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# Fabric Defect Detection Based on the Improved Cascade R-CNN

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***Abstract:*** *There is a large amount of fabric produced in the process of industrial production, thus fabric defects automatic detection can bring great benefits to enterprises. With the development of computer technology, deep learning has more advantages on fabric defect detection compared with traditional image processing. By comparing the advantages and disadvantages of different target detection models, we chose to use the Cascade R-CNN model for fabric defect detection finally. However, due to the large size of fabric image, small number of partial defects and complex image background, there are many difficulties in fabric defect detection. To solve the difficulties, we propose some methods to improve the accuracy of defect detection. First, in order to enhance the detection accuracy of small targets, we cut large fabric images into blocks for training and detection, and combine the detection results. Then, to solve the problem of the small number of partial defects in the fabric Dataset, a new method of multi-morphological data augmentation was proposed to increase the number of the Dataset. Finally, we improved the Feature Pyramid Networks module to enhance positional accuracy of defect detection. Experimental results show that the model can complete the task of defect detection efficiently and improve the accuracy of target detection effectively.*

***Keywords:*** *Fabric defect detection, cascade R-CNN, defect detection*

## 1. Introduction

The textile industry is one of the largest industries in the world. In the process of fabric production, a large number of the fabric with defects will be produced. The production efficiency can be improved only when we strictly control the quality of fabric. At present, the inspection of fabric quality uses the semi-automatic method[1]. In the process of the fabric rolling machine, the workers check the quality of fabric through the eyes and mark on the fabric[2]. The manual detection of fabric defects has many shortcomings such as slow speed, low efficiency and easy fatigue. So the automatic detection of fabric defects has a good prospect.

In recent years, many enterprises and scholars have been trying to apply computer vision technology to the fabric production process[3], using automatic fabric inspection system instead of manual inspection to enhance production efficiency. It is obvious that the algorithm of defect detection determines the speed and accuracy of the automatic fabric inspection system.

At present, defect detection algorithms are mainly divided into two kinds, which are the traditional image processing methods and the algorithm based on deep learning. The traditional defect detection algorithm is relatively dependent on the external environment such as illumination and background, and when the external environment changes, the accuracy of the algorithm decreases. However, deep learning target detection adopts end-to-end training without complex parameter adjustment process. At the same time, it has the advantages of fast detection speed, strong adaptability to the environment and high accuracy.

## 2. Related Work

In recent years, many researchers have tried to apply deep learning to fabric defect detection in the fabric production process. For example, Junfeng Jing et al.[4] completed defect detection of fabric using the improved YOLOv3 model. They mainly added the detection layer on the different feature maps, combined the low-level features with the high-level information to improve detection accuracy

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of the small target. Jun Wu et al.[5] applied the Faster R-CNN model to the defect detection of the fabric. They mainly designed a dilated convolution module, and got multi-scale features by connecting features map of different scales to improve the accuracy of fabric defect detection. Zhiyong Zhao et al.[6] proposed the improved Cascade R-CNN network for fabric defect detection. They mainly used the classification network to judge the fabric type, then selected different detection parameters to improve the detection result.

Although fabric defect detection based on deep learning has achieved some results, most of the research is focused on small size and simple fabric background images. At present, there is still a great challenge for fabric defect detection about complex background and the large size of image.

## 3. Related Work

In this paper, we chose the Cascaded R-CNN as baseline model for fabric defect detection by comparing the characteristics of different deep learning models, and then we came up with our own tricks based on the characteristics of the fabric Dataset. First, we propose a new data enhancement method in order to solve the problem of poor detection precision in the small number of defects. At the same time, we come up with the block recognition method to enhance detection results of small targets. Finally, we improve the FPN module to enhance the positioning accuracy of the model.

### *3.1. Baseline Model*

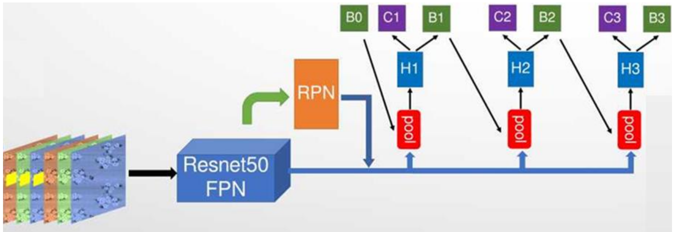


*Figure 1: Cascade R-CNN Net work.*

We chose the Cascade R-CNN network as the baseline model. The Cascade R-CNN[7] network is improved based on the Faster R-CNN[8] network. This network uses multiple detection models, and the output of the previous detection model is used as the input of the later detection model. The detection results of the model are improved by increasing the IOU threshold. As shown in Figure 1, the Cascade R-CNN network is mainly composed of Feature Extraction module, RPN module and ROI Head module. The Feature Extraction module is used to generate the feature map, the RPN(Region Proposal Network) module is used to generate the Proposal box, and the ROI Head module is used to classify and regression.

### *3.2. Multi-morphological Data Augmentation*

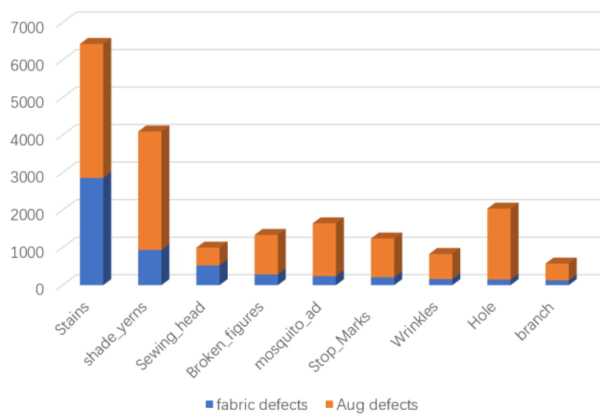


*Figure 2: The numbers of defects.*

As the blue section shown in Figure 2, the quantity of fabric defects varies extremely between

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different classes, the detection result of a small number of defects is so bad. Therefore, data augmentation is required to increase the Dataset of small number of defects[9]. However, although the traditional data enhancement method increases the amount of the image through random cut, rotate and other methods. But the added images are similar, so the accuracy of the model is limited eventually.

Therefore, we use the traditional image processing technology to develop a multi-morphological data enhancement method independent of the background, to increase the Dataset of the small number of defects.

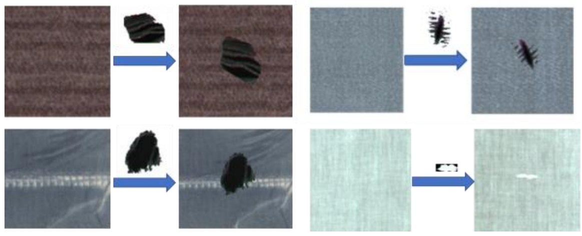

*Figure 3: Multi-morphological data augmentation.*

This method mainly uses the traditional image processing method to extract the detection target without background, and then the defect is added or replaced with the original image after random gray scale transformation, mirroring, morphological transformation and other image processing methods. As the orange section shown in Figure 2 and Figure 3, this approach can effectively simulate defects of different forms and increase the number of defects.

### *3.3. Improved FPN*

In the process of feature extraction, the FPN[11] module generates feature maps of different scales through bottom-up pathway, and then merges feature maps of the same size through top-down pathway and horizontal connections. Finally, target prediction is made on each merged feature layer to enhance the recognition accuracy of different target sizes.

FPN can identify the large target on the small feature map, but the connection path between the small feature map and the large feature map is very long, so it is difficult to obtain accurate positioning information. PAFPN[12] creates a bottom-up connection based on FPN, which is used to shorten the path so as to improve the positioning accuracy of the feature pyramid by using precise positioning signals stored in the large-scale feature map.

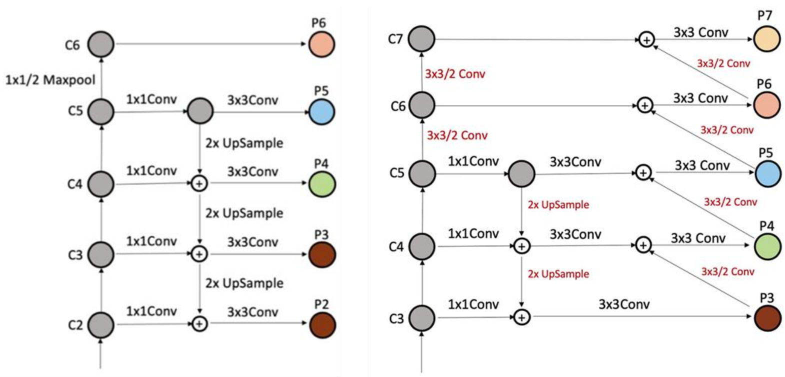


*Figure 4: FPN and PAFPN.*

### *3.4. Block Recognition*

Through the analysis of the fabric Dataset, it can be seen that the size of different types of defects varies greatly, and the aspect ratio of some defects is very large, so it is hard to train the model. At the same time, the training of large size images has a high demand for computer video memory. Therefore, we propose a detection method of block training for large images. First of all, we cut images with resolution of 4096*1800 and 4096*1696 into small images with size of 1460*992 as shown in Figure 5, and use small images to train the model. Then, we designed an algorithm for automatic block detection of large images. We used the trained model to block and detect large images, and combine the

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detection results according to the IOU(Intersection Over Union)[10] of the same defect class. This method can detect defects in images of different sizes, if the image size is larger than the train image.

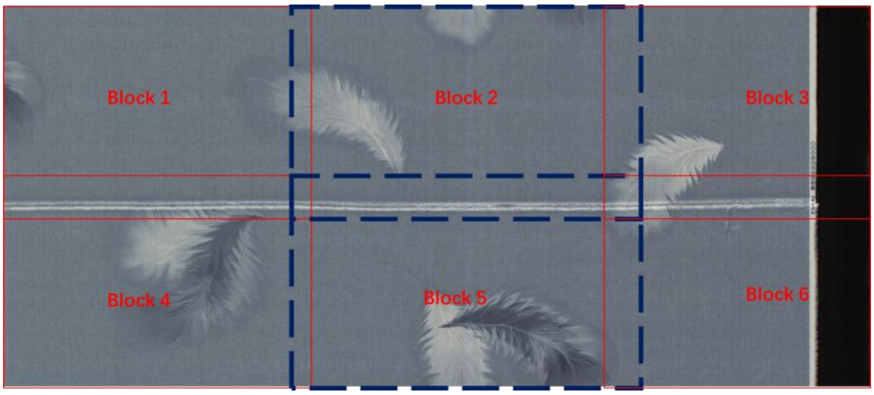


*Figure 5: Image block.*

Through the improvement of the baseline above, the network we use is shown in the Figure 6.

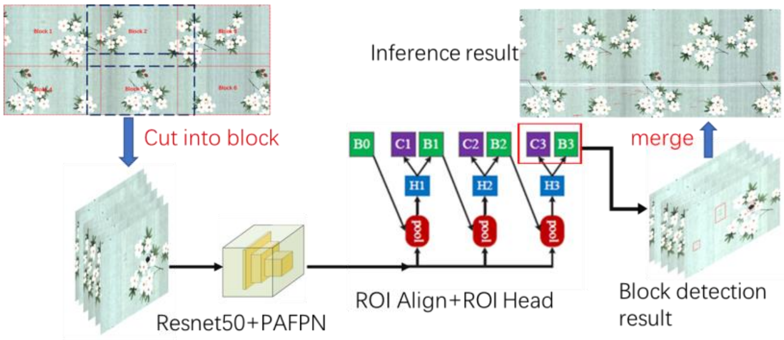


*Figure 6: Cascade R-CNN + Resnet50 + Pafpan + Block Recognition.*

## 4. Experiments

To verify our model, the Dataset of fabric images was built, which includes 1603 images, 19 different backgrounds and 9 different kinds of defects. The size of the image includes 4096*1696 and 4096*1800. The operating system we use is Windows, and the GTX 1060 graphics card which has 6G of video memory is used for accelerated training. Our initial learning rate is 0.00125, and the number of iterations is 36.

### *4.1. Dataset Partitioning*

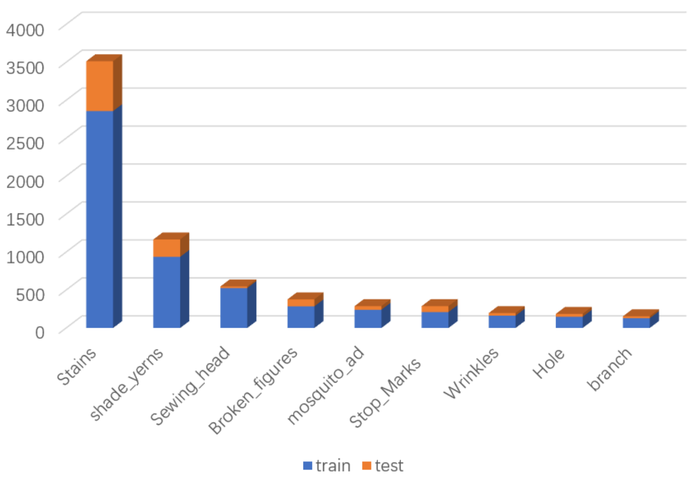


*Figure 7: Dataset Partitionin.*

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We all know that not only the construction of the deep learning model is essential, but the division of the Dataset is also important. We divided the Dataset into the training Dataset and the test Dataset, in which the training Dataset contains 1408 images and the test Dataset contains 195 images.

The number of different defects in the training Dataset is shown in the blue part of the Figure 7, while the number of defects in the test Dataset is shown in the orange part of the Figure 7. According to the block detection method, we cut the image of the training set into a small image with the size of 1460*992, and then collate the Dataset for model training.

### *4.2. Evaluation Indicator*

To evaluate the training model, we used MAP(Mean Average Precision) as the evaluation indicator.

*Table 1: Variable meaning.*

| Label / Predict | positivte | negative |
|---|---|---|
| positivte | TP | FP |
| negative | FN | TN |

First, when we set different scores, and calculate the different precision and recall value of the test results. Then we obtain the PR curve according to the above values, and this AP value is the area enclosed by the curve and the coordinate axis. Finally, the evaluation index MAP is calculated according to equation (4).

$$\text{Precision}=\frac{TP}{TP+FP} \tag{1}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{2}$$

$$AP=\int_0^1 p(r)d_r \tag{3}$$

$$MAP=\frac{\sum_c AP}{m} \tag{4}$$

The meanings of TP, FP, FN, TN are given in Table 1. The m represents the number of defects, and the IOU value selected in this experiment is 0.5.

## 5. Conclusions and Prospect

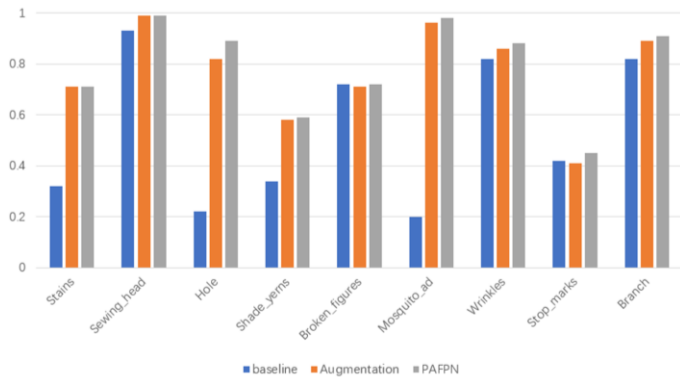


*Figure 8: Detection results of different model.*

We chose Cascade R-CNN as the baseline model, and then proposed three mainly optimization strategies according to the characteristics of fabric image. First, we proposed the strategy of block detection. This method successfully completes the preliminary detection of high-resolution fabric images, and the MAP value is 53.48%. Then, we proposed a multi-morphological Data Augmentation method independent of the background. This method effectively improves the detection efficiency of the small number of defects, and the MAP value increases from 53.48% to 77.33%. Finally, we improved the FPN module to improve the positioning accuracy of the network model, and the MAP value reached 78.93% eventually. The detection results of different types of defects in different model are shown in Figure 8.

*Table 2: MAP styles.*

| Baseline | Data Augmentation | PAFPN | MAP(%) |
|---|---|---|---|
| ✓ | | | 53.48 |
| ✓ | ✓ | | 77.33 |
| ✓ | ✓ | ✓ | 78.93 |

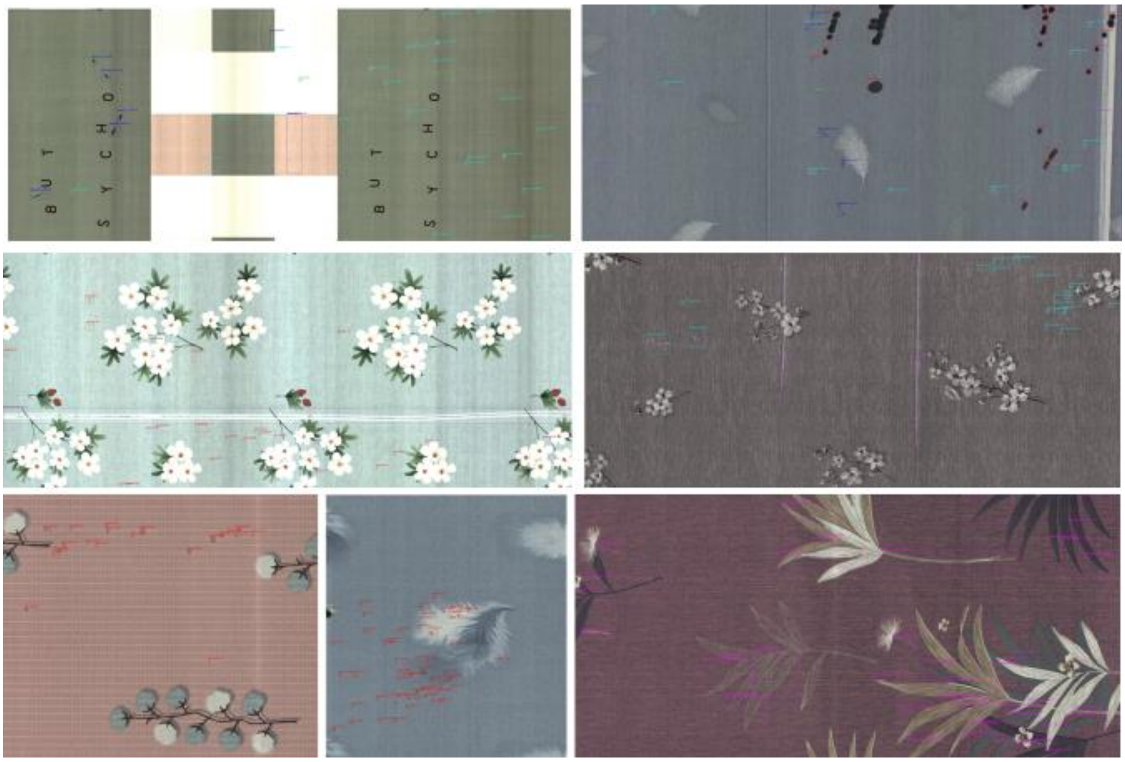

*Figure 9: The fabric defect detection results.*

We completed the defect detection of high-resolution fabric images finally, and the test results as shown in Table 1I. As the detection result shows in Figure 8 and Figure 9, our model solves the detection problems of extremely large defects, extremely small defects, small number of defects and dense defects, and the detection accuracy is higher than human eyes, has practical industrial application value.

The future work will focus on the parallel computing of the blocked images, the improvement of the detection results merging algorithm, and the detection accuracy of small targets.

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