Fabric Defect Detection Method Based on Improved U-Net

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Abstract. Computer vision builds a connection between image processing and industrials, bringing modern perception to the automated industrials. At the same time, defect detection based on deep learning has played an important role in automated detection. In this paper, an improved convolutional neural network CU-Net for fabric defect detection is proposed. In this method, the classical U-Net network was improved. On the basis of network size compression, attention mechanism is introduced and a new compound loss function is used for training. Using the public AITEX defect fabric data set as the test sample, the experimental result shows that the accuracy and recall of the proposed method are 98.3% and 92.7%, respectively. Compared with the highest scores of other detection methods, they are improved by 4.8% and 2.3%, which improves the detection accuracy of fabric defect significantly.

1. Introduction
As fabric is widely used in various fields, such as clothing, medical treatment and military enterprise, a large amount of fabrics are produced each year. In the industrial production, due to yarn problems, improper operation and excessive stretching, the fabric produced has various defects, and the defective fabric leads to low quality products, which reduce the price of the product by 45-65%[1]. Surface defect is common but serious, including broken yarn, big knot and weft curling. Therefore, in order to ensure the value of the product, it is necessary to detect the surface defects of the fabric in the productive process.

Up to now, there are a large number of successful fabric detection methods. The paper [2] proposed a new deep convolutional neural network (PTIP), which used local images in the training stage and whole fabric images in the testing stage. The paper [3] proposed a full convolutional neural network named U-Net, which adopted the pixel-to-pixel training way and achieved satisfactory results in medical image segmentation. In order to solve the real-time problem and the unbalanced sample of positive and negative data under the actual production conditions of fabric factory, The paper [4] proposed an efficient convolutional neural network, Mobile-UNET. The model used the median frequency balancing loss function to overcome the unbalanced sample problem, and in addition, it introduced depth-wise separable convolution, which greatly reduces the complexity and model size of the network.

In this paper, an improved U-Net model is proposed for fabric defect detection, and the detection results are compared with the methods mentioned above. The results show that the model in this paper performs well in fabric defect detection.

2. Proposed Approach
In this part, the process of fabric defect detection is introduced. The method is an end-to-end architecture for accurate defect target localization, which mainly consists of defect object segmentation and post-processing.
2.1. Defect object segmentation

This paper proposes an improved U-Net (CU-Net) method for defect segmentation. In U-Net, the pixel-to-pixel mapping is achieved by abandoning all the full connection layers, and the context information is transferred to the higher feature map through the skip connection between the contracting path and the expansive path. However, the classic U-Net has two serious disadvantages: on the one hand, its segmentation accuracy is not high; on the other hand, due to the large size of the model, it takes a long time to consume. Therefore, we analyzed its features and made several significant improvements.

2.2. Post-process

After CU-Net processing, the image is output as a binary segmented image. Based on this segmented image, the defect area of the fabric is marked with a rectangular frame in the post-processing stage. The final results showed that the defect areas through post-process were more visible and more likely to be recognized by technicians.

3. CU-Net Network Model

3.1. Basic architecture

In order to speed up the training and testing of the model, the number of feature channels and downsampling is pruned, where channels are reduced from 64,128,256,512,1024 in basic U-Net to 32,64,128,256 in CU-Net. In the CNN, the smaller feature map contains more semantic information for classification task, while the larger feature map contains more spatial information for localization task. Fabric defect detection is a binary classification problem, so more attention should be paid to localization. Due to the reduction of number of downsampling, the smallest feature map of CU-Net is quadruple larger than U-Net, which lead to higher localization precision. The CU-Net architecture is shown in Figure 1.

3.2. Attention mechanism

Considering that some fabric images include tiny defects, which are easy to be neglected in the segmentation process, the attention mechanism is introduced in the skip-connection.

![Figure 1 Network structure of CU-Net](image)

Attention mechanism is used to explicitly model the dependencies between feature channels. In the CU-Net, it is introduced in skip-connect to suppress the characteristic response of unrelated regions and reduce the number of redundant features. The introduction of this module will only increase a few parameters and memory burden to the model, but significantly improve the predictive ability of the model. It is shown in the figure 2.
The module consists of three phases: squeeze operation, excitation and weight distribution. Through global mean pooling, each channel of the input feature map is squeezed, thus the global information of each feature dimension is obtained. The calculation formula of the squeeze operation is:

$$y_c = S(x) = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{ci}$$

(1)

Where $x_c$ represent the $c$-dimensional feature of the input feature map; $H$ and $W$ are the width and height of feature map; $S$ is the squeezing function.

Excitation is similar to the gate mechanism of recurrent neural network. Two full connection layers can better fit the complexity between channels. Therefore, it is selected to generate weights for each feature channel. The calculation process is expressed as:

$$E(x) = \sigma(W_r \delta(W_s(x)))$$

(2)

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

(3)

Where, $x$ is the feature map after squeezing; $W_r$ and $W_s$ represents the full connected layers of compression and refactoring, respectively; $\delta$ and $\sigma$ is Sigmoid and ReLU function, respectively; $E$ is the weight function.

The previous feature map is multiplied by the corresponding element of the weight function to highlight the target region and suppress the irrelevant response.

3.3 Compound loss function

Fabric defect detection is modeled as a binary classification problem, the pixels in image belong only to the defect or the background. Cross-entropy is often used as the loss function in the case, and it is defined as:

$$L = -\frac{1}{n} \sum_{j=1}^{n} (y_j \log(p_j) + (1 - y_j) \log(1 - p_j))$$

(4)

However, this loss function is more suitable for the case of positive and negative sample balance. In the actual fabric image, the proportion of pixels occupied by the defect is much smaller than that of the background area, which causes the model to focus more on the recognition of the category with a higher proportion. With this in mind, the compound loss function, which is obtained by adding the cross-entropy loss and the Dice loss[5], is proposed to be applied to the defect detection of fabrics. DiceLoss is defined as:

$$L_{Dice} = 1 - \frac{2 \sum_{i=1}^{N} p_i \times y_i}{\sum_{i=1}^{N} p_i + \sum_{i=1}^{N} y_i}$$

(5)

4. Experiment and Result Analysis

We implemented a series of experiments on a computer loaded with an Intel Core i7 8700K and a Nvidia GeForce GTX1080Ti (11GiB). The Ubuntu16.04 operating system was adopted, and the PyTorch deep
learning framework was used for programming. In addition, we used AITEX\cite{6} data set for training and testing. After data enhancement, the whole data set contains 595 samples. According to the proportion, the data set was randomly divided into training set, verification set and test set, which contained 415, 119 and 61 samples, respectively. Some samples of the data set are shown in Figure 3.

4.1. Evaluation metrics
In order to quantitatively evaluate the performance of the method proposed in this paper, we introduced two different evaluation indexes: accuracy (ACC) and recall (RE). The calculation result is determined by the following equation:

\[
Acc = \frac{TP + TN}{TP + TN + FP + FN}
\]

(6)

\[
RE = \frac{TP}{TP + FN}
\]

(7)

Figure 3 Parts of sample in AITEX fabric data set

4.2. Implementation details
In addition, the Adam optimizer was used to update the network weights, because it can adjust the learning rate adaptively during training\cite{7}, and has a faster convergence speed. We set the initial learning rate at 0.001, and the \(\beta_1=0.9\), \(\beta_2=0.999\), respectively. Considering the influence of memory, during the training stage, bitch_size was set to 2, and a total of 100 generations of training were conducted.

4.3. Result
After 100 iterations, the model fully learned the defect characteristics of the fabric, and the training process curves obtained were shown in Figure 4 and Figure 5.

Figure 4 The loss curve during training
Figure 5 The Accuracy and Recall during training
The model after training was used to predict the images of the test set, and other detection methods mentioned in the paper were compared, as shown in Figure 6. The results show that the detection method in the paper can express the defects in fabric more intuitively.

In order to prove the advancement of the method in the paper, the ACC and Re of the detection results of the proposed method were quantitatively compared with those of the above methods. The results are shown in Table 1. On the AITEX dataset, the ACC and RE of the proposed method reached 98.3% and 92.7%, respectively, which were 4.8% and 2.3% higher than the highest scores of other detection methods.

Figure 6 Detection results comparison of different algorithms. (a) Defect images; (b) Ground truth; (c) PTIP; (d) U-Net; (e) Mobile-Unet; (f) Our method

Table 1. Detection accuracy and recall comparison of different algorithms

| Algorithm | PAcc (%) | Pred (%) |
|-----------|----------|----------|
| PTIP      | 85.6     |          |
| U-Net     | 89.3     |          |
| Mobile-Unet | 93.5   |          |
| Ours      | 98.3     | 92.7     |

5. Conclusion
Inspired by the convolutional neural network, this paper proposes an effective deep learning model for fabric defect detection. The model was evaluated on the AITEX dataset and compared with other detection methods in the literature. The results show that the accuracy and recall rate of the model in this paper are improved. Due to various interference factors in the actual industrial testing, this paper did not conduct experiments in complex environment to test the robustness of the model. The following work will be carried out in this respect.

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