Research on Fabric Defect Detection Technology Based on EDSR and Improved Faster RCNN

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Abstract. In order to solve the problems of various kinds of defects, defect ratio varies greatly, imbalanced defect aspect ratio and high integration degree with background in fabric defect detection, a method combining super-resolution reconstruction technology and deep learning detection was proposed. Firstly, the enhanced deep residual networks for single image super-resolution is used to enrich the defect feature information, reduce the fusion degree of defect and background texture, and enhance the extraction ability of various defect features. Then, the defect features are analyzed according to K-means clustering algorithm. Based on the three default anchor frame ratios provided by Faster RCNN, six new types of anchor ratios are added. Then, FPN module and DCNv2 module were introduced in Faster RCNN to improve the ability to identify defects with different areas and shapes. Finally, the pooling mode of ROI layer was modified to eliminate the error caused by quantization operation. The results of the three kinds of comparative experiments show that the method based on EDSR and improved Faster RCNN has a better overall recognition rate for multiple kinds of fabric defects than other current methods, and can be used in the production and operation of textile enterprises.

Keywords: Fabric defect detection · EDSR · Faster RCNN

1 Introduction

Fabric defect detection is an important part of improving product quality and reducing product cost in textile enterprises. Some common defects (as shown in Fig. 1 below) are elongated and have a high degree of integration between defects and background. So it will not only affect the appearance and wearing comfort of cloth, but also lead to an average reduction of 45%–65% of the price of cloth [1]. However, the current manual detection method used by enterprises has problems such as fatigue of workers, high cost, slow speed, missed detection, false detection. Therefore, it is very necessary to study automatic and accurate detection methods.

At present, automatic fabric defect detection methods can be divided into two categories. The first type is based on traditional machine learning technology, mainly using statistical analysis, spectrum and model-based methods. The second category is the method based on deep learning.

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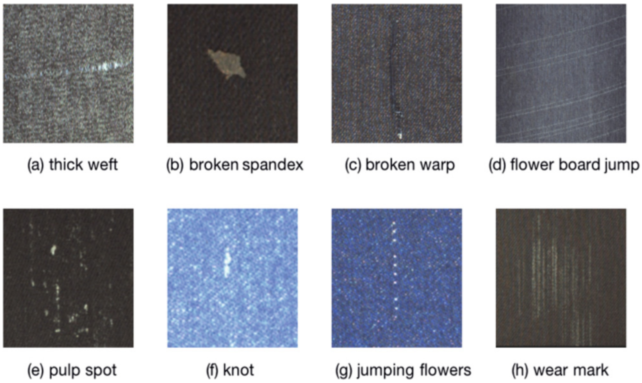


Fig. 1. Figure of some enlarged defects

Among the methods based on statistical analysis, Banumathi proposed a method based on gray level co-occurrence matrix combined with artificial neural network to detect six kinds of defects [2]. Sourav Tola et al. used Haralick parameters related from distance and direction and sparse autoencoder with appropriate sparsity for detection [3]. The biggest problem of the method based on statistical analysis is that the defects need to be large enough.

In the method based on spectrum, Gabor filter has good locality in both spatial domain and frequency domain. Tang et al. proposed a method combining Gabor filter and Histogram of Oriented Gradient (HOG), which used HOG to eliminate the influence of background texture and noise on defect detection [4]. Tong et al. used compound differential evolution to optimize the parameters of Gabor filter and realized feature extraction of fabric defects [5]. However, the detection performance of the spectral based method depends on the selection of filter, which requires large manual intervention and is not strong generalization.

In the model-based approach, the commonly used strategy is Gaussian Markov random field (GMRF). Xu et al. proposed a model based on GMRF, which can obtain the parameter distribution of GMRF model from defect-free fabric image for subsequent defect detection [6]. However, this methods also require a large enough texture region.

Among the method based on deep learning, Wang et al. proposed an RFB model to fuse shallow features and then extract features through the attention mechanism module [7]. Xie analyzed the influence of YOLOv3 using different backbone networks on the detection efficiency and accuracy of defects [8]. In addition, Liu et al. detected defective fabric through SSD network and had a good effect on small defect detection [9]. Wei et al. used VGG16 as the backbone network to complete the detection of four defects by reducing the number of anchor and the complexity of the model [10]. By adding feature fusion network and deformable convolution into Cascade RCNN, An achieved the detection of 20 defects [11]. Although the detection accuracy of these method have been improved, it is still difficult to detect defects with high integration degree with the background, such as hundred feet, which often plays a crucial role in the quality assurance of modern fabric defects detection.

All of the above methods failed to put forward general solutions to the problems of multiple types of defects, high coincidence degree with background, large difference in proportion area and extreme aspect ratio. Therefore, this paper proposes a method combining EDSR [12] and improved Faster RCNN. First, the EDSR network is used to reconstruct the image, extract the overall features of flaws and reduce the influence of background texture. Then, the reconstructed image is input into the detection network for defect classification. The detection network is based on Faster RCNN. FPN module [13] is introduced to deal with defects with small proportion area, DCNv2 module [14] is introduced to deal with defects with extreme aspect ratio. In the RPN module, K-means clustering algorithm is used to set the ratio of anchor. In the ROI module, ROIPooling is replaced by ROIAlign [15] to eliminate the errors caused by the two quantization operations. Finally, the obtained feature images were sent to the full connection layer for defect regression and classification. Subsequently, this paper studies 20 kinds of defects that have a great impact on fabric quality in the production process of enterprises, and verifies the accuracy of the model by setting three kinds of comparative experiments. The results show that the proposed method achieves an average detection accuracy of 85.0%, and the overall recognition rate is significantly higher than other methods, which can be put into production.

2 Model Structure Based on EDSR and Improved Faster RCNN

Based on the above analysis, this paper proposes a detection method combining EDSR and improved Faster RCNN, as shown in Fig. 2 below.

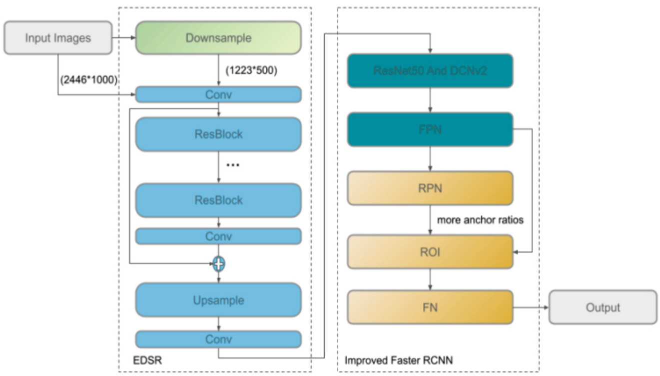


Fig. 2. Model structure based on EDSR and improved Faster RCNN

First, a 2× downsampling is performed on the input image to obtain a low resolution data set, and then the image is fed into the EDSR network. Then defect types were classified and identified based on Faster RCNN. The basic characteristics of flaws were analyzed by clustering to find out the similarity of each flaw type in size, so as to improve the anchor frame ratio of the original Faster RCNN. FPN module can effectively improve the multi-scale capability of the network, and DCNv2 module can enable the network to independently learn the size of deformable convolution kernel. By introducing the above two modules into the Faster RCNN network, the network's ability to identify small flaws and defects with misadjusted aspect ratio can be enhanced. Considering that ROIPooling is used in the ROI module of the original Faster RCNN network, which adopts double quantization rounding, affecting the accuracy of the final classification, this paper improves it into ROIAlign to increase the accuracy of the final classification by replacing the rounding operation and finally completing the defect detection.

2.1 EDSR Network

Super resolution (SR) technology refers to the technology of reconstructing corresponding high resolution (HR) images from low resolution (LR) images. Among them, the enhanced Deep Super Resolution Network (EDSR) was the champion solution in the NTIRE2017 Super Resolution Challenge. As shown in Fig. 3 below, EDSR mainly includes ResBlock module and Upsample module. The ResBlock module is used to learn the mapping between LR and HR. Considering that the information of LR and HR is similar, ResBlock no need to learn the high-frequency information in LR and HR, but only learn the difference between them. ResBlock consists of convolution layer (Conv), activation layer (Relu), and residual-scaling layer (Mult). The Conv layer and Relu layer are mainly used to extract image features and increase the non-linear transformation capability. The Mult layer multiplies the convolution processed data by the scaling number before adding residual blocks, so as to prevent too many ResBlocks from leading to unstable training. Upsample module is used to enlarge image pixels, including Conv layer and Shuffle layer. In the Conv layer, the channels of the input feature graph are doubled, and then feature maps of the two channels are inserted into each other to double the size through Shuffle layer, so that the input image is finally reconstructed with super resolution.

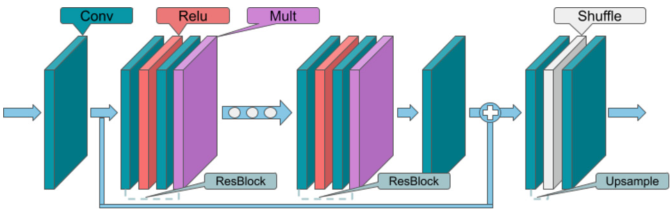


Fig. 3. EDSR network structure

Peak Signal to Noise Ratio (PSNR) is an important evaluation index of EDSR reconstruction effect. The key point of using EDSR network to improve the accuracy of defect detection is to reduce noise and improve PSNR. Considering the complexity of defects, the PSNR threshold is set at 43.27 in this paper to ensure that the image reconstructed by EDSR has enough clear defects in less time. After the PSNR threshold is reached, the reconstructed image is obtained and sent to the deep learning detection network for defect recognition and detection. At the same time, the model proposed in this paper will add a sub-sampling module before EDSR, which will acquire LR images corresponding to data sets through Bicubic algorithm, and then transform LR images and original data sets into DIV2K data sets by changing image names, so as to facilitate training in EDSR network.

2.2 Initial Network of Faster RCNN

Faster RCNN proposed in 2016 is a typical representative of the two-stage detection model. It puts target classification and location in the same network model.Schematic diagram of the Faster RCNN network structure model is shown in Fig. 4.

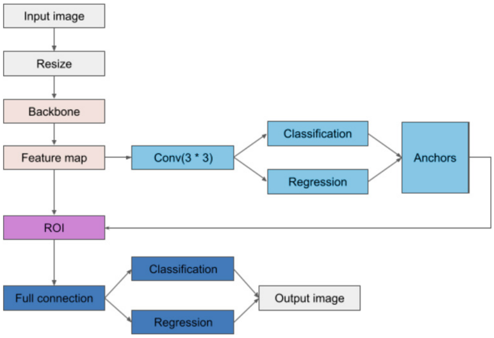


Fig. 4. Schematic diagram of Faster RCNN network

First, all images entered into the network are adjusted in length and width. Then the feature extraction network carries out feature extraction on the input image. Faster RCNN uses VGG16 as the trunk feature extraction network. Although simple, its detection accuracy is too low, and it has problems of gradient disappearance and gradient explosion. In recent years, Faster RCNN uses ResNet50 as a feature extraction network. ResNet50 introduces residual wiring and Batch Normalization while increasing the number of network layers to address poor detection accuracy and gradient-related issues. The final feature map is then fed into the Region Proposal Network (RPN). RPN first carries out 3×3 convolution for the input feature graph, and then carries out two 1×1 convolution. The obtained results are respectively classified and predicted by regression. Softmax function and linear regression are used for coordinate adjustment during classification, and then the sliding window mechanism is used to generate candidate boxes to extract feature information. The main process of sliding window is to use a 3×3 convolution kernel to slide on the feature graph. During each sliding process of the convolution kernel, each center point of the sliding window will generate 9 anchors, namely candidate boxes. The candidate box has three scales $\{1{:}1, 1{:}2, 2{:}1\}$ and three scales $\{128^2, 256^2, 512^2\}$. Finally, As the size of candidate boxes is not uniform, the prospective suggestion boxes judged by RPN will be sent into the ROI Pooling layer for adjustment, and then intercepted on the shared feature map, and then predicted through classification prediction and regression prediction network.

2.3 Improved Faster RCNN

In this paper, four main improvements are made to Faster RCNN, namely, resetting the anchor ratio, introducing FPN module and DCNv2 module, and adjusting ROIAlign to ROIPooling.

Adjust Anchor Frame Proportion. The original Faster RCNN anchors have a total of nine styles. However, these patterns are obtained from standard VOC datasets and are not applicable to the fabric defect detection data set in this paper. Considering the different shapes of defects, large differences in length-width ratio and large variation in proportion area, the method of self-defining the ratio of anchor is adopted. In this paper, K-means clustering method is adopted to generate anchor ratio. K-means algorithm considers that the closer the distance between two targets is, the higher the similarity is. Therefore, for a given sample set, the sample set is divided into K clusters according to the distance between samples. Make the points in the cluster as close together as possible, and make the distance between clusters as large as possible. In this paper, K is set as 9, and the training will stop when the training times or thresholds are given. Finally, a total of 9 anchor frame ratios are obtained, which are {1:50, 1:20, 1:10, 1:2, 1:1, 2:1, 10:1, 20:1, 50:1} respectively.

Introduce the FPN Module. FPN mainly solves the multi-scale problem in target detection. This network structure enables the output of each level to combine the rich semantic information of high-level features with the precise location information of low-level features, so the model can detect objects of different sizes and scales, and the pyramid feature graph at the bottom can better detect small defects. In this paper, FPN is placed after ResNet50. It consists of three paths: bottom-up, top-down, and lateral connections. Figure 5 shows the implementation of FPN. In bottom-up path, the scaling multiple of the last four residual blocks generated by the previous network relative to the original image is {4, 8, 16, 32}, and the 32-fold feature graph is obtained by 1 * 1 convolution. In the top-down path, M4, M3, M2 and M1 are successively obtained by M5 through 2 times up-sampling (using Nearest Neighbor algorithm). In lateral connections, 1 * 1 convolution operation is performed on C5 first to change the channel number to 256D, and then the corresponding positions of C5 and M5 are combined to fuse features. Finally, P5 is obtained by 3 * 3 convolution to reduce the alibration effect caused by the Nearest Neighbor algorithm. In turn, feature maps P4, P3 and P2 of different scales after fusion are obtained, which all contain rich multi-scale feature information of defects.

Introduce the DCNv2 Module. In Faster RCNN backbone network, the convolution operation every time just for computing the pixels and the pixels around (the number depends on the size of the convolution kernels, the shape of rectangular) convolution operation, mainly including sampling and weighted sum of two steps, used by the formula below formula 1, which R is the size of the receptive field, p_n is all pixels in R, w is the weight, p_0 is each position of the input to x, and y is the output.

$$y(p_0) = \sum_{p_0 \in R} w(p_n) \cdot x(p_0 + p_n) \tag{1}$$

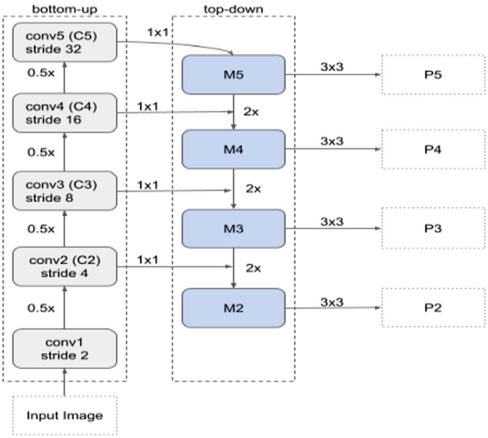


Fig. 5. Network structure diagram

As can be seen from Formula (1), no matter how deep the network is, the receptive field is always rectangular and of fixed size, which cannot adapt to the characteristic of special shape of defects. In particular, traditional convolution operation cannot achieve a good detection effect for defects with extremely mismatched aspect ratios such as thick warp, slack end and thin and dense paths. Therefore, in this paper, deformable convolutional network is introduced into Faster RCNN, see Formula (2) below. DCNv2 enhances the dynamic sampling capability of the module by using additional offset (Δ_{p_k}), which can dynamically learn the size of the convolution kernel and better adapt to the irregular shape of defects.

$$y(p) = \sum_{k=1}^{K} w_k \cdot x\left(p + p_k + \Delta_{p_k}\right) \cdot \Delta_{m_k} \tag{2}$$

Adjust the ROI Layer Pooling Method. In ROI module, ROIPooling is improved to ROIAlign. This is because in the process of ROI pooling, there will be two quantization and round operations, which are respectively to map the original area marked by candidate boxes to the feature graph and then divide the feature graph with a size of 7 × 7 from the feature graph for subsequent full connection. Two round operation will bring slight network deviation, ROIAlign can eliminate the deviation caused by quantization round through bilinear interpolation.

3 Experiments and Results

3.1 Experimental Setting and Datasets

The experimental environment of this paper is unified. All experiments were based on Ubuntu20.04 LTS operating system with 32 GB memory, two RTX 2080Ti graphics cards, MMDetection deep learning framework, PyTorch 1.8 and Python 3.7. The learning rate of all experiments was set to 0.0025, and each experiment was trained for 24 epochs.

The experiment in this paper uses the same data set, which comes from Ali Tianchi Fabric defect Detection Contest and is the picture collected by Tianchi and Guangdong Provincial government in actual textile enterprise production. There were a total of 9576 samples, among which 5913 contained defects, with a total of 34 types of defects, which were relatively complete. However, considering that there is little difference between the types of some defects, this series of experiments divided them into the same category, and finally obtained 20 types of defects. They are: hole, water stain, three silk, knot, flower board jump, hundred feet, wool grain, thick warp, slack end, broken warp, hanging warp, thick weft, weft shrinkage, pulp spot, warping knot, jumping flowers, broken spandex, thin and dense paths, wear mark, double warp, and label them in sequence as 1–20. In addition, all defect images were divided into training set, validation set and test set in 8:1:1 ratio.

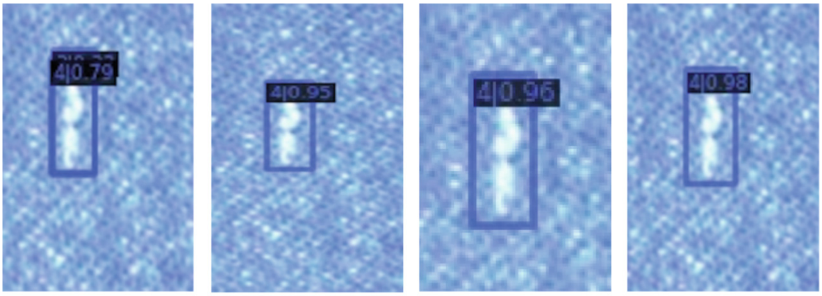
3.2 Comparison and Analysis of Experimental Results

Experimental Results and Analysis Before and After Improvement of Faster RCNN. The first type of experiment is mainly to verify the improvement of detection effect by different improvement points of Faster RCNN. There are four groups of experiments, which respectively train the original Faster RCNN model, the Faster RCNN model integrating FPN, the Faster RCNN model integrating FPN and re-setting anchor for defects, and the DCNv2 integrated Faster RCNN model. Finally, the experimental model is used to verify the test set. Table 1 below shows the final results.

Table 1. Results of Experiment 1

Object detection algorithm	mAP@[IoU = 0.5]
(a) Faster RCNN baseline	41.2%
(b) Faster RCNN + FPN	45.3%
(c) Faster RCNN + FPN + Anchor ratio setting	59.0%
(d) Improved Faster RCNN proposed in this paper	64.2%

In Fig. 6, the pictures labeled (a), (b), (c) and (d) are generated by the model labeled in Table 1 above. It can be seen from the figure that before and after FPN fusion, the knot recognition rate of the model has been greatly improved, but the subsequent improvement of the anchor frame proportion and the newly added DCNv2 do not greatly improve the detection accuracy, because the original anchor ratios has been able to adapt to the changes of knot defects.



(a) (b) (c) (d)

(a) Faster RCNN (c) Faster RCNN + FPN + anchor ratio setting
(b) Faster RCNN + FPN (d) Improved Faster RCNN proposed in this paper

Fig. 6. Test results of knot defect detection using each model

The results of the first type of experiment show that the improved model can improve the detection accuracy of small and slender defects. However, due to its high degree of integration with the background, the detection accuracy of defects such as thin and dense paths is only 45.8%, which proves that it is not enough to rely only on the improvement of Faster RCNN. Therefore, this paper continues to verify EDSR's detection of defects.

Experimental Results and Analysis Before and After Introducing EDSR Network. In order to improve the recognition rate of the whole defect and the defect with higher impurity with the background texture, an EDSR module was added to the above model to conduct the second type of experiment. Table 2 shows the experimental results.

Table 2. Results of Experiment 2

Object detection algorithm	mAP@[IoU = 0.5]
Improved faster RCNN proposed in this paper	64.2%
Improved faster RCNN + EDSR proposed in this paper	85.0

Table 3 makes statistics on the increase and decrease of detection rate of each type of defects, and Fig. 7 shows the test results of thin and dense paths.

As can be seen from the above two tables, the detection ability of all categories has been improved after the introduction of EDSR module. Among them, broken warp, weft shrinkage and thin and dense paths have been greatly improved after the application of EDSR because the defects are slender and have a high degree of integration with the background.

Table 3. Detection results of various defects in the three algorithms

Defect	Faster RCNN baseline	Improved Faster RCNN (this paper)	Improved Faster RCNN + EDSR (this paper)
Hole	72.9%	93.5%	93.6%
Water stains	59.5%	58.4%	88.0%
Three silks	62.3%	73.9%	91.0%
Knot	37.6%	58.8%	73.0%
Flower board jump	63.0%	71.0%	94.7%
Hundred feet	31.2%	69.7%	84.8%
Wool grain	42.9%	47.7%	60.8%
Thick warp	0%	84.8%	94.8%
Slack end	31.5%	68.8%	93.6%
Broken warp	40.5%	51.3%	88.3%
Hanging warp	13.1%	52.1%	87.7%
Thick weft	50.2%	66.2%	80.6%
Weft shrinkage	31.5%	37.9%	65.9%
Pulp spot	57.7%	79.5%	95.9%
Warping knot	65.2%	70.2%	89.7%
Jumping flowers	38.8%	79.0%	94.9%
Broken spandex	57.3%	60.0%	66.5%
Thin and dense paths	6.7%	45.8%	72.1%
Wear mark	38.9%	56.2%	92.6%
Double warps	24.1%	59.2%	90.4%

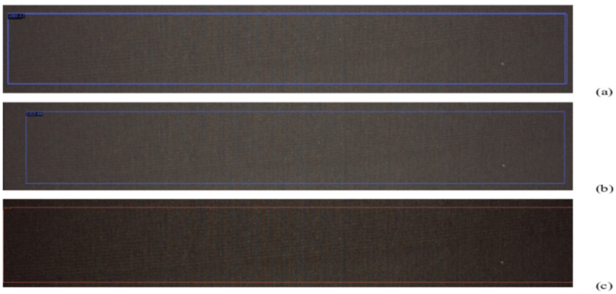


Fig. 7. Test results of thin and dense paths

Figure 7 above shows the detection results of thin and dense paths. (c) shows the test results of the final model after incorporating EDSR. It can be seen from the naked eye that the defect characteristics of fine files are significantly strengthened.

Compare the Experimental Results and Analysis of Other Methods. Cascade RCNN is also a common model in two-stage detection network, while Yolo is a common model in one-stage detection network. In order to compare the difference between the algorithm and other algorithms, Cascade RCNN is used in this paper to set up 6 groups of comparison experiments. The backbone network of Cascade RCNN uses ResNet50 and ResNetX101 respectively. Table 4 shows the final result.

Table 4. Results of Experiment 3

Object detection algorithm	mAP@[IoU = 0.5]
Cascade RCNN (ResNet50) + FPN	52.4%
Cascade RCNN (ResNet50) + FPN + anchor setting	64.2%
Cascade RCNN (ResNet50) + FPN + anchor setting + DCNv2	66%
Improved Cascade RCNN (ResNet50) + EDSR	67.4%
Cascade RCNN (ResNetX101) FPN	57.9%
Cascade RCNN (ResNetX101) + FPN + anchor setting	68.7%
Cascade RCNN (ResNetX101) + FPN + anchor setting + DCNv2	68.2%
Improved Cascade RCNN (ResNetX101) + EDSR	69.6%
Yolov3 [8]	32.54%
EDSR + Improved Faster RCNN (this paper)	84.9%

Experimental results show that the proposed algorithm based on EDSR and improved Faster RCNN has obvious advantages over networks such as Cascade RCNN and Yolov3 in detecting multiple kinds of defects.

4 Conclusion

This paper mainly made relevant improvements based on EDSR and Faster RCNN. Firstly, the EDSR module is introduced to reconstruct the super-resolution image, and the defect and background information are separated. Then, FPN and DCNv2 network modules are integrated based on Faster RCNN, and the ratio of anchor is reset by K-means, and the network accuracy of ROIAlign is increased by replacing ROIPooling, so as to deal with the problem of large difference in defect area and extreme aspect ratio of defects. In order to verify the usability and precision of the model, three kinds of comparison experiments were conducted on 5913 high-resolution images. The final experiment proves that the proposed method can effectively improve the accuracy of defect recognition compared with other current methods. However, the method in this paper still has some problems, such as unsatisfactory detection of defects such as wool grain and weft shrinkage, and slow detection due to the complicated network structure of the model, which need to be further improved in the future.

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