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Rocket Image Classification Based on Deep Convolutional Neural Network

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***Abstract*—In the field of aerospace measurement and control field, optical equipment generates a large amount of image data. Thus it has great research value for how to process a huge number of images data quickly and effectively. With the development of deep learning, great progress has been made in the task of image classification. This paper attempts to classify the task images generated by optical measurement equipment using the deep learning method. Firstly, based on residual network, a general deep learning image classification framework, a binary image classification network namely rocket image and other image is built. Secondly, on the basis of the binary cross entropy loss function, the modified loss function is used to achieves a better generalization effect on those images difficult to classify. Then, the 2689 visible image data downloaded from optical equipment is randomly divided into training set, validation set and test set. The data augmentation method is used to train the binary classification model on a relatively small training set. The optimal model weight is selected according to the loss value on the validation set. Finally, the trained model achieved a 100% precision and a 83.33% recall on the test set of 97 images which include 24 rockets images. This paper has certain value for exploring the application of deep learning method in the intelligent and rapid processing of optical equipment task image in aerospace measurement and control field.**

Keywords; aerospace measurement and control ;residual network;deep learning ; image classification

I. INTRODUCTION

In the field of aerospace measurement and control, optical equipment generates a large amount of task image data for each task. Thus it has great research and application value for how to process such a large number of task image data quickly and effectively. The current image post-processing algorithm is generally based on the traditional image processing method, which exists many shortages including requiring manual design of image feature extraction, relying too much on prior knowledge, poor adaptability, only extracting location information and no extracting semantic information.

Deep learning is a hot research topic in recent years. deep learning has made great progress in the field of image processing, computer vision, driverless technology and artificial intelligence. Compared with the traditional image processing method, the biggest advantage of deep learning is that it does not rely on the artificial design of features, and can adaptively learn the feature description in the image. Therefore, the stability and adaptability of the algorithm are better than the traditional image processing method. [1]

This paper attempts to classify the task images generated by optical measurement equipment using the deep learning method. Firstly, based on residual network, a general deep learning image classification framework, a binary image classification network namely rocket image and other image is built. Secondly, on the basis of the binary cross entropy loss function, the modified loss function is used to achieves a better generalization effect on those images difficult to classify. Then, the 2689 visible image data downloaded from optical equipment is randomly divided into training set, validation set and test set. The data augmentation method is used to train the binary classification model on a relatively small training set. The optimal model weight is selected according to the loss value on the validation set. Finally, the trained model achieved a 100% precision and a 83.33% recall on the test set of 97 images which include 24 rockets images. This paper has certain value for exploring the application of deep learning method in the intelligent and rapid processing of optical equipment task image in aerospace measurement and control field.

II. DATA SET

A total of 2689 color images are downloaded from the previous images saved by the optical equipment. These images are labeled as two types, one kind is rocket image, and the other is none rocket image. All the image was then randomly divided into a training set (2392), a validation set (200), and a test set (97) at a rough ratio 7:2:1. The training set is used to train the weights of the built deep convolutional neural network. The validation set is used to verify the generalization ability of the model, and the model weights are selected to save according to the loss function value on the validation set. Finally, the saved model weights is tested by the test set to obtain the test results of the model.

III. MODEL

A. Development Enviroment

Anaconda is configured in the Ubuntu 18.04 operating system. The driver of the graphics card GTX 1070 with 8G memory is configured. the CUDA acceleration package CUDA 9.0 and cudacnn 7.0 is installed, and then some related packages such as tensorflow 1.8 keras 2.0 and opencv-python are configured.

B. Network Framework

Based on the residual network ResNet18[2], a rocket image binary classification model is built. The structure diagram is shown in Fig. 1, and the parameters of each layer are shown in Table I. ResNet18 includes five basic conv modules which consists of two same residual module.

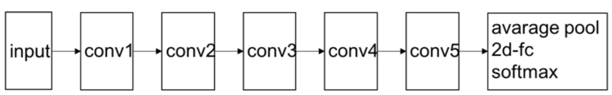

Figure 1. Framework of the ResNet18

TABLE I. PARAMETERS OF RESNET18'S EACH LAYERS

Layer name	18
Conv1	7x7, 64, stride 2
Conv2	3x3 maxpooling, stride 2
	$\begin{bmatrix} 3x3 & 64 \\ 3x3 & 64 \end{bmatrix}$x2
Conv3	$\begin{bmatrix} 3x3 & 128 \\ 3x3 & 128 \end{bmatrix}$x2
Conv4	$\begin{bmatrix} 3x3 & 256 \\ 3x3 & 256 \end{bmatrix}$x2
Conv5	$\begin{bmatrix} 3x3 & 512 \\ 3x3 & 512 \end{bmatrix}$x2
Output	average pooling, 2-d fc, softmax

C. Residual Module

The basic idea of residual module is to replace the fitting f(x) in the traditional convolution module with the fitting residual x - f(x). with residual's sensitivity related to the error, the gradient disappearance phenomena of deep network can be effectively fixed.[2]

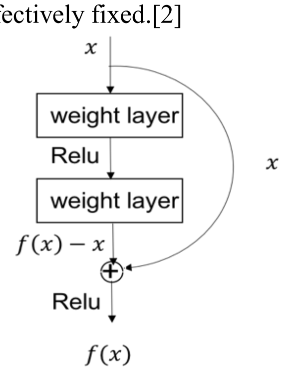

Figure 2. Architecter of the residual module

D. Loss Function

The ordinary binary cross entropy loss function is as Equation 1,

$$CE(p,y) = \begin{cases} -\log(p)\,, if\ y = 1 \\ -\log(1-p)\,, otherwise \end{cases}, \tag{1}$$

Where, p denotes the predict probability; y is the label.

It can be rewritten as Equation 2 and Equation 3.

$$p_t = \begin{cases} p, if\ y = 1 \\ 1-p, otherwise \end{cases}. \tag{2}$$

$$CE(p_t) = -\log(p_t). \tag{3}$$

A new loss function is adopted to modify the weights of those image that is difficult to classify. Meanwhile, a factor is designed to fix the unbalance between different class. The new loss function is as following[4].

$$FL(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t). \tag{4}$$

The fundamental principle of the new loss function called focal loss can be explained as Figure 3[4]. For a positive sample labeled as 1, the loss value can be close to 0 if the probability of ground truth class is close to 1. With the factor γ, the weight of those well-classified samples to the whole loss is reduced. Thus the model trained with focal loss gain better generalization performance.

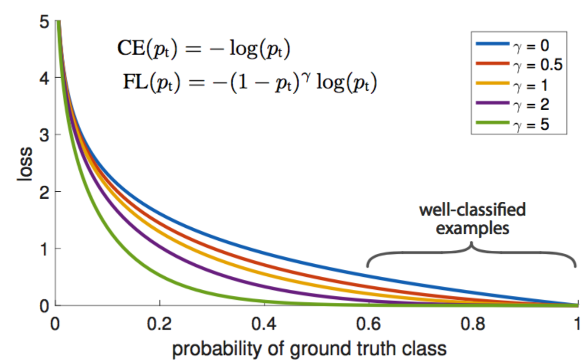

Figure 3. A explain of the focal loss

IV. TRAIN AND TEST

A. Train the Module

Optimization algorithm Adam is selected and the initial learning rate is set to 0.00025. The batch size is set to the maximize value 8 due to the memory limit of the GTX1070. the model is trained 30 EPOCH with data augmentation using the function generator in Keras. The optimal model weights is selected by built in class ModelCheckpoint according to the validation loss value. Train and validation loss and accuracy curves are as following.

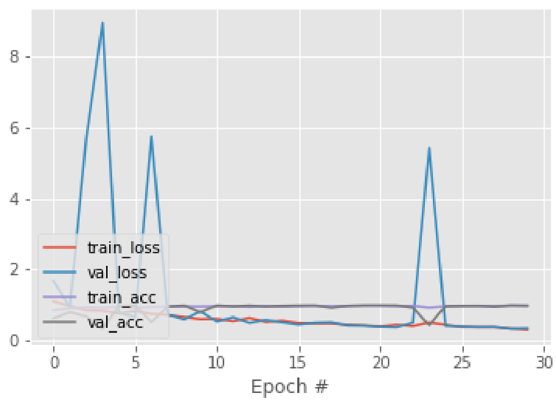

Figure 4. Loss and acc curve in train and validation

After training for a certain round, the training loss value and the validation loss value are not declining. From the train and validation curve, it can be seen that the model has been converged.

B. *Test Result*

The test set is used to evaluate the generalization ability of the trained model. The test set contains 24 rocket images and 73 non-rocket images. The non-rocket images include flying ball, positive azimuth, anti-azimuth, moon and Jupiter. The results of the test are as follows.

TABLE II. TEST RESULTS

	Rocket	***Non-rocket***
Rocket(24)	20	4
Non-rocket(73)	0	73

The recall rate and precision is two index commonly taken to evaluate the classifying performance. Table 3 is the so-called confusion matrix. Precision is defined as $P = TP/(TP + FP)$. Recall is defined as $R = TP/(TP + FN)$. F1 score is defined as $F1 = 2PR/(P + R)$. Thus, the precision rate is 100%.The recall rate is 83.33%. F1 value is 95.87%.

TABLE III. CONFUSION MATRIX

	Positive	***Negative***
True	True Positive(TP)	False Negative(FN)
False	False Positive(FP)	True Negative(TN)

And the following is some correctly classified rocket and non-rocket image. The green point on the left and up side of the image shows the probability that the model classifies to the corresponding class.

Fig. 5 and Fig. 6 are all labeled as rocket image. These two rocket image have totally different feature, but are all correctly classified as rocket at a probability 98.54% and 93.04%.

Figure 5. Correctly classified rocket image

Figure 6. Correctly classified rocket image

Figure 7 Figure 8 and Figure 9 are all labeled as non-rocket image and are all correctly classified as non-rocket at a probability 92.72% 98.77% and 93.04%.

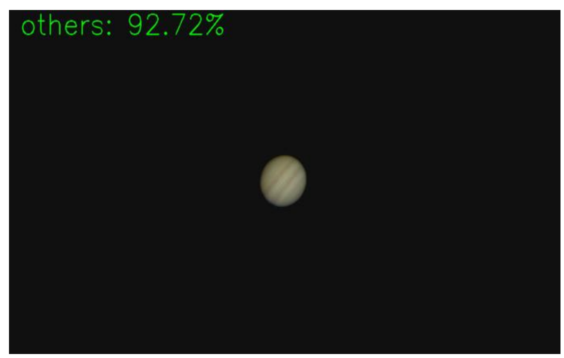

Figure 7. Correctly classified non-rocket image

Figure 8. Correctly classified non-rocket image

Figure 9. Correctly classified non-rocket image

C. Failure Mode Analacis

The recall rate was 83.33% and the precision rate was 100%. 4 rocket samples of the 24 rockets images were incorrectly classified as non-rocket images. Following are some bad cases.

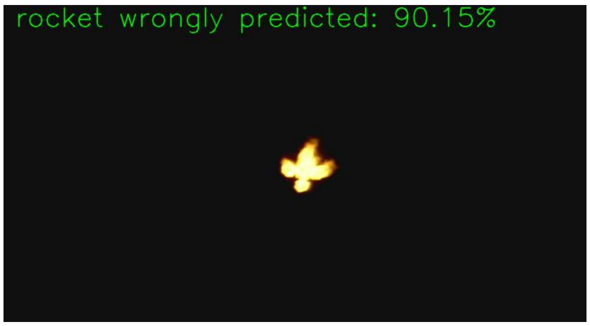

Figure 10. Mistakely classified rocket image

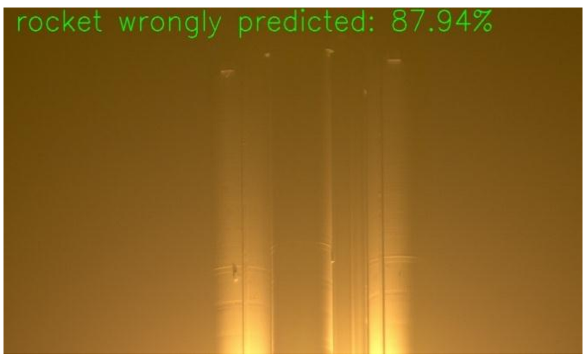

Figure 11. Mistakely classified rocket image

These failure modes may own to some reasons. Firstly, the characteristics of the rocket target in the bad case are relatively weak due to illumination or long observation distance. Secondly, the train datasets volume is relatively small, which means the deep neural network is easy to fall in overfitting.

Subsequent research will continue to study the problem of misclassification in the case of weak target features through model improvement, data enhancement, and transfer learning.

V. Conclusion

In this paper, Firstly, a binary image classification network namely rocket image and non-rocket image classification model is built based on residual network. Secondly, on the basis of the binary cross entropy loss function, the modified loss function is used to achieve a better generalization effect on those images that is difficult to classify. Then, the 2689 visible image data downloaded from optical equipment is randomly divided into training set, validation set and test set. The data augmentation method is used to train the binary classification model on a relatively small training set. The optimal model weight is selected according to the loss value on the validation set. Finally, the trained model achieved a 100% precision and a 83.33% recall on the test set of 97 images which include 24 rockets images. This paper has certain value for exploring the application of deep learning method in the intelligent and rapid processing of optical equipment task image in aerospace measurement and control field. Subsequent research will continue to study the problem of misclassification in the case of weak target features through model improvement, data enhancement, and transfer learning.

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