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Detecting of Circular Knitting Fabric Defects Using VGG16 Architecture

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Deep learning,
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Abstract: Although the conventional image processing methods can detect fabric defects, fabric defect detection is an open research problem due to the diversity of defect types. In this paper, the feasibility of VGG16 deep learning architecture for fabric defect detection has been demonstrated. A new fabric defect database is used. The pre-trained model of VGG16 architecture on the new database is built. Thus, the training time of the model is reduced. The experimental results show that the VGG16 model outperforms the traditional Shearlet transform and GLCM methods.

VGG16 Mimarisi Kullanılarak Yuvarlak Örgü Kumaş Hatalarının Tespit Edilmesi

Anahtar Kelimeler
Kumaş hatası,
Derin öğrenme,
Hata tespiti

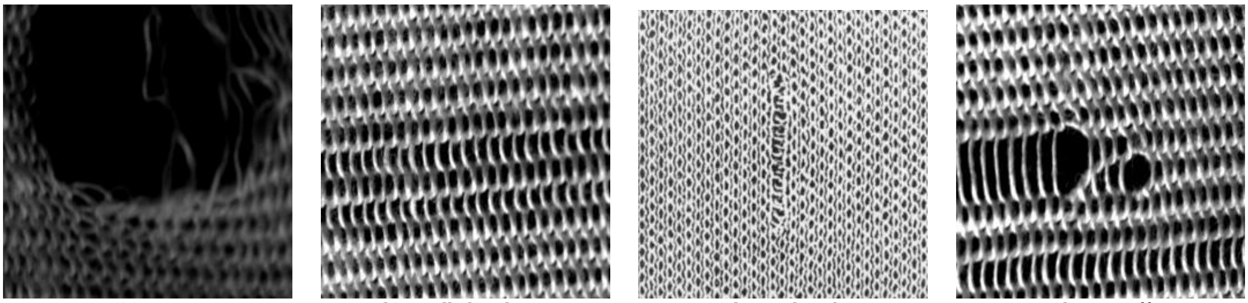
Öz: Geleneksel görüntü işleme metotları kumaş hatalarını tespit edebilmelerine rağmen kumaş hatası tespiti hata tiplerinin çeşitliliği yüzünden açık bir problemdir. Bu çalışmada VGG16 derin öğrenme mimarisinin kumaş hatası tespiti için uygunluğu gösterilmiştir. Yeni bir kumaş hatası veri tabanı kullanılmıştır. Daha önceden eğitilmiş VGG16 mimarisi veri tabanı üzerinde inşa edilmiştir. Böylece modelin eğitim süresi azaltılmıştır. Deneysel sonuçlar VGG16 modelinin geleneksel Shearlet dönüşümü ve GLCM metotlarından daha iyi olduğunu göstermektedir.

1. INTRODUCTION

Today, the demand for fabric and fabric products is increasing. Fabric quality is a determining parameter in the demand for the product. Fabric defect control, which has traditionally been human-oriented, includes different problems. For example, labor costs, carelessness and mistakes cause important mistakes to be overlooked. Therefore, the importance of automatic fabric defect detection systems is increasing. With automatic systems, information about the location, size and type of the defects can be obtained. Some well-known types of circular knitting fabric defects are shown in Figure 1.

Until now, many different defect detection methods have been developed using image processing and machine learning methods. These methods can be examined in two main groups [1]: traditional image processing methods and convolutional neural networks (CNNs)-based methods. Traditional methods rely on extracting color and texture-based features of the fabric image. Regular texture breaks down when errors occur in fabric images with regular texture [2]. This degradation is also reflected in the extracted features. Well-known methods such as Fourier transform, histogram-based approaches [3], gray level co-occurrence matrix (GLCM) [4], and local binary pattern [5] are used to determine this distortion. In particular, metrics such as energy calculated on the image in GLCM-based methods emphasize the change in images with distortion [6]. Spectral methods such as Fourier transform and wavelet transform are used to detect fabric defects. On the other hand, Vermak et al. [7] analyzed the real and imaginary parts of the wavelet coefficients of the fabric image based on energy. Thus, they calculated detailed information about the defect. Shearlet transform was used to classify defects in terms of textural properties of fabric images in different scales and directions [8]. Thus, multi-scale methods have been developed that can effectively detect the presence of a defect. Thanks to the sensitive texture information provided by the Shearlet transformation, the defective pixel regions can be detected.

In recent years, it has been tried to detect difficult fabric defects by using deep learning algorithms. The ability of CNN-based methods to obtain high-level features from fabric images has enabled them to be used extensively in this field. Chen et al. [1] developed a defect detection system by using Gabor transform, genetic algorithm and CNN architecture. By integrating Gabor kernels into the Faster R-CNN architecture, the feature calculation capability of the CNN architecture has been improved. On the other hand, Li and Li [9] developed a defect detection system with multi-scale training with the Cascade R-CNN model. Fabric images were analyzed at different resolutions with a multi-scale approach. Liu et al. [10] proposed a fabric defect detection system called DLSE-Net, using semantic information generated by connecting different network layers. Thus, instead of a single network layer, the entire network was optimized and information such as noise and background were tried to be distinguished from defects. In another study, a convolutional denoising autoencoder network was developed to detect fabric defects. By designing an architecture that can calculate the probability of defects, fabric defects can be successfully detected with the help of some prior knowledge [11]. The success of the CNN architecture has been improved with the mechanism called the pairwise-potential activation layer. In a CNN architecture designed to segment fabric defects and decide if there are faults, the network is split in two. [12]. The first part is segmentation and the second part is decision making. With this method, which can also work in real-time, a specific fabric defect detection-based deep learning architecture is proposed.



(a) tear (b) needle breakages (c)dropped stiches (d)press-off

Figure 1. Circular knitting fabric defects

With the use of deep learning methods, successful results have been obtained without the need to calculate complex hand-craft features. However, deep learning models have some limitations in fabric defect detection. For example, it is sometimes difficult to determine the size of the training dataset to obtain a good result. Especially when examining different types of woven and knitted fabrics, it is necessary to build databases containing fabric type-specific defects. This causes intensive labor and raw material loss in the fabric factory. Therefore, it is necessary to optimize the training data needs of existing deep learning models. For this purpose, it is necessary to work on CNN models that produce successful results with less training data. Existing studies mostly focused on woven fabric defects. However, there is a need for a CNN model that can produce successful results in knitted fabric types.

In this study, a deep learning-based defect detection system is proposed that can detect the types of defects frequently encountered in knitting fabrics produced on circular knitting machines. The results obtained by testing the performance of the VGG16 [13] CNN architecture in knitting fabric defects were analyzed. The database used is problem-specific and has been used in traditional image processing methods before. Thanks to this study, the performances of traditional methods and VGG16 deep learning architecture will be compared for the first time in detecting knitting fabric defects. Thus, detailed information will be given to the reader about the performance difference between the methods in the detection of knitting fabric defects.

In Section 2, information about the database used and the VGG16 network architecture is given. In addition, the traditional image processing methods used in the comparison are briefly mentioned. The experimental results are discussed in Section 3. In Section 4, some conclusions are presented.

2. MATERIAL AND METHOD

In this study, a database containing the types of defects frequently encountered in circular knitting fabrics has used. Defect detection has been made by using the created database both with traditional methods and VGG16 deep learning architecture. In this section, firstly, information about the database will be given. Then, the basic information and parameters of the methods used will be explained.

2.1. Fabric Dataset

Although there are different databases containing woven fabric defects in the literature, there is almost no database containing defects in circular knitting fabrics. In this study, the database developed by Hanbay et al. [8] has used. This database is constructed with video images obtained from the image acquisition mechanism installed on the circular knitting machine. A line-scan camera was used for image acquisition. The recording process was started by finely adjusting the line light source according to the line sensor position. Defective and defect-free fabric images were recorded in video form. Then, the database images were obtained by dividing each of them into 250×256 images. In the last case, a database consisting of a total of 13820 defective and defect-free fabric images was built. The database contains the most common fabric defects such as needle breakages, hole, press-off and gout. Some defect-free and defective images can be shown in Figure 2.

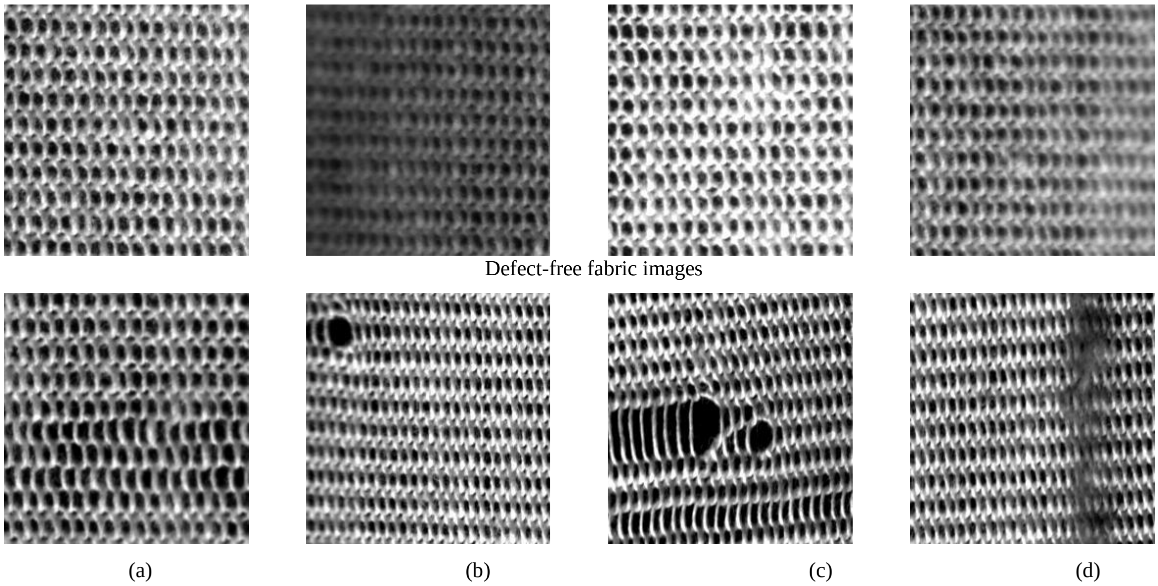


Figure 2. Examples of the popular defect-free and defective images. First row: defect-free fabric images. Second row: defective images (a) needle breakages, (b) holes, (c) press-off, (d) gout

2.2. VGG16 Network Construction

The VGG16 deep network used in this study generally consists of 5 block convolution layers. There are two convolution layers in the first two blocks and three in the last three blocks. The last three convolutional layers are fine-tuned layers. The step size of the convolution layer is 1 and each is 3×3. The size of the input layer is 224×224×3. There are max-pooling layers in every 5 blocks. The 5 maximum pooling layers have a step size of 2, each 2×2 in size. There are 3 fully connected layers. For training the VGG16 architecture, the BatchSize value is 32. Parameters are optimized with the Adam optimization method. VGG16 architecture is given in Figure 3.

The transfer learning approach is also used in this study. The main purpose of transfer learning is that convolutional weights are frozen during training. Weights are fixed and thus all parameters of the deep network are not trained. Fully connected layers are added to the deep model. Thus the transfer learning approach and the pre-trained weights of VGG16 architecture are used to solve fabric defect detection problems.

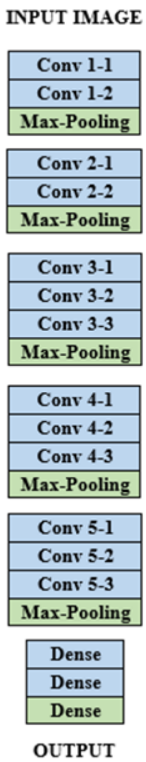


Figure 3. VGG16 architecture

2.3. Traditional Comparison Methods

The results obtained from the VGG16 architecture are compared with traditional image processing and machine learning methods. Thus the strengths and weaknesses of the method of the VGG16 architecture have been revealed. The study using the Shearlet transform on the same fabric database was used in the comparison [8]. The 1×24 feature vectors obtained from the Shearlet transform were classified by an artificial neural network. Another method used in comparison uses GLCM features. Contrast, energy, correlation and homogeneity parameters were calculated from the GLCM information of the fabric image. By combining the obtained features, a feature vector with the size of 1×236 was obtained. The artificial neural network was used for classification.

3. EXPERIMENTAL RESULTS

In this section, VGG16 deep learning architecture is run on the fabric database containing circular knitting fabric defects. In addition, a comprehensive comparison was made by obtaining the results of traditional image processing methods. There are 3000 defective and 15320 defect-free fabric images in the database.

In the Shearlet transform method, feature vectors were created by analyzing images in different directions and scales. In the GLCM method, 4 different features of each image are calculated and combined into a single feature vector. The learning rate in VGG16 architecture is taken as 0.0001.

Table 1 shows the defect detection results of the VGG16 architecture. Very high classification success has been achieved with VGG16. Stable results are obtained for the other 3 parameters. The VGG16 architecture is trained faster with the transfer learning approach. In addition, the layer structure of the network has a structure to analyze fabric defects. In the first layers, the convolutional structure is used to characterize the defected pixel regions. Thus, the spatial location of the defect is revealed. The layer structure, which can make more precise calculations, is used for defect analysis and detection in the next layers.

Table 1. Classification results of VGG16 architecture

Method	Precision	Recall	f1-score	Accuracy
Defected	99.97	99.79	0.98	99.98
Defect-free	99.86	99.74	0.98	99.84

The Receiver Operator Characteristic (ROC) curve of the method is shown in Figure 4. ROC analysis is an indicator of the stable operation of the trained deep model. As can be seen from the ROC curve of defected fabric, fabric defects are stably and accurately distinguished.

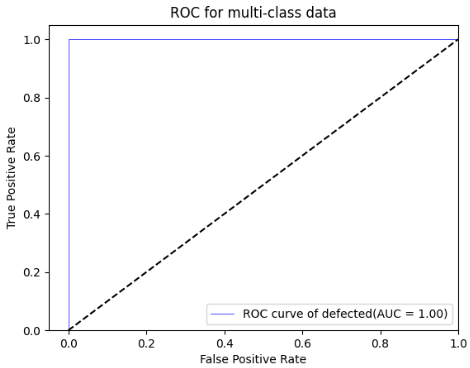


Figure 4. The ROC curve of VGG16 architecture

The data of the accuracy and loss function on the database of the VGG16 architecture are given in Figure 5. As can be seen, classification accuracy has steadily improved iteratively. In addition, the loss function curve has progressed iteratively and reached a reasonable level. Thus, the network has done the learning process without overfitting and in a determined manner.

In the last comparison, VGG16 architecture and traditional methods have been compared in terms of classification accuracy. The results obtained are shown in Table 2. Shearlet transform and GLCM features are classified by the artificial neural network. As can be seen from the results, the VGG16 model achieved better results. By obtaining high-level features of fabric images, defected pixels can be distinguished. Also, the proposed model is able to distinguish defect-free fabrics from defected ones. This prevents false positive results.

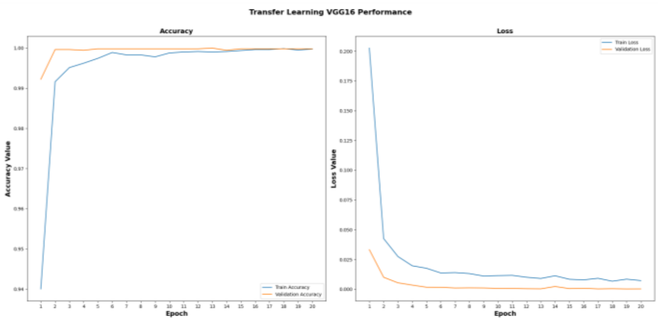


Figure 5. Classification accuracy (a) and loss function (b) of training and validation sets along with epochs

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Table 2. Classification results of VGG16, Shearlet transform and GLCM features

Method	Accuracy (%)
VGG16	99.98
Shearlet transform	95.46
GLCM	93.00

4. CONCLUSION

In this study, the defect detection success of VGG16 deep learning architecture in circular knitting fabrics has been investigated. A new fabric database is used that has not been tested in the VGG16 architecture before. By making use of the positive contributions of the transfer learning approach, the training period has been kept to a minimum. The success of the method is also compared with two traditional feature extraction methods as Shearlet transform and GLCM method. The feature vectors of these traditional methods are classified by the artificial neural network. The experimental results show that the VGG16 architecture gives much better results than traditional methods in detecting fabric defects. In the future, it is considered to improve the convolution layers of the VGG16 architecture. Thus, it is planned to carry out studies for real-time use in fabric defect detection.

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