Defect Detection in Fabrics using Modified CNN

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***Abstract:* Fabric defect detection is an important measure for quality control in a textile industry. Many fabric defects are very small and undistinguishable, which are very difficult to detect .Mostly fabric defects are due to Loom malfunctions. In this paper, a modified Deep Learning algorithm was developed for an on-loom fabric defect inspection system by combining the techniques of image pre-processing, fabric motif determination, candidate defect map generation and convolutional neural networks(CNNs). First, the fabric image is decomposed into local patches and labelled. Then the labelled patches are transmitted to the pretrained modified deep CNN for transfer learning. Finally, defects are detected during the inspection phase by sliding over the whole image using the trained model, and the category and position of each defect is obtained. The proposed method is validated on three public and two self-made fabric database. The experimental results demonstrate that our method significantly outperforms selected state-of-the art methods in terms of quality, cost, time and robustness.**

***Index Terms*: Convolutional Neural Networks, Fabric Defect,Trained Model**

I.INTRODUCTION

Due to yarn and mechanical problems in a power loom various defects can be formed on the surface of fabrics, there are more than 65 defects in the fabric which leads to the reduction of price from 30-40% so it is important to detect the defects. It can be reduced by different defect detection methods. Hence it is necessary to take important measure in the industry to detect the defects .Normally the defects are detected through human which will take more time and cost so we need to reduce the time ,error and cost. Here we using updated automatic inspection method. It will helpful in major ways as it can reduce the time and cost. Most of the textile industry are adapted this method. Auto-fabric inspection systems are based on computer vision techniques and it including image acquisition and defect segmentation algorithms. There are various algorithms in the fabric defect system they are statistical ,spectral , model- based ,learning approaches and hybrid. Hybrid approach is mostly used for high robustness .while in other fields BB and ER are used for fabric defect detection. The detection rate of BB and ER is above 96% on patterned fabrics, they are used to detect the defects only greater than the repetitive unit of fabric.The convolutional netural network is efficient in defect detection.the defect in the fabric image are double pick, mispick, coarse pick. During the use of CNN for fabric defect detection. There are two important parameters need to be considered. preservation of fine structures and treatment of imbalanced dataset.The involvement of too many convolutional layers cause missing of fabric image,it can be avoided by using CNN.

In this paper,we adopt a modified CNN for fabric defect detection. Themotif of a fabric is calculating by use of the autocorrelation of a fabric image.It can be used to represent the repeated texture in the fabric. To relate the node point count in a motif region to the defect judgment the statistical rule can be used. In a newly designed CNN to improve the fabric defect detection performance.

II.RELATED WORKS

Most of the existing works on fabric inspection is mainly focused on homogeneous fabrics including plain as well as twill fabrics. These methods can be classified into four main categories: (i) statistical; (ii) spectral; (iii) model-based; and (iv) learning-based approaches .Learning-based approaches are also popular in detecting defects, using labelled samples to train classifiers that distinguish between defective and non-defective samples. Convolutional networks have good fault tolerance, parallel processing capabilities, generalisation capabilities, and self-learning capabilities that can handle complex environmental information issues. Since the early 2000s, with the rapid development of big data and artificial intelligence, convolutional networks have been applied with great success to the detection, segmentation [28] and recognition [29] of objects and regions in images, especiallyin tasks with a large number of labelled samples. The Felzenszwalb's segmentation [40] is applied to accurately locate the size and location of defects in the heatmaps, but it incurs a huge computation time to generate heatmaps. Model-based methods are used to solve the defect detection problem by assuming that the texture obeys a particular distribution model and that the model's parameters are estimated In statistical approaches, the AF and the co-occurrence matrix (CM) have been successfully applied to detect defects.

III.PROPOSED MODEL

1.CNN'S ACTIVATION LAYER

Normally we identify an object, by useful informatios like shape, color, smell, feeling, and prior knowledge. The success rate and the response speed of object recognition can be significantly influenced by prior knowledge .For object identification CNN selects only one from large amount of generated features. To regulate the contributions of different features by general activation layer. The primitive way of filter features is binary activation layer, because of zero gradient function it does not improve the network evolution.

Comparing to binary the linear activation function has a similar problem, The error cannot be reduced by constant value of its derivation during the back propagation.There are two Non-linear activation functions like Sigmoid and Tanh.They can achieve breakthroughs than linear functions.when the values of gradients curves of Sigmoid and Tanh functions leads to zero.The network sparse becomes efficient by ReLU activation function because the coefficient of a negative neuron is becomes zero, and yielding dead neurons are deactivated. If too many dead neurons are generated by the ReLU,So the surviving neurons does have a enough powerful to recognize objects correctly. The dead neurons are avoided by using leak ReLU.The activation function is used in a CNN is sigmoid or tanh.

2.NATURE OF CNN

Convolutional neural networks (CNNs) are skilled in dealing with related machine learning problems. Because they are multilayer networks,It also performs large-scale image classification tasks.The input images features could be extracted layer by layer during the training process of convolutional netural network and finally the defect information is obtained through feature fusion.There are three parts in the CNN, The convolutional layer, The pooling layer, and the fully connected layer. The core of the CNN is to traverse the input image and to obtain the corresponding feature map CNN uses the multiple convolution kernels.


(a)


(b)


(c)


(d)

Figure 1 represents the different types of fabric defect samples (a)Hole (b)Carring (c)Knot (d)Dark spot

IV.ARCHITECTURE

The extraction ability of Deep convolutional neural network was strong. According to the computer vision, fabric defects are considered as one of the fine structures the small number of pixels in an image can be used to indicate the defect.it is only way to detect the defect. A deep CNN model can be designed to improve the fine structure detection, the features would be extracted by using 3×3 convolution kernel. In the forward propagation process, By adjusting the step size of convolutioncore plays a major role to realize the dimension transformation of tensor instead of max pooling layer, so the reduction of the loss of feature informationand improving detection accuracy.To reduce the computational load of the network and to improve the detection speed,the choice should be lightweight, high-speed network structure, which increases the performance of the convolutional layer and full connection layer of CNN to realize real-time detection of fabric defects.

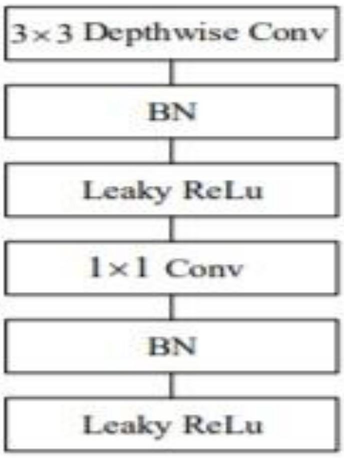

Figure 2 represents the flowchart for layer activation

Depthwise Separable Convolution Network

In convolutional neural networksConvolution kernelscan be included as three filters:channel dimension,spatial dimension, standard convolution. The operations of standard convolution are actually joint mapping of channel correlation and spatial correlation. The input channel can be taken as a whole by using standard convolution, without any segmentation,All input channels can be applied by single filter and performing feature fusion.

$$D_k \times D_k \times N$$

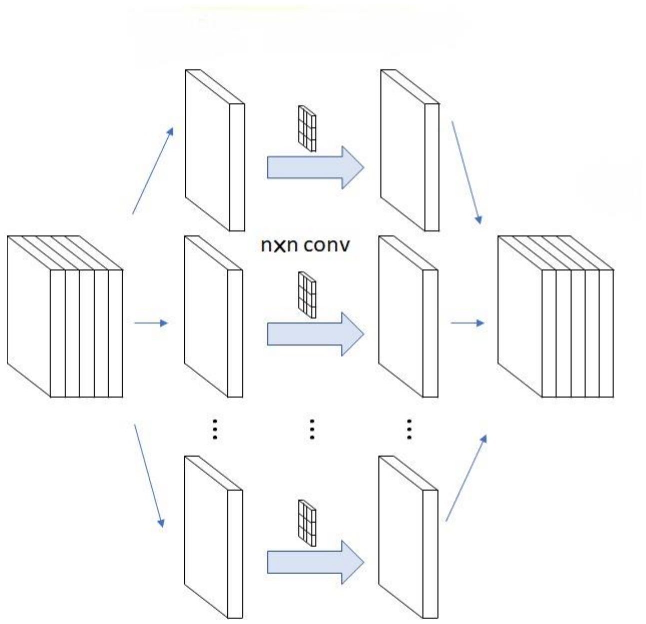

Figure 3 Architecture of a deep convolutional neural network

Based on depthwiseseparable convolutionDefectNet is a factorized convolution.standard convolution can be factorizes into a depthwise convolution and a pointwiseconvolution.In thismodel applies for each input channel can be applied with one single filter by standard convolution, then applies a convolution to combine all the outputs of the depthwise convolution.Filtering channels combines with combining channels and extracting spatial features by using standard convolution Depthwise separable convolution can be divided into two layers, they are filtering channels and combiningchannels.The calculation and model size should br reduced by this factorization.The required parameters can be reduced more by depthwisesearable convolution compared with ordinary convolution.The main function of the depthwise separable convolution converts the standard convolution operation into a convolution operation it includes both the channel and the region. The region can be considered as first and then considers the channel. The channel and region are separated Depthwise separable convolution can be derived by two steps, depthwise convolutions and pointwiseconvolutions.The depthwise convolution can be used to use a single filter for each input channel.The linearcombination of the output of the depthwise layer can be created by pointwise convolution.

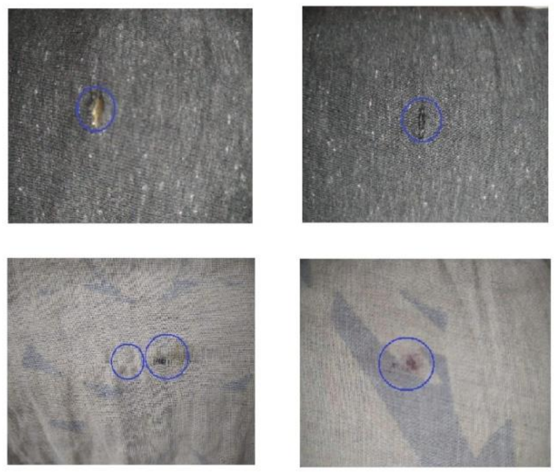

Figure 4. The fabric defect inspection results for the fabric image

V. CONCLUSION

The algorithm that we proposed is a new fabric defect detection method which can deal with various types of fabrics. Our method does not directly take the original image as input. Instead, we divide the fabric input image into multiple patches along the inherent period of the fabric surface.That are used as an operation object to train deep CNN. Our algorithm achieved good results on three datasets, which can achieve accurate detection of common defects in yarn-dyed fabric, such as Carrying, Thin Bars, Scratches, Knots, BrokenEnd, Stains, and Holes. Compared with traditional shallow learning method our proposed method can effectively learn defect features by adaptively adjusting the parameters. And also our method can improve efficiency in various parameter, shortening the time of measurement, and obtaining an accurate defect image. In the future, we will focus on defect segmentation and also on achieving high accuracy.

VI. RESULT

We have compared our method with other methods including GLCM, RCT, LBP, LeNet, AlexNet and VGG16
in the same fabric database. The GLCM method often needs to manually set the threshold between the template image and the image, and it is easy to fall into the dimension disaster in the process of computing the Euclidean distance. The statistical characteristics of the fabric image are obtained by fitting the coefficients of RCT using a finite mixture of a generalised Gaussian model, which has invariance to fabric translation and scale changes. The disadvantage of this method is that the fitting process is lengthy, which leads to the slow speed of the algorithm and poor real-time performance. Similarly, the LBP operator can also describe the texture information of the fabric, but the number of the sampling points has a great influence on the extraction and recognition of texture features.

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