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Fabric Defect Detection Using Customized Deep Convolutional Neural Network for Circular Knitting Fabrics

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Keywords
Fabric defect detection, Deep learning, Neural networks, Model optimization

Abstract: Visual inspection is a main stage of quality assurance process in many applications. In this paper, we propose a new network architecture for detecting the fabric defects based on convolutional neural network. Four different pre-trained and customized model network architectures have compared in terms of performance. Results have been evaluated on a fabric defect dataset which consist of 13820 images. Among the existing Inception V3, MobileNetV2, Xception and ResNet50 methods, the InceptionV3 model has achieved 78% classification success. Our designed deep network model could achieve 97% success rate. The experimental works show that the designed deep model is effective in detecting the fabric defects.

Yuvarlak Örgü Kumaşları İçin Özelleştirilmiş Derin Evrişimsel Sinir Ağı Kullanarak Kumaş Hatası Tespiti

Anahtar Kelimeler
Kumaş hatası tespiti, Derin öğrenme, Sinir ağları, Model optimizasyonu

Öz: Görsel denetim, birçok uygulamada kalite güvence sürecinin ana aşamasıdır. Bu çalışmada kumaş hatalarının tespiti için derin evrişimsel ağa dayalı yeni bir ağ mimarisi önerdik. Önceden eğitilmiş ve özelleştirilmiş 4 farklı ağ mimarisi performans açısından karşılaştırılmıştır. 13820 görüntü içeren kumaş hatası veri tabanı üzerinde sonuçlar değerlendirilmiştir. Mevcut Inception V3, MobileNetV2, Xception ve ResNet50 metotları arasında, InceptionV3 modeli %78 sınıflandırma başarısı elde etmiştir. Bizim dizayn ettiğimiz derin ağ modeli %97 başarı elde etmiştir. Deneysel çalışmalar dizayn edilen derin modelin kumaş hatalarını tespit etmede etkili olduğunu göstermiştir.

1. INTRODUCTION

Fabric defects are a significant challenge in the textile industry when it comes to assessing quality control. One of the most essential approaches for evaluating fabric quality is detecting the defect and then classification for those defects. The classification of fabric defects is an important step in the quality assurance process. The machine could alter and enhance its processing technique by supplying defect information. The primary challenges to defect detection are: 1) commonalities between various types of defects. It could be difficult to discriminate between broken picks and slub defects. 2) Classification of various fabrics and extraction of features for the same defect across multiple fabrics takes a long time. 3) Low-resolution, low-contrast defects. 4) Defects of various scales.

Defect identification is now done in most production utilizing human inspection and conventional feature extraction for each fabric. Fabric surface defect detection algorithms could not successfully identify and distinguish different types of fabric defects due to the complexity of textile defects. Visual inspection by skilled employees using man-made classification criteria is used to assess fabric problems. Due to the limited separation capability of the handicraft features, traditional detection algorithms are less accurate and efficient in distinguishing diverse fabric defects.

Furthermore, traditional algorithms are frequently unable to generalize diverse inspection processes.
Model-based, statistical, and spectral are the three types of classic fabric defect detection methods. Approaches that use models: This approach is appropriate for fabric pictures with surface variations related to defects like yarn breakage and needle breakage. Model-based defect detection techniques have the benefit of being able to generate fabric textures that are similar to the observed fabric textures [1]. Statistical methods: Defect detection seeks to divide the inspection picture into statistically distinct sections. Textural characteristics derived from fractal dimensions, co-occurrence matrix, edge detection, cross correlation, first-order statistics, eigen filters, morphological operations, and a variety of local linear transforms are all included in this class [2].

Spectral approaches: The location of the fabric defect must be determined using spatial domain information. A wide range of studies on fabric defect detection have focused on spectral techniques. The intention of spectral techniques is to remove the fundamentals of image texture and by doing that they were able to generalize the fundamentals of texture using spatial layout. Many standard low-level statistical methods, such as detecting an edge, fail to detect a variety of fabric defects, which appear as minor intention transitions. As a result, it's vital to look into additional reliable computer-vision algorithms for recognizing fabric defects [3].

In computer vision applications, deep convolutional neural networks (CNN) being used for a variety of use cases, including image classification and object recognition [4,5]. Recent researches have created CNN-based algorithms for fabric defect detection in the textile sector, which were inspired by the applications. Bing Wei [6] suggested an approach for improving accuracy in fabric defect samples using a small portion of defective instances and CNN to classify features space using compressive sampling. To detect defective photos, Mei Zhang [7] proposed a deep convolution neural network-based one-class classifier, to train the neural network model, they created a loss function with a correction term based on Euclidean distance. Zhao [8] proposes that an integrated CNN model based on visual long-short-term memory (VLSTM) might alleviate the problem of fabric defects that are difficult to distinguish against a textural background. The strategy they offer is based on human visual perception and memory mechanism. Generative adversarial network (GAN)-based framework is suggested by Liu [9] for defect detection which able to learn existing fabric defected test results and automatically adapt itself to various fabric textures during different situations of application. The proposed method can detect different defect types by optimizing a deep semantic segmentation network. According to gray histogram back-projection, Guodong [10] developed a fast defect-detection-framework (Fast-DDF), To address the problem of adjusting network model parameters and long training time, an end-to-end multi convoluted network model is used for defect classification, as well as batch normalization of samples and a network fine tuning process. Jing [11] introduces a deep convolutional neural network-based (CNN) detection approach for autonomous fabric defect detection. There are three key steps to it. The fabric image is first divided into local patches, which are labeled. The labeled patches are subsequently given to a deep CNN that has been pre-programmed for transfer learning. Eventually, during the inspection step, the whole image is moved using the trained model, and defects are recognized, as well as the category and position of each defect. Investigating deep Convolutional Neural Network (CNN) design configurations and the impact of different hyper parameter settings for improved defect detection findings, Weimer [12] investigates a new machine learning paradigm, called deep learning. They propose that CNN can automatically produce powerful features from enormous numbers of training data using hierarchical learning algorithms with minimum human involvement.

To use a pre-trained network that has been trained on a big dataset is a frequent and successful technique to deep learning on small datasets, usually a large-scale image categorization. Large picture datasets were commonly used to train CNN architectures such as InceptionV3 [13], VGG16 [14,15], AlexNet [16], and ResNet [17]. This research compares an FCN-based fabric defect detection system with a custom-designed neural network architecture. On a circular knitting machine fabric picture dataset [15, 18, 19], they begin by analyzing and comparing various pre-trained deep CNN architectures for image classification with our own CNN developed model. Then, utilizing flawed and defect-free fabric photos, the suggested method performance is confirmed.

2. RELATED WORKS

2.1. Methodology

We might be able to find some advanced convolutional neural network models and use them to classify fabric defects. The state-of-the-art model topology, on the other hand, is frequently excessively complicated. The ResNet, for example, has excellent classification accuracy but has too many layers, making it difficult to train and evaluate. The GoogleNet model, on the other hand, has many fewer parameters but still can reach excellent classification accuracy. For both fabric defects, an FCN is trained from end -to-end to classify an image of a defect in to the "defected" and "defect-free" pixels. On a circular knitting machine fabric picture dataset, tests are first done to assess the performance of several pre-trained CNNs for classification tasks. The FCN network's backbone will be the pre-trained model that has been chosen. Annotated database pictures with defects are used to train deep models in this research. The FCN is trained on a subset of the same dataset that includes fabric images that have been labeled.

2.2. Defect Classification Using Pre-Trained Neural Networks

(CNNs) are multi-layer neural networks that assess visual inputs and perform tasks including image categorization, segmentation, and object recognition. A convolutional layer, a pooling layer, and an activation unit are all included in each layer. The convolution layer applies convolution to the output of the preceding layers, utilizing filters or kernels to extract important features for image categorization. Two convolutional blocks are used in some previous network architectures, such as LeNet-5. CNN designs have recently become more complex, including VGG16, Inception, and ResNet, which have enhanced layer configurations.

The majority of past research has presented defect detection approaches based on network training from the scratch. Transfer learning, on the other hand, has also been shown to boost the defect classifier's training efficiency and accuracy.

The accuracy of four distinct pre-trained CNN models, including InceptionV3, VGG16, AlexNet, and ResNet, was tested in this research. ResNet has 152 layers of residual nets, which is 8 times more than the VGG model. Despite of having a simpler model than ResNet, the VGG model outperformed ResNet in classification contests such as ILSVRC 2015 and ILSVRC & COCO 2015 [14]. The models' structures are depicted in Figure 1. The network depth and parameter configuration of the models have been shown in Table 1.

Table 1. Number of parameters and depth of networks

Model	Number of parameters	Depth
InceptionV3	23.851.784	159
ResNet50	25.636.712	152
MobileNetV2	3.538.984	88

For transfer learning, first we need to normalize the fabric images then separate images into train and test folders after that images divided into 80% train and 20% for the test purpose. After the data has been prepared, we are loading a pre-trained model.

Deep neural networks are multi-layered structures with numerous tunable hyperparameters. The initial layers' role is to capture generic features, whereas the later layers focus more on the explicit task at hand. We can retrain some of the model's layers while leaving others frozen in training. A binary cross-entropy loss is used to construct the model. As an optimizer, the rmsprop technique is utilized. Our Fabric defect classifiers are trained on Nvidia 2080 TI GPU with the Keras framework and TensorFlow backend which is an open-source machine learning framework [20].

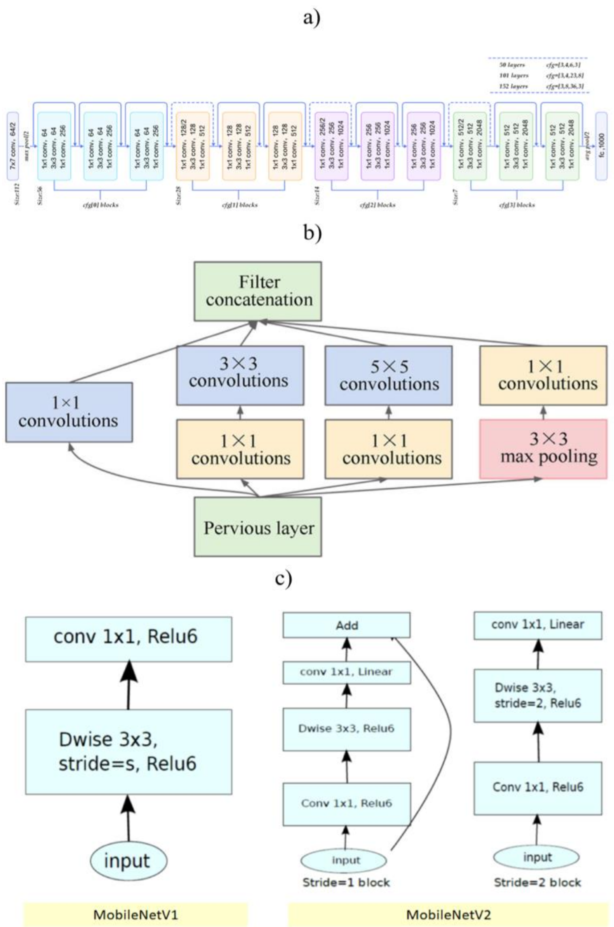

Figure 1. a) ResNet b) Inception c) MobileNet network architectures

2.3. Fabric Image Dataset

The dataset of fabric images which has the total 13820 images organized according to a list of 2 categories on circular knitting machine. Image size is 250x256 pixels [15, 19] where 10820 are defect-free and 3000 are defected images for classification process. The sample images are shown in Figure 2.

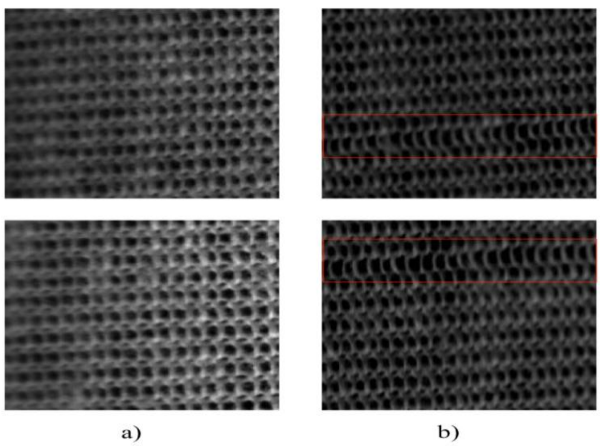

Figure 2. a) defect-free b) defected fabric images

3. RESULTS

3.1. Classification of Defected Images Using Pre-Trained Networks

In this part, we'll compare the pre-trained and customized models in terms of performance. We utilize the same environment and database to provide a proper comparison. We did the same thing with the pre-trained weights, setting them as the model's initial value and then training it. The pre-trained models: InceptionV3, MobileNetV2, Xception, and ResNet50 are primarily fine-tuned for model training. All of the models utilize the same training datasets.

Table 2. Classification performances of different deep architectures

Model	Epoch	Accuracy (%)	Image Size
Our Model	14	97%	250 x 256
InceptionV3	20	78%	250 x 256
MobileNetV2	20	49%	250 x 256
Xception	20	69%	250 x 256
ResNet50	20	22%	250 x 256

The customized model classifier is trained for 20 epochs which has batch size of 64 and 0.9 is used for momentum term, while training with datasets, InceptionV3 classifier achieved over 78% accuracy higher than other pre-trained networks, ResNet based classifier produces the minimum accuracy between all models and all results. Our designed model could be considered one block VGG model which consist of one convolution layer followed by max pooling then output of previous layer flattened and connected to ReLU activation function and finally one layer of Soft-max which predict the classes for defected and defect-free classification. The custom designed model provided in Figure 3 and the accuracy of all classifiers shown in Table 2.

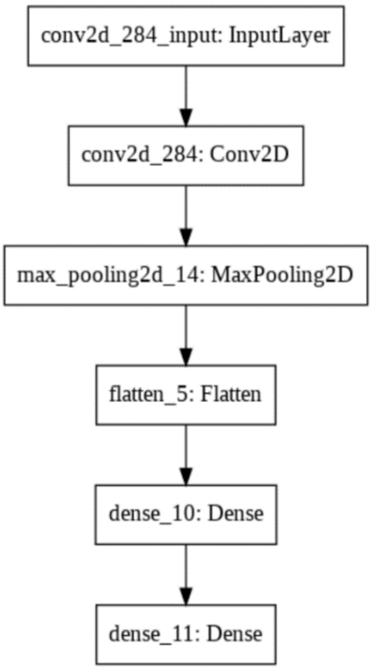

Figure 3. The proposed convolutional neural network architecture

3.2. Fully Convolutional Network Training

The pre-trained weights of ImageNet are used to generate the weights of all layers of fully convolutional networks. We used the circular knitting machine fabric image dataset to train the model. Figure 4 displays the result of validation accuracy and validation loss. By looking at the results, we can see the simple in-depth network could achieve good results. In some cases, adding the one layer of dropout regularization could help the overall accuracy but for our classification problem we have 250x256 image size which by adding the dropout layer our feature sets do reduced and caused lower accuracy. Another important factor in FCN is the over-fitting, we observed that training for higher epochs could cause over-fitting in model training, in our case 14 epoch is the optimal number for our model to achieve higher accuracy.

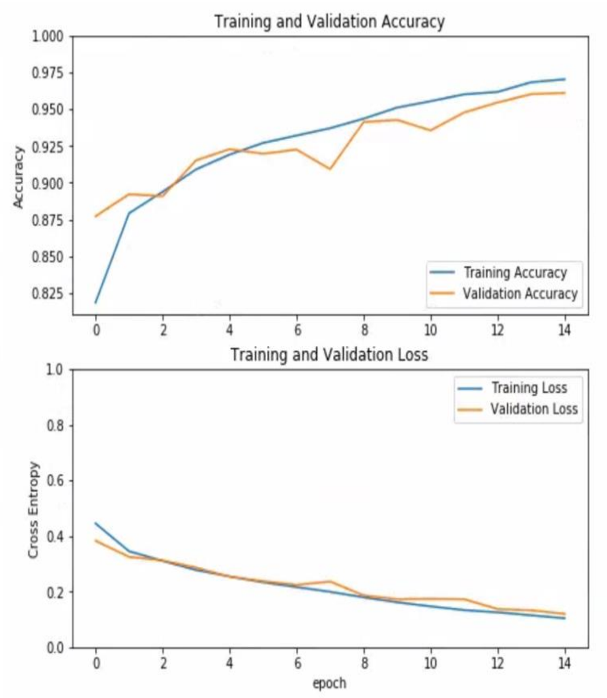

Figure 4. The classification results of the base-model in terms of accuracy and loss

Adding more layers will help the network to extract more features and do better classification for specific recognition tasks but we could do that up to a certain extent. After we surpass the threshold, instead of extracting more features we are getting in to the over-fitting phase. Overfitting could lead to errors in some or the other form like false positives. We tried to add more layer to the model and by adding additional layer to our base model after 10 epochs our model start to produce the sign of over-fitting as shown in Figure 5.

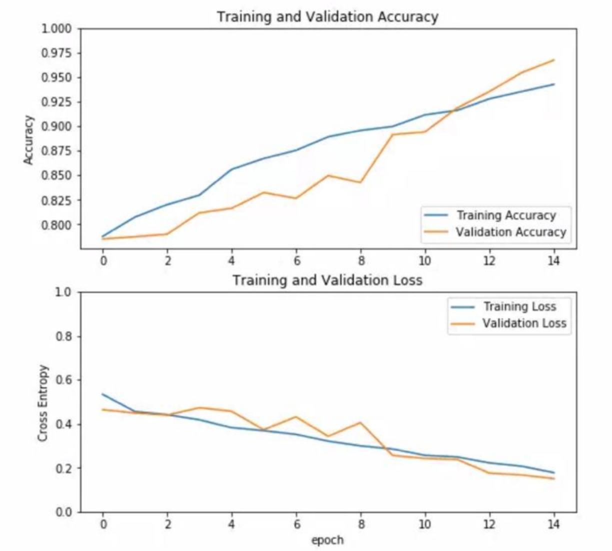

Figure 5. The classification results of the additional layer on top of base-model in terms of accuracy and loss

3.3. Testing

The database is divided into two folders, one for defect images and another for defect-free images. The class numbers are the same as the name convention which is 2. In a dataset including 600 defective fabric images, 562 defected images and 38 defect-free images were recognized, with a TNR of 96.3 %. Overall, the system has a 97% detection accuracy, and each input image is detected in an average of 15.4 milliseconds. Table 3 compares the performance of the InceptionV3 to that of the original.

Table 3. TNR: True Negative Rages; TPR; True Positive Rates

Model	TNR	TPR	Model size
Our Network	96.3	98.3	70 MB
InceptionV3	79.9	80.5	95 MB

4. DISCUSSION AND CONCLUSION

For fabric defect identification and accuracy evaluation, a vision-based technique based on deep convolutional networks is suggested in this paper. For fabric-defect recognition, we compared the accuracy of a pre-trained neural network and a customized neural network model. Then we trained all network with same database and examined the custom designed model with smaller in-depth and lower in-params could achieve better results than pre-trained neural networks with much deeper and much higher parameters. We proposed a simpler model that can be applied to detect fabric defects which produced via circular knitting machine in factory. As a result, applications of the proposed fully connected neural network in circular knitting machine fabric manufacturing should be researched further. Although the suggested approach has successfully collected defected images, quantifying defect for various textiles remains a challenge. As a result, future research should concentrate on how to enhance the suggested approach in order to make defect detection more robust on various fabric sorts and noisy defects.

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