ISSN: 2664-9640

Predictive fire image recognition based on convolutional neural networks

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Abstract

This project combines traditional image processing technology with convolutional nerve. In addition, a two-layer fire smoke identification model is built, and the area is extracted by using the motion detection algorithm of forest fire or fire smoke location. Complex scenes are quickly removed without a lot of interference information, and the fire image recognition is completed. Using the ResNet model in the convolutional neural network, the network performance is improved when the number of network layers increases. Using this model, the results show that the structure of residual network is simple, the performance degradation problem of deep convolutional neural network is solved under extreme depth conditions, and the classification performance is excellent.

Keywords

Convolutional neural network, Forest fire recognition, ResNet.

1. Introduction

Recently, among all kinds of hazards, fire is one of the major disasters that most frequently and universally threaten public safety and social development. Fires are easy to break out and difficult to control. It is necessary to output the fire image quickly and effectively and analyze it accurately. Traditional fire smoke detection systems mainly rely on old-fashioned sensors to detect smoke.In the past, when a large-scale fire occurs, the sensor cannot detect and monitor the smoke signal in time. Unfortunately, sensors are vulnerable to environmental factors such as smog, dust, and human intervention, which can result in poor sensor accuracy[1,2]. Moreover, since the weight of neurons on the same include mapping surface is the same, the arrange can learn in parallel, which is additionally a major advantage of convolutional arrange compared with the arrange with associated neurons.CNN innovation has been connected to fire picture acknowledgment by numerous analysts[3,4,5].

At present, the relationship between CNN has been investigated many researchers.At the begin of, Chen et al. demonstrated block detection method for fast video preprocessing of forest fire images, which greatly decreased the running time of the whole system[6]. What's more,Bobing Tong proposed a probabilistic two-layer adaptive measurement (PTLNN) algorithm for smoke detection. The method were combined to optimize the local and global sample distribution and improve the performance of the algorithm[7].After that, Lujia Feng adopted the MD_CNN model and built a two-layer fire smoke identification model by using the target area location layer to quickly remove the interference information. The influence of irrelevant features in the input data on the recognition results is reduced[8].In the end,the latest research in 2020, by the Weihua Xiong et al use pooling operation to make the road feature extractor to extract the characteristics of the figure to match the size. The test results can achieve 96.82% and 97.96% accuracy on Firedetect Data and MIVIA data sets, respectively[9].

Past inquire about has made a certain commitment to the fire picture acknowledgment and the picture precision is exceptionally tall. In specific, the picture of multi-dimensional input vector can be straightforwardly input into the organize, which dodges the complexity of information recreation within the handle of include extraction and classification.However,there are moreover a few downsides, the fire picture depends on the determination of candidate districts, the arrange is complex, the number of tests is tall, and the utilization of time is as well much. These are self-evident calculate.

Due to the above factors, the subject combines traditional image processing technology with convolutional nerve. Identification model and the construction of two layers of fire smoke, the use of forest fire or fire smoke positioning of the motion detection algorithm to extract the area, rapid removal of complex scenes has nothing to do a lot of interference information,complete the fire image recognition.

2. Method

2.1. Data Generation And Preprocessing

In recent years, deep learning models based on CNN have achieved great success in flame image recognition of large fires, such as machine learning and image recognition.CNN is a multi-layer neural network composed of input layer, convolution layer, pooling layer, full connection layer and output layer.

In the convolution layer, the input image is convolved through convolution check, local features are extracted and offset items are added.

f(·) stands for $y_m = f(y_{m-1} * x_m + b_m)$ activation function; *ym-1* represents the characteristic diagram of the *m-1* layer; * speaks to the convolution operation; *xm* speaks to the convolution part kernel part bit of the *m* layer; *bm* speaks to the counterbalanced term of the *m* layer.

The feature graph obtained by convolution operation is relatively large, so it is essential to decrease the dimension of the feature graph obtained by convolution.

$$y_m = f[\lambda_m \cdot d(y_{m-1}) + b_m]$$

λm is the pooling parameter of the *m* layer. *d (·)* denotes the pooling function.

To sum up, using convolutional neural network to identify fire smoke has obvious advantages. In order to overcome the problem of network degradation, this paper adopts the ResNet learning method to improve the accuracy of recognition[10,11].

2.2. RESNET MODELl STRICTURE

ResNet refers to the VGG19 network and is modified on this basis. Compared with the ordinary network, the short circuit mechanism is added between every two layers in ResNet to form residual learning.

The basic idea of a deep residual network is to introduce a "Shortcut Connection" that can skip one or more layers, as shown in Figure 1 below. ResNet proposed two sorts of mapping: one is character mapping, the other is leftover mapping.The final output is *y=f(x)+x*. This simple addition does not add additional parameters and computation to the network, but it can greatly increase the training speed of the model and improve the training effect.

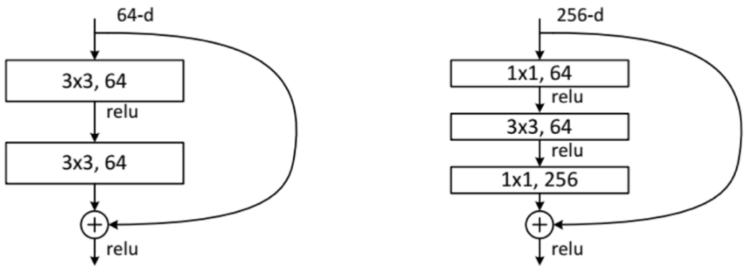

Figure 1. Different residual elements.

For these two structures, ResNet34 and ResNet50/101/152, respectively. The "Block Design" on the right is 1 more than the "Building Block" on the left. The purpose of adding 1*1 convolution is to reduce the number of parameters and reduce the amount of calculation.

It can be seen from the table 1 that for 18-layer and 34-layer ResNet the residual learning between two layers is carried out. When the network is deeper, it carries out residual learning among three layers, and the three-layer convolution kernel is 1x1, 3x3 and 1x1 respectively. It is worth noting that the number of feature maps of the hidden layer is relatively small, and it is 1/4 of the number of output feature maps[12].

Compare the network effects of 18-layer and 34-layer in Table 1, as shown in Figure 2. It can be seen that ordinary network degradation phenomenon, but ResNet is a good solution to the degradation problem[13,14].

Table 1. ResNet at different depths.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		[3×3, 64 3×3, 64] ×2	[3×3, 64 3×3, 64] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3
conv3_x	28×28	[3×3, 128 3×3, 128] ×2	[3×3, 128 3×3, 128] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×8
conv4_x	14×14	[3×3, 256 3×3, 256] ×2	[3×3, 256 3×3, 256] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×23	[1×1, 256 3×3, 256 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512 3×3, 512] ×2	[3×3, 512 3×3, 512] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

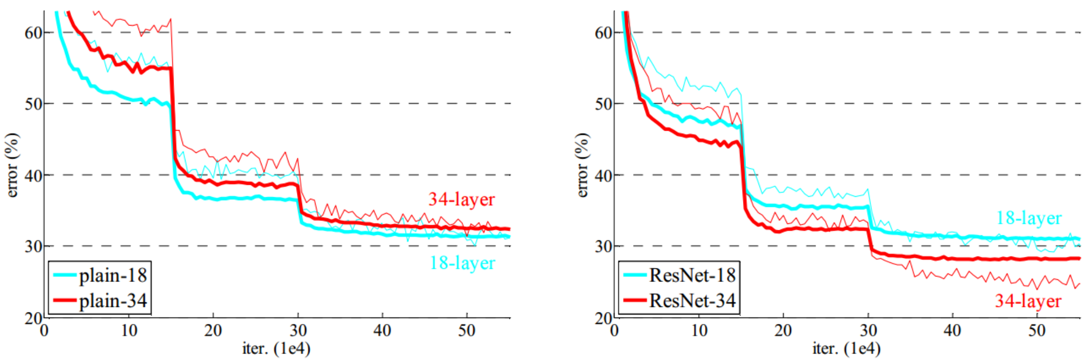

Figure. 2 Convergence performance of "flat" and residual networks on ImageNet dataset for 18-layer and 34-layer networks.

ISSN: 2664-9640

3. RESULT

Figure 3 is a fire image with a lot of complex background information removed. Leave only the target fire area.And you can see that the image of the fire is much clearer and much more specific.

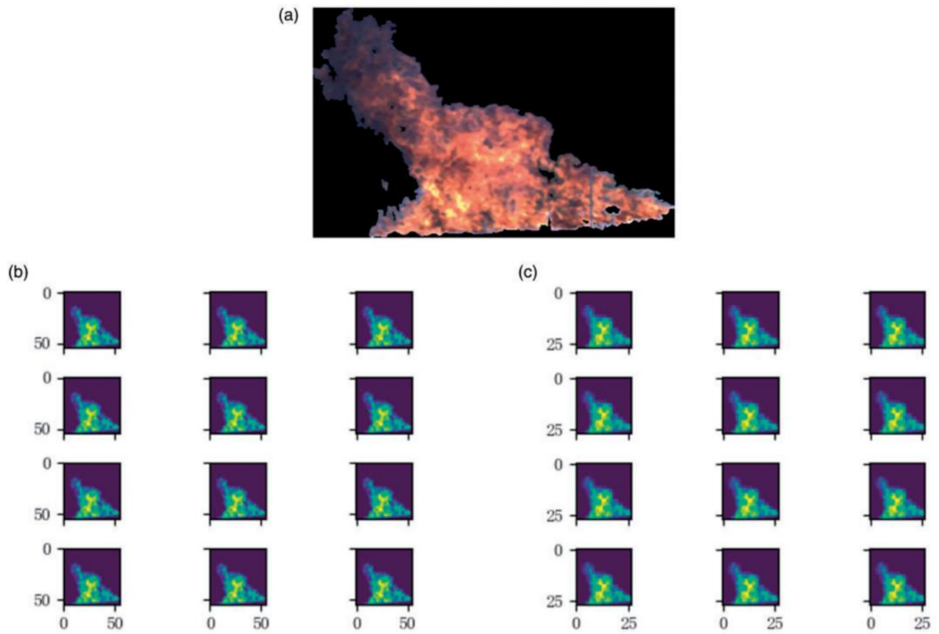

Figure 3 is a fire image with a lot of complex background information removed.

The structure of residual network is simple, which solves the problem of performance degradation of deep convolutional neural network under the condition of extreme depth, and the classification performance is excellent. In more than half a year since ILSVRC 2015, the widespread use of residual networks has promoted the performance of various tasks of computer vision to a new level. When a lot of irrelevant background information is excluded, different batch sizes of image data are entered.The network structure of different batch size flame and non-flame training datasets is shown in the table 2 [15,16].

Table 2. Training results under different batch size.

Batch size	512	256	128	64	32	8	1
Total epochs	500	500	500	500	500	500	500
Total iteration	1	2	4	7	13		
Time of one epochs	42.93	36.06	32.73	29.82	25.22		
Achieve 0.99 Accuracy at epoch	327	149	69	35	27	Cannot converge	
Time of achieve 0.99 accuracy	10,266.84	4810.26	1720.10	753.14	352.15		
Final training error (500 epochs)	0.0281	0.0084	0.0030	0.0015	0.0028		
Test score (%)	56.25	45.83	68.75	82.42	64.58		

4. Disscussion

On the basis of predecessors, convolutional neural network solves the problem of relying on candidate regions and outputs images in a relatively short time to solve the computing bottleneck.

CNN can recognize variable patterns and is robust to geometric deformation. At the same time, it can naturally extricate more profound highlights of pictures, dodging the visual deficiency and complexity of conventional include extraction calculations. These preferences are great for taking care of changes in smoke color, surface, shape and other characteristics.A show for the profundity residuals,it can be found that the execution of the remaining organize framework is

ISSN: 2664-9640

by and large higher than that of the past great models since the number of layers is by and large higher than that of the over models and there are supporting premises.

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