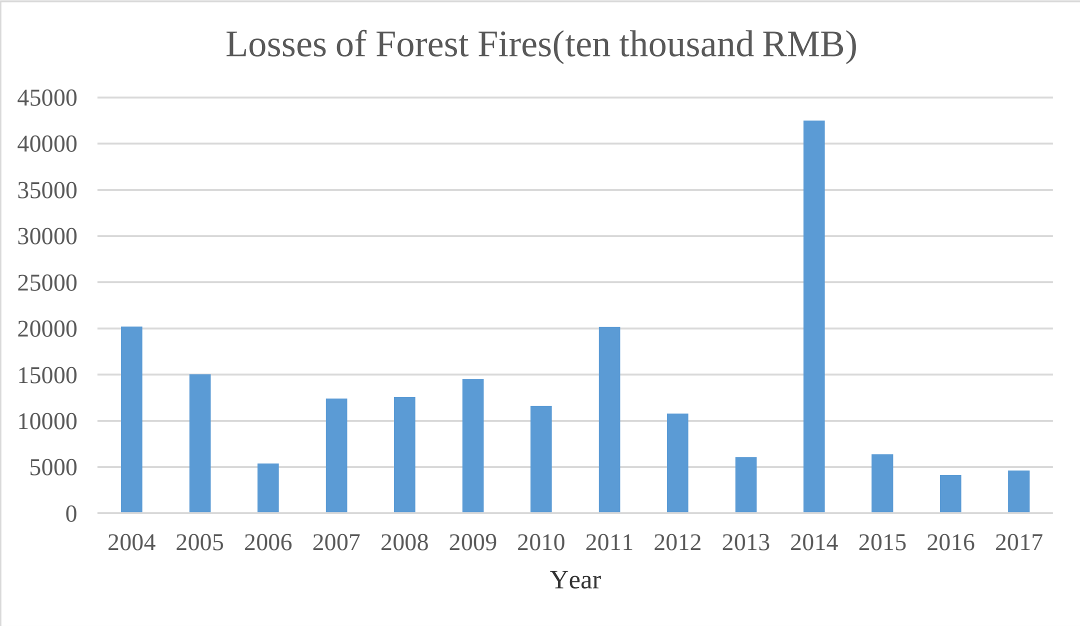

Figure 3. Losses of forest fires in China from 2004 to 2017.

The huge amount of losses caused by forest fires is unneglectable, thus we have to seek measures to solve the problems we are faced with. One company named Silvia Terra, which is one of Microsoft's grant winners, uses satellite data derived from USGS and NASA to map the national forest. The map can provide information to the forestry bureau and environmental organizations, e.g., the size and species of the specific location of trees. An experimental project of video monitoring system for forest fire prevention has been launched in the Great Khingan mountains of China. The thermal imaging adopts the latest Hikvision DS-8031 series heavy load camera platform, which is equipped with 150mm thermal imaging and 750mm visible light lens, and can identify fire point with a 2m*2m size and smoke with 10*10 pixels from 5 kilometers away. With laser ranging functionality, it can precisely locate the fire point. The center iVMS - 9830 visualization management platform is integrated with emergency command platform for forest fire prevention, which conducts locating fire, analyzing fire, analyzing fire trend, emergency command, and evaluating the damage after fire. It has been embedded into a platform of forest fire prevention, rescue and security system. A San Francisco company named Salo Sciences is developing a system to analyze dead and dying trees and map the highest risk of areas with forest fires, which has been tested in California.

In the traditional firefighting process, firefighting institutions know the fire only after receiving the alarm call, and cannot know the cause of the fire, the source of the fire and the specific time of the current fire range, so the traditional method cannot effectively control forest fire. With recent development of artificial intelligence, deep learning[6] represented by deep neural networks have been applied to many different domains and achieved tremendous improvements, including image recognition[7], medical image analysis[8], video classification[9], traffic forecasting[10] and activity recognition[11]. If the neural networks can be used to effectively monitor and even predict forest fires, then we can effectively control the fires in the early stage, protect the forest resources, and avoid huge economic losses.

In this paper, I will discuss several effective neural networks for forest fire prediction and classification in detail. First, I give a brief description of forest fire detection systems and their functionalities in Chapter 2. Then, I summarize the data collected for forest fire detection in Chapter 3. I introduce the methodologies, especially those based on deep neural networks in Chapter 4. I analyze these models in Chapter 5. Finally, I point out the future research directions in Chapter 6.

Systematical Description

Forest fire prediction and recognition are not new stories, but the attempts of applying deep neural networks only happen in recent years and show promising results in both theory and practice. In this paper, I will analyze several kinds of models (Table 1) in the application of forest fire forecasting and recognition, so we can draw some conclusions and possible improvements about the model's performance.

Table 1: Functionalities of forest fire detection systems

Functionality	Relevant papers
Forest Fire Prediction	Model 1[12], Model 6[17]
Forest Fire Image Classification	Model 2[13], Model 3[14], Model 4[15], Model 5[16]

Forest Fire Prediction. For monitoring forest fires, fire prediction is a very effective method. If the location of the fire can be predicted before the fires occur, the damage caused by the fire can be reduced to the minimum. By weather station, temperature, humidity sensors and other equipment, we can gather a lot of useful information, such as temperature, humidity, rainfall, wind speed, etc. Using the information as well as the historical forest fire data, we can train the corresponding neural network to predict fire area and time. Next time before the fire, we can have more time to eliminate it for reducing the loss brought by forest fires.

Forest Fire Image Classification. After the fire occurs, if the traditional method is adopted and the corresponding firefighting measures are taken after the alarm call, we will miss the golden time to extinguish the fire and avoid the causalities and property loss. There are some traditional manual monitoring methods, such as using helicopters to patrol the forest to determine whether there is a fire or not, which consumes a lot of time and money. However, it cannot be real-time monitoring, so the combination of satellite-based remote sensing technology of forest fire to photograph remote sensing images and deep neural networks for identifying fire is definitely efficient and cheap. Additionally, we can also use the unmanned aerial vehicle with fire recognition system to practice, which also uses the deep neural networks for the recognition. In short, using neural networks for fire identification has greatly advantages over the traditional methods.

Dataset

A large amount of training data is required in the training process of the model. The following data collection methods are mainly adopted: satellite remote sensing images, Internet-of-things sensor data, weather station data, online data, and fire experiment data, as shown in Table 2.

Table 2: Different data set types of models

Data set type	Model
Satellite remote sensing image	Model 5
IOT sensor data	Model 6
Data from weather station	Model 1
Online data set	Model 2&3
Data from fire experiment	Model 4

Satellite Remote Sensing Images. The data set of model 5 is collected from the satellite remote sensing images of the United States from 2016 to 2017. They are screened from the 30m resolution images returned by the resource exploration satellite 8 launched by OLI (Operational Land Imager) in 2013. These images cover an area of 185km×180km. The fire images are cut into 224×224 pixel size.

At the same time, some 224×224 pixel size of non-fire images are randomly cut from each group of satellite images for training neural network. The whole data set is divided into the training set with 39642 images, the verification set with 4955 images, and the test set with 4957 images.

Weather Station Data. The weather data of model 1, provided by the LARI (Lebanese Agricultural Research Institute), covers all Lebanon's weather data from 2000 to 2008. The weather data includes six characteristic values, namely, daily minimum temperature, daily maximum temperature, average humidity, average wind speed, solar radiation, and annual cumulative rainfall. As to annual accumulative rainfall, the accumulative rainfall is calculated from October 1 of each year, because the algorithm is only used in fire seasons, which correspond to June, July, August, September and October.

Data Set of IOT Sensors. Model 6 uses IOT technology to collect real-time data. Compared with the traditional data collection methods, the application of the Internet-of-things technology is more timely, efficient and reliable. The model is based on Internet of fire monitoring system of the Arduino Uno platform, and the collected information can be accessed on the web at any time. The data set includes temperature, humidity and some gases such as CO_2, CO and CH_4.

Online Data. The training data of the neural network must be collected from the real surroundings. After processing and screening, the data that is most conducive to the training of the model with a high prediction rate is selected. The data set of model 2 is composed of 882 images, which are divided into four categories as shown in Table 3.

Table 3. The number of images of different classes.

Class	Images
Daytime（fire）	247
Daytime（non-fire）	448
Night（fire）	101
Night（non-fire）	86
	Total：882

The data set of model 3 is selected from the online video resources, and has a total number of 25 pieces of video, including 21 positive training set (fire), 4 negative training set (non-fire). Then every frame of the video is adjusted to 204x320 size for feeding to the neural network, and the images are manually annotated the exiting fire patches with 32 ×32 bounding boxes. A small part of the data set is used as a test set as shown in Table 4.

Table 4. The number of images, patches, positive patches and negative patches in training set and test set.

	Images	patches	Positive patches	Negative patches
Training set	178	12460	1307	11153
Testing set	59	4130	539	3591

Fire Experiment Data. Model 4 data are collected from the fire experiment data. A total 10985 fire images are collected, and 12068 non-fire images are collected.

Methodologies

In this paper, we discuss several models, using different benchmark methods to build the neural network model. Model 1 proposed a four-classes model based on a two-classes SVM model. Model 2 designs a fire detection system using Inception-V3 for image processing and then conduct classification. In model 3, fire images are processed with different approaches to generate different data sets, and fire images are identified by SVM and CNN. Both model 4 and model 5 test the performance of several neural network methods in fire identification. Model 6 uses Internet-of-things technology combined with neural network to predict forest fires. We summarize in Table 5.

Table 5. Methodology of each model.

Model	Methodology
Model 1	SVM
Model 2	Inception-V3
Model 3	SVM CNN
Model 4	AlexNet GoogLeNet modified GoogLeNet modified VGG13 VGG13
Model 5	VGG InceptionV3 ResNet50 Custom ConvNet
Model 6	Feed-forward fully connected neural network

In model 1, SVM is adopted for classification. For classification problems, SVM has an excellent performance. Compared with the familiar SVM two-classification method, this model proposes a four-classification method. As Figure 4 shows, this model uses SVM1 to divide the result to two classes, and then SVM2 and SVM3 divide the result into four classes. The final results are determined by the results of each SVM, as shown in Table 6.

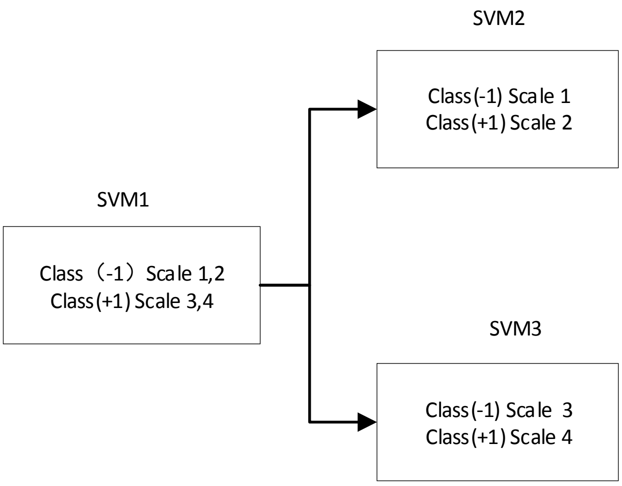

Figure 4. Four-classification SVM.

Table 6. Final result determination scheme.

SVM1	SVM2	SVM3	Output Scale
-1	-1	NA	1
-1	+1	NA	2
+1	NA	-1	3
+1	NA	+1	4

Each predicted result level corresponds to a different number of fires, as shown in Table 7.

Table 7. The scales correspond to the number of fire.

	Scale 1	Scale 2	Scale 3	Scale 4
June	0	1-3	4-7	≥8
July	0	1-4	5-8	≥9
August	0	1-3	4-15	≥15
September	0	1-4	5-16	≥17
October	0	1-7	7-11	≥12

Model 2 designs a neural network system for fire identification. Combined with smoke detection and fire detection, the model adopts the following judgment system for fire identification to improve the judgment accuracy. In Feature Extraction, the model uses DCNN Inception-V3 network to process the images into multi-dimensional vector to describe the images, and then the vectors are inputted to the classification model. The classification model will output two class: fire or non-fire. When the image is classified into fire, the system will use CAFE method to estimate the fire area. The whole process is shown in Figure 5.

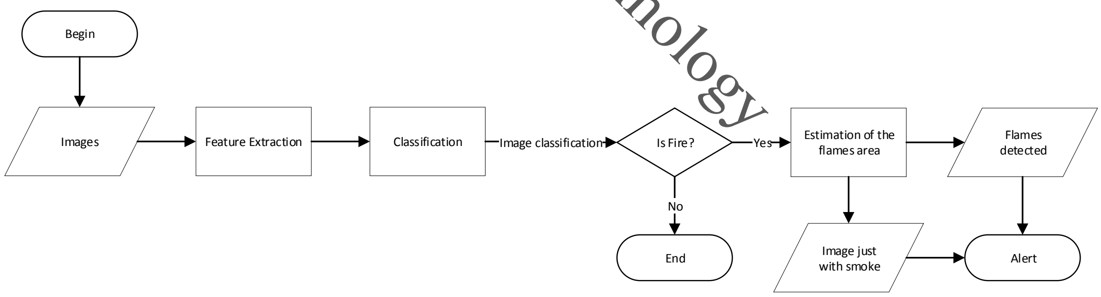

Figure 5. Work-flow of model 2.

In model 3, we adopt two methods for fire identification: first, we only carry out fire identification for image blocks. In the previous data processing, we manually mark images with bounding boxes, which contain fire patches and non-fire patches. Non-fire patches are significantly more than fire patches. During identification, we adopt two methods respectively, linear SVM and CNN neural network for fire identification, and the second one uses CNN for fire identification of the whole image, not the patches.

In model 4, five CNN neural network methods, namely AlexNet, GoogLeNet, modified GoogLeNet, VGG13 and modified VGG13, were adopted to evaluate the performance of the model.

Model 5 adopts five CNN methods of VGG, InceptionV3, ResNet50, Arch 1 and Arch 5 for evaluation.

Model 6 adopts a simple feed-forward neural network to predict forest fires. The neural network has two hidden layers, each with 50 neural nodes. We fine-tune our weights using Stochastic Gradient Descent (SGD) algorithm, with the learning rate of 0.0001 and momentum of 0.9 and a cross-entropy loss.

Experimental Results and Analysis

Results. While different models may use different metrics to evaluate their performances over traditional methods, the key objectives of these models are to improve the prediction and classification accuracies and minimize the processing time and complexity.

Model 1 uses the average error and scale error on the number of fire predicted as its main evaluation metric. Its results show that the average scale error is less than 0.8 except for four cases and drops as low as 0.2.

Model 2 evaluates day and night classifiers separately and the day and night models have an accuracy of 94.1% and 94.8% respectively.

Model 3 uses accuracy, detection rate and false alarm rate to evaluate the performance. The fire patch detector proposed can obtain 97% and 90% detection accuracy on training and testing datasets respectively, with 1.2% and 2.,3% false alarm rate respectively. The per image processing time is also considered, which shows that the full image classification is the dominant time consumption for about 1.42 seconds, while the neural network consumes less than 0.01 second in practice.

Model 4 considers both classification accuracy and training time. GoogLeNet achieves a highest accuracy of 99.0% and the modified GoogLeNet gets a second highest accuracy of 96.9%, but manages to decrease the training time from 3.1 hours to 1.5 hours.

Model 5 focuses on the training and test accuracy and shows that a fairly simple ConvNet architecture can be used to predict a fire with up to 86% accuracy.

Model 6 also uses the accuracy as its evaluation metric. It achieves 96.7% accuracy on the test data after 100,000 epochs of the training data and shows that as the number of iterations increases, the accuracy of the model increases.

Analysis. For model 1, although we have achieved good results in data, this model has great limitations:

1. Data sources. The model's data only comes from Lebanon, where the accuracy is relatively high, but there is no guarantee that it will be the same in other places, especially with different climates, animal and plant species.

2. Unclear results. Although we can predict the number of fires in the region in the future, we cannot get the specific location and specific time of fire through the number of fires, and then take corresponding measures to effectively eliminate the fire, so the results generated by this model are not of great practical significance.

The detection system adopted in model 2 combines smoke detection and fire detection and makes use of the relationship between them to greatly improve the accuracy of results and reduce the possibility of misjudgment. Although the final accuracy does not reach a very high level, the judgment system of this model is significantly referential.

From model 3, we can see that manual annotation of the fire area, and then the regional block fire recognition cannot improve the identification accuracy. Compared with the patch recognition, the whole image recognition is better. Model 4 and 5 are all on the same data to compare different CNN methods, but model 5's accuracy is not high with every method, so satellite images for CNN model is not a good choice. Model 6 uses IOT technology, which has great advantages in collecting data. It is more real-time and efficient for fire monitoring, and the data is more reliable. Although the neural network model does not adopt a very complex model, the final prediction accuracy is surprisingly good.

Conclusion

Forest fire happened every time with great damage. With the promotion of artificial intelligence, using neural network to predict forest fire and recognition to solve such problems points out a very effective way. Compared with traditional methods, the application of artificial intelligence is more efficient and cheaper. While artificial intelligence still faces with many problems, such as the accuracy is not high enough, AI application should be run in specific condition, the large amount of calculation and so on, its great advantages attract numerous researchers to constantly improve it. There are a lot of countries begin using artificial intelligence technology to forest fire monitoring and have achieved great success. In the future, artificial intelligence technology will be universally promoted, and may completely solve the problem of forest fires.

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