

Airport Perimeter Damage Detection Method Based on Alexnet Optimization

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Abstract: With the continuous development and expansion of airports, people pay more and more attention to the security of airport boundary. The damage of the boundary is one of the main factors leading to the security of the boundary, so it is very important to develop an automatic detection method of the boundary damage. Based on AlexNet deep learning model, this paper proposes an airport boundary damage detection method. By processing the collected video of the airport boundary, making the boundary damage data set, and then optimizing AlexNet, the experimental results show that compared with the original AlexNet network model, the improved AlexNet network model has shorter training time and significantly improved recognition accuracy, which can effectively identify the boundary damage.

Keywords: Airport perimeter, Damage detection, Deep learning, AlexNet.

1. Introduction

As one of the important guarantees of airport security, the security situation of airport boundary has been concerned by people. Boundary damage is one of the main factors of airport boundary security, and the traditional boundary inspection method has some problems, such as insufficient manpower and blind area, so it is very important to develop an automatic boundary damage detection method for airport security.

At present, there are few literatures on airport boundary damage detection, and no relevant reference methods have been found. The main reason is that it is difficult to obtain airport boundary data, and the probability of airport boundary damage is low. Similar to the study of boundary breakage is the feature extraction of grid images. There are two types of related algorithms for grid image research. One is to extract grid features by using the unity of the grid. Its disadvantage is that the processed grid image must be free of any background interference except the grid. The other is to use the regularity of grid changes to extract grid features, which requires that the grid covering the top of the image must be complete. The above studies are all based on traditional methods, such as edge detection, texture analysis, morphological operation, etc., which require manual selection of features and parameters, have various limitations and cannot be applied to airport boundary damage detection in complex environments. Deep learning methods can automatically extract high-level features of images by learning features in data sets, so as to achieve more accurate and robust object detection. Representative models of deep learning methods include AlexNet, VGG, GoogLeNet, ResNet, etc. These models have achieved great success in image classification and object detection.

In recent years, deep learning technology has made great progress in the field of image processing, especially in object recognition and object detection. Unlike traditional manual extraction of image features, deep convolutional neural networks do not need manual extraction of image feature information, and can learn appropriate network parameters from a large number of training samples. The essence of airport boundary damage detection is to mark the location of

damage in the image containing damage. According to the nature of the problem, it can be classified as a target detection problem, that is, to accurately locate objects with certain target type characteristics from a given image, and assign corresponding category labels to the objects. However, because the airport boundary damage data is difficult to obtain, it is not enough to support the training of target detection model, so the boundary damage detection is decomposed into a classification problem. AlexNet is one of the classical models in the field of deep learning, and its performance on the ImageNet dataset has attracted wide attention. Based on AlexNet model, an airport boundary damage detection method based on AlexNet optimization is proposed in this paper.

2. Technical Overview

2.1. Data set construction

In this paper, we use the perimeter video taken by the airport perimeter inspection robot to make the data set of algorithm training. First, the video collected by the inspection robot is processed, the video containing the boundary is converted into a picture of 1912*1080, and then the picture is processed, only the part containing the boundary is retained, and finally the picture containing the boundary is cut into a picture of size 64*64 for algorithm training. After a series of processing of the video taken by the inspection robot, a total of 5200 images were obtained. After manual screening, 4450 intact boundary images and 750 boundary images that could be regarded as damaged boundary images were obtained. The intact boundary image is shown in Figure 1, and the damaged boundary image is shown in Figure 2. The sample is divided into a training set and a test set by 8:2.

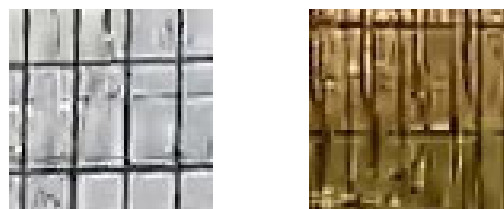


Figure 1. Boundary image

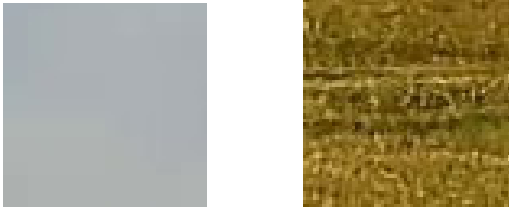


Figure 2. Damaged boundary image

2.2. AlexNet

In this experiment, AlexNet network model is used to build, train and test the network on Pytorch deep learning framework. AlexNet supports GPU acceleration, and drop neurons can obtain good fitting and are more sensitive to two-dimensional data, which is suitable for linear features of bounding images. The AlexNet convolutional neural network model consists of 5 convolutional layers, 3 pooling layers and 3 fully connected layers. The model has the following characteristics: First, it adopts the running mode on dual GPU. Secondly, the Local Response Normalization (LRN) strategy is used to normalize the results of each operation. Third, the overlapping maximum pooling method is adopted, and the step size is smaller than the pooling window, so that each pooling has overlapping parts, which can avoid overfitting phenomenon to a certain extent. Fourth, the ReLU activation function is selected and the Dropout method is adopted at the full-connection layer, which speeds up model training to some extent and avoids overfitting phenomenon. The flow of AlexNet neural network is shown in Figure 3.

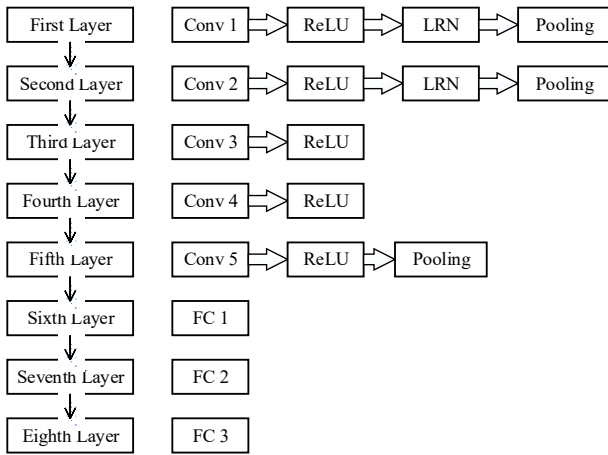


Figure 3. AlexNet network flowchart

2.3. Model Improvement

2.3.1. Leaky ReLU activation function

Replace the AlexNet convolution layer's activation function ReLU function with the Leaky ReLU function. The mathematical expression of Leaky ReLU function is:

$$f(x) = \text{LeakyReLU}(x) = \max(\alpha x, x)$$

The function value is the largest of all the input variables. An image of the Leaky ReLU function is shown in Figure 4, where it can be seen that the value of the function ranges from negative infinity to positive infinity. Where the value in the positive interval is the input variable x , and the value in the negative interval is not equal to 0, which is due to the introduction of the parameter α in the function. Usually the value of α is 0.01 or something very small like that. Since the introduction of α gives the function a smaller slope in the negative interval, it increases the range of values of the

function and helps to speed up training. Since the value of Leaky ReLU function in the positive and negative interval is not zero, the problem of neurons not learning after ReLU function enters the negative interval is avoided to some extent, thus effectively solving the problem of neuron necrosis caused by ReLU function. Therefore, in the process of feature extraction, The Leaky ReLU function can effectively improve the integrity and utilization of feature information.

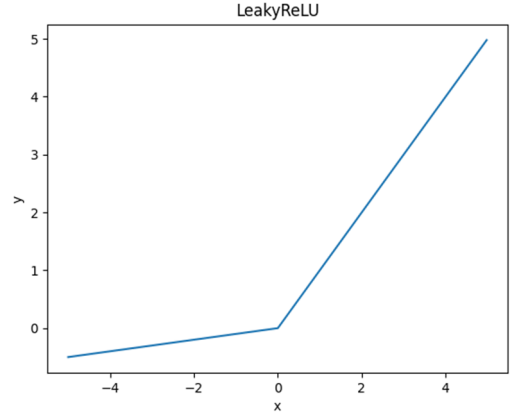


Figure 4. Leaky ReLU

2.3.2. Batch Normalized Processing

What neural networks learn is the distribution of training data, and when the distribution of training data is inconsistent with that of test data, the generalization ability of the network will decline. The network adopts local response normalization (LRN) operation, which enhances the generalization ability of the model and improves the recognition rate by 1%~2%. However, later studies found that LRN has little effect on the network, and it also increases the amount of computation.

The basic idea of BN (batch normalization) algorithm is to insert a normalization layer in each layer of the network input, that is, to do a normalization process (normalization to the mean of 0, variance of 1). BN layer is a network layer that can learn parameters, which can make the distribution of input data in each layer of the network relatively stable, accelerate the learning speed, and thus make the network learning more stable. Its calculation process is to calculate the sample mean first, then calculate the sample variance, and then standardize the sample data, and finally carry out translation and scaling processing. By introducing two learnable reconstruction parameters, γ and β , the network can learn to recover the feature distribution that the original network needs to learn. After the BN algorithm is used to normalize the model, the problem of gradient disappearance can be prevented. At the same time, BN algorithm can also play a regularization effect to prevent the model from overfitting. The BN algorithm is as follows:

$$\begin{aligned} \mu_B &\leftarrow \frac{1}{m} \sum_{i=1}^m x_i \\ \sigma_B^2 &\leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2 \\ \tilde{x}_i &\leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \\ y_i &\leftarrow \gamma \tilde{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \end{aligned}$$

Compared with the LRN algorithm, BN algorithm can greatly improve the training speed and training effect of the network, and improve the generalization ability and classification effect of the network. Therefore, this paper uses a better batch normalization method instead of a local corresponding normalization operation to optimize the processing.

2.3.3. Improved AlexNet network

TAN et al. proved that AlexNet model has the strongest feature extraction ability in Conv-3 and Conv-4 layers, and the classification effect of the fourth layer is slightly better than that of the third layer. In this paper, a convolution layer is inserted after the fourth layer network, which is consistent with the structure of the fourth layer. By adding convolution operations, more effective features can be filtered out. Through repeated verification, it is found that this operation can extract features more accurately, and the accuracy of the new model after training is better than that of the original AlexNet model. Meanwhile, the activation function ReLU of AlexNet convolution layer is replaced with Leaky ReLU function to improve the integrity and utilization of the model to extract effective feature information. Since a convolutional layer is added to the network and the training time of the model is increased, the batch normalization processing method is used instead of the local corresponding normalization operation to optimize the processing, so that the distribution of input data in each layer of the network is relatively stable, the learning speed is accelerated, the network learning is more stable, the problem of disappearing

gradients is prevented, and the generalization ability and classification effect of the network are improved. The optimized network structure of the model is shown in the figure below.

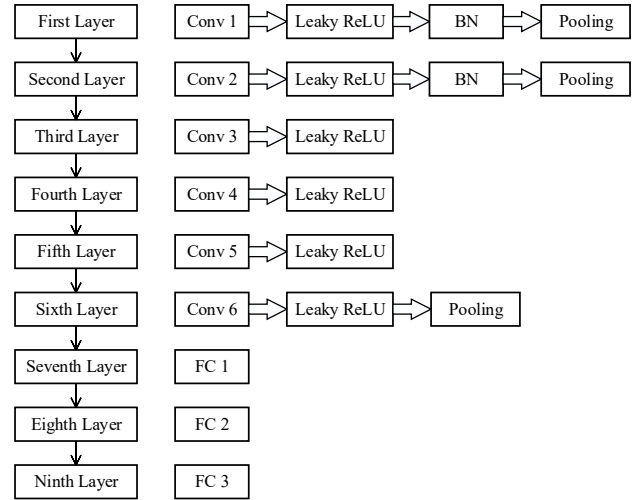


Figure 5. Improved AlexNet network flowchart

3. Experimental Results and Analysis

3.1. Experimental environment

The software and hardware information of the experimental environment is shown in Table 1.

Table 1. Configuration of experimental software and hardware information

Category	Configuration
Operating system	Win10, 64位
RAM	64GB
CPU	Intel(R) Core(TM) i7-10750H
GPU	NVIDIA Quadro P620
Framework	Pytorch 1.11.0
Language	Python 3.8
Environment management	Anaconda3-2022.10

In this experimental environment, the operating system is Windows10, the CPU model is Intel(R) Core(TM) i7-10750H, and the GPU model is NVIDIA Quadro P620. The deep learning framework uses Pytorch 1.11.0, which is based on the python language. When the learning rate of the network is set too small, the convergence of the network will become slow. When the learning rate is set too large, the gradient will continue to oscillate around the minimum value, and the network will be difficult to converge. Therefore, according to the experience value, the initial learning rate of the network in this paper is set to 0.001, and the exponential attenuation strategy is adopted in the training process to dynamically adjust the learning rate. The optimizer is Adam, Dropout is set to 0.5, and Batch Size is set to 32. A total of 100 epochs are trained. In this paper, 80% of the pictures of each type of sample are selected as the training set, and the rest are used as the test set.

3.2. Result Analysis

In this experiment, AlexNet network and improved AlexNet network were used for training. In the process of network training, with the increase of the number of iterations, the accuracy of boundary recognition gradually improved and

became stable when training 100epoch, and the value of loss function also became stable. The experimental results show that the training time of AlexNet 100epoch is 3.54h, which is higher than the 2.46h of the improved AlexNet model. The experimental results of AlexNet and improved AlexNet model are shown in Table 2.

Table 2. Comparison of AlexNet/ improved AlexNet models

Experimental index	AlexNet	Improved AlexNet
Cost time/h	3.54	2.46
Training set recognition rate /%	93.94	99.73
Test set recognition rate /%	89.87	98.95

The AlexNet model has an accuracy of 89.8% on the test set and 93.94% on the training set. The improved AlexNet model is 98.95% accurate on the test set and 99.73% accurate on the training set. The improved AlexNet model is superior to the AlexNet model in recognition accuracy and

convergence speed. The result of inference by selecting representative boundary data is shown in the figure below. Figure 6 is the recognition result of normal boundary, Figure 7 is the recognition result of damaged boundary, where a is the AlexNet recognition result figure, b is the improved AlexNet recognition result figure. The confidence of AlexNet for normal boundary identification is 91.5%, the confidence of damaged boundary identification is 83.1%, and the confidence of improved AlexNet for normal boundary identification is 99.2%, an increase of 7.7%. The confidence of damage boundary identification is 93.1%, an increase of 10%.

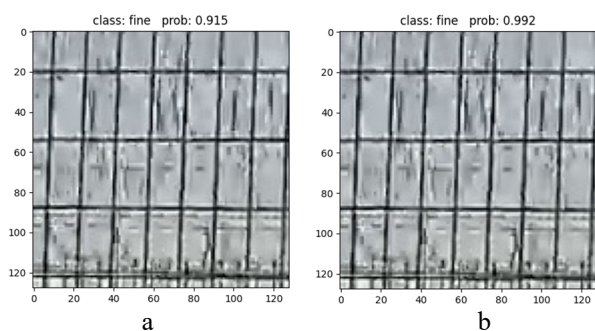


Figure 6. boundary

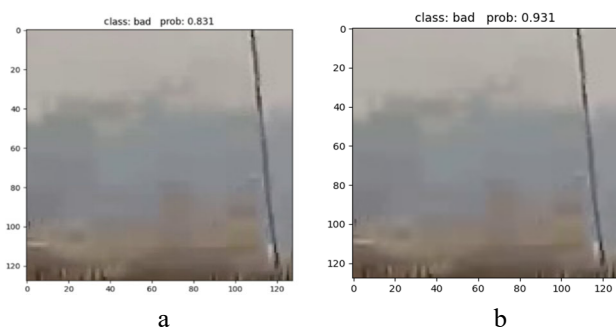


Figure 7. Damaged boundary

4. Conclusion

In this paper, an improved AlexNet network model is proposed for the identification of airport boundary damage. By modifying the activation function, replacing the local corresponding normalization with batch normalization, increasing the number of network layers and other operations to optimize the AlexNet network, the accuracy rate of the optimized AlexNet model is improved by 9.08% compared with the original, and it has better recognition effect. At the same time, during the training process, the convergence speed of the model is faster and the training time is shorter.

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