Volume 12, Issue 4, Page 63-68, 2023 https://doi.org/10.46810/tdfd.1327971 Research Article

BİNGÖL UNIVERSITY

Türk Doğa ve Fen Dergisi
Turkish Journal of Nature and Science
www.dergipark.gov.tr/tdfd

Classification of Circular Knitting Fabric Defects Using MobileNetV2 Model

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(Received: 15.07.2023, Accepted: 16.11.2023, Online Publication: 28.12.2023)

Keywords
Fabric defect detection,
Deep learning,
Image processing,
Circular knitting

Abstract: Fabric defects cause both labor and raw material losses and energy costs. These undesirable situations negatively affect the competitiveness of companies in the textile sector. Traditionally, human-oriented quality control also has important limitations such as lack of attention and fatigue. Robust and efficient defect detection systems can be developed with image processing and artificial intelligence methods. This study proposes a deep learning-based method to detect and classify common fabric defects in circular knitting fabrics. The proposed method adds a fine-tuned mechanism to the MobileNetV2 deep learning model. The added fine-tuned mechanism is optimized to classify fabric defects. The proposed model has been tested on a fabric dataset containing circular knitting fabric defects. Obtained results proven that the proposed method produced desired results in fabric defect detection.

MobileNetV2 Modeli Kullanılarak Yuvarlak Örgü Kumaş Hatalarının Sınıflandırması

Anahtar Kelimeler
Kumaş hatası tespiti,
Derin öğrenme,
Görüntü işleme,
Yuvarlak örgü

Öz: Kumaş hataları hem işçilik ve hammadde kayıplarına hem de enerji maliyetlerine neden olur. Bu istenmeyen durumlar tekstil sektöründeki firmaların rekabet gücünü olumsuz etkilemektedir. Geleneksel olarak, insan odaklı kalite kontrolü dikkat eksikliği ve yorgunluk gibi önemli sınırlamalara sahiptir. Görüntü işleme ve yapay zeka yöntemleri ile sağlam ve verimli hata tespit sistemleri geliştirilebilir. Bu çalışma, yuvarlak örgü kumaşlarda yaygın kumaş hatalarını tespit etmek ve sınıflandırmak için derin öğrenme tabanlı bir yöntem önermektedir. Önerilen yöntem, MobileNetV2 derin öğrenme modeline ince ayarlı bir mekanizma eklemektedir. Eklenen ince ayarlı mekanizma, kumaş hatalarını sınıflandırmak için optimize edilmiştir. Önerilen model, yuvarlak örgü kumaş hataları içeren bir kumaş veri seti üzerinde test edilmiştir. Elde edilen sonuçlar, önerilen yöntemin kumaş hatası tespitinde istenilen sonuçları verdiğini kanıtlamıştır.

1. INTRODUCTION

Fabric defect detection is the process of identifying and localizing defects or flaws in textile fabrics using automated or computerized methods. This can be done using image processing and machine learning techniques that analyze images of the fabric and identify any areas that differ from the normal fabric pattern, such as holes, stains, or discolorations. Fabric defect detection is important in ensuring the quality of textile products and reducing waste in manufacturing processes. The goal of fabric defect detection is to improve quality control in textile industry and ensure that only high-quality products are released to the market.

Traditional human-oriented fabric defect detection methods include various difficulties such as labor cost and eye strain. Therefore, artificial intelligence-based defect detection methods have been developed. Fabric defect detection studies made with machine learning and image processing methods can be examined in two groups in general: Motif-based methods and non-motif-based methods. The motif-based methods use a defect-free ground truth fabric image for comparison of the all fabric motifs. But in practice it is difficult to work with these methods as there are so many fabric and defect types. Therefore, there has been more interest in non-motif-based studies. The five primary categories of non-motif-based investigations are structural [1], statistical [2], model-based [3], learning-based [4] and spectral [5].

This study focuses on the ability of deep learning methods to detect circular knitting fabric defects. To classify different fabric patterns, robust and efficient methods have been developed by using deep learning architectures separately or together. Fabric images have regular shape and patterns. When defects occur, these regular shape and patterns are broken. At this point, these deteriorations are detected with strong pattern analysis and deep learning methods. In this paper, powerful deep learning model (i.e., MobileNet) is used to obtain better performance for specific fabric defects. To keep the model's initial learned parameters, alternative architecture is designed in a parallel configuration. Thus the proposed model achieves high defect detection results for circular knitting fabric defects.

From this point of view, this paper uses the MobileNetV2 deep learning model to detect common defects in circular knitting fabrics. The most important innovation point is that the proposed transfer learning-based model has been designed for circular knitting fabric defects. In addition, there are several advantages of the employed deep learning method:

Improved accuracy: The proposed approach, which makes use of the MobileNetV2 model, outperforms more established techniques like the shearlet transform and GLCM models in terms of accuracy.

Increased robustness: The proposed deep learning model can be more robust to noise and low contrast in the fabric images. By incorporating different convolution layers, the overall model can be more resistant to overfitting and generalization errors.

Faster training: Our deep learning model can often be trained more quickly than other deep models.

The rest of the paper is organized as follows. Section 2 introduces the prior works about the fabric defect detection. Section 3 presents the proposed hybrid deep learning model. Section 4 provides the experimental results and Section 5 concludes the paper.

2. LITERATURE REVIEW

Fabric defect detection is traditionally performed in a human inspection way. However, artificial intelligence and image processing methods are used in modern defect detection systems. There are many related literature papers about fabric defect detection. Also, there are different comprehensive reviews of fabric defect detection techniques using computer vision, including both traditional and deep learning-based approaches [6,7]. Mak et al. [8] presents a method for fabric defect detection that uses Gabor filters and morphological operations to enhance the texture and identify the defect regions. Huang and Xiang [4] developed a defect detection model based on CNN model and repeated pattern analysis. Their model uses both DeeplabV3+ and GhostNet to perform lightweight fabric defect detection. Zhou and Wang [9] proposed a unsupervised defect detection model by using local patch approximation. They used 2D maximum entropy model to distinguish defective pixel regions from the abnormal map. High detection rates were taken on 54 defective fabrics.

An another paper proposes a texture analysis-based approach for fabric defect detection using support vector machines (SVMs) [10]. The method extracts texture features from the fabric image and uses SVMs to detect the defective regions. Zhao et al. [11] performed a defect detection system based on deep learning using a Faster R-CNN network. They used a normalization step to reduce some undesired situations such as brightness changes and noise. They performed detailed experimental works to compare the proposed model. The proposed model achieved more high detection results than Yolo, Yolov3 and SSD models. In a recent study, deep learning and contrast enhancement method were used together [12]. Inception v3 model was used to extract fabric feature extraction. The three types of defective fabric that this model can identify are holes, vertical defects, and horizontal defects. In a study using the MobileNetV2 model, fabric defect detection was made quickly on the NVIDIA Jetson Nano card [13]. Deep neural network model consists of a channel attention mechanism. This mechanism emphasizes defect features and suppress background noise components. Comprehensive analyzes were performed in a study comparing the discrete curvelet transform, wavelet transform and GLCM methods [14]. The best results have been achieved by using the discrete curvelet transform and GLCM features together. CNN-based architecture with adaptive threshold-based have been developed to determine fabric defect classes [15]. Adaptive threshold mechanism is used for class determination. Two different real fabric datasets are used. The proposed model achieved an average of 90% success in defect detection. Pourkaramdel et al. [16] proposed a local quartet patterns based method to obtain discriminative texture features of fabric images. This model is robust to noise and it can be use in industrial defect detection problems.

Recently, deep learning-based defect detection models have been developed. Vgg16 deep learning model was used to detect circular knitting fabric defects [17]. The proposed method produced better results than shearlet transform and GLCM methods. In a recent study, a specific deep learning architecture has been developed to detect circular knitting fabric defects [18]. This architecture has obtained more high defect detection rates than InceptionV3, MobileNetV2, Xception and ResNet50 models. A model was developed based on the YOLOX-Nano model to develop an optimized deep model for defect classification [19]. To classify the woven fabrics which distributed along the warp and weft directions, proper convolution kernels have been developed. The proposed deep model has a balance in terms of fabric size, accuracy and speed for defect detection. In a recent study, circular knitting fabric defects were detected using 3 different deep learning architectures [20]. Detection of fabric defects with the machine vision mechanism installed on the circular knitting machine is an important and valuable task. Fabric defects were detected with 98% success with ResNet architecture. An intelligent automation system was developed for fabric inception machines [21]. The developed intelligent and PLC-controlled system examines and reports the fabric rolls in terms of quality control.

The results of the literature review revealed that the studies on fabric defect detection may be divided into two primary categories. The first group is studies using traditional image analysis and machine learning approaches such as GLCM, wavelet transform and support vector machines. The second group uses deep learning methods. It is pointed that defect detection methods made with deep learning methods stand out as very powerful and highly distinctive studies. However, deep learning based works have some disadvantages such as computational cost and numerous parameters. Especially the number of methods developed to detect circular knitting fabric defects is very limited. However, knitted fabrics are widely used in daily life including t-shirts, sweaters, socks, leggings and tights, hats and scarves. Overall, knitting fabrics are versatile and widely used in the production of various types of clothing due to their stretch ability, comfort, and ability to provide texture and warmth.

3. MOBILENETV2-BASED FABRIC DEFECT DETECTION

There exist different deep learning models like VGG19, MobileNet, ResNet and InceptionV3. These models have been shown to work well in a variety of computer vision applications, including pattern recognition and texture classification. In this paper, MobileNetV2 model is used to defect circular knitting fabric defects. However, it is aimed that the model produces the best results by performing different ablation studies.

MobileNetV2 a deep learning architecture that was specifically developed for efficient computation on mobile and embedded devices [22]. This architecture was developed by researchers at Google and is based on a combination of depth wise separable convolutions and pointwise convolutions. Depth wise separable convolutions are a form of convolution that factorizes a standard convolution into a depth wise convolution and a pointwise convolution. This approach reduces the computational cost of the deep model.

The pre-trained MobileNet presents a module that contains inverting residual structure. The initial of MobileNetV2 begins with fully convolutional layers. This first layers include 32 filters and 19 residual bottlenecks. The obvious structure of this block can be examine in Table 1 [22].

Table 1. Bottleneck residual block (Here k , s and t show the channel, stride and expansion factor, respectively).

Input	Operator	Output
$h \times w \times k$	1×1 conv2d, ReLU	$h \times w \times (tk)$
$h \times w \times k$	3×3 dwise s= S ReLU	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	Linear 1×1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

As shown in Table 1, MobileNetV2 layer blocks include commonly composed of 1×1 convolution and 3×3 depth wise separable convolutions (DW Conv). Therefore MobileNetV2 deep network model consists of a series of a convolution and DW Conv blocks [13]. In this model, linear bottlenecks and depth wise separable convolutions has been integrated into inverting residual structure with linear bottlenecks. Two types of convolution layers in MobileNetV2 architecture can be seen Figure 1.

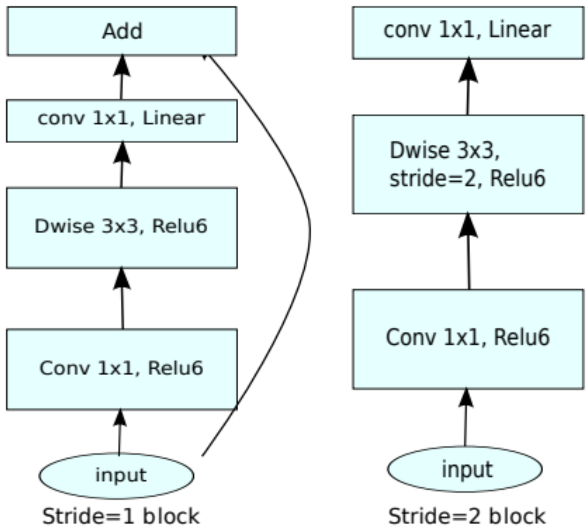


Figure 1. The block structure of MobileNetV2 [22]

In this paper, ReLU6 activation function is used to ensure non-linearity and enhance sparsity. Thus MobileNetV2 model is robust to conditions such as low-precision computation. During training, kernel size is used as 3×3 . Also dropout and batch normalization operations are used. Constant expansion strategy is used except for the first layer. As a result of the experimental studies, expansion factor is determined as 5. This means that if a bottleneck layer takes 64-channel input tensor, it generates a tensor with 128 channels. Therefore intermediate expansion layer has 64x5=320 channels [22].

Original MobileNetV2 architecture cannot give the desired results in circular fabric defect detection. In this paper, the images in the circular knitting fabric database contain some undesirable situations such as noise, light change and rotation. At this point, it is necessary to perform parameter optimization and fine-tuning of the MobileNetV2 model.

Fine-tuning is a well-known optimization strategy for enhancing model performance. To increase the accuracy of the MobileNetV2, fine-tuned block can be added following the 16 blocks of the MobileNetV2 architecture. Based on similar studies in the literature [23], this paper uses a fine-tuned block to enhance the classification performance of MobileNetV2. Thus, an efficient MobileNetV2 architecture is developed for detecting the defects in circular knitting fabrics. Fine-tuned block includes 3 main sub-layer: feature extraction, pooled feature map and last block. Especially feature extraction layers in fine-tuned block have critical role since MobileNetV2 model performs over-abstract representations fabric images. Over-abstraction leads to lose of distinctive defect features. The structure of the fined-tuned block used in the proposed model and the layers it contains are shown in the Figure 2. As shown in Fig. 2, fine-tuned block has the two convolution layer, batch normalization, a dropout layer, flatten layer and dense layer. Pool size of AveragePooling2D is 2x2. Dropout layer and ReLU activation function have 32 channels. Finally, fine-tuned block consists of the flatten and dense layers. Learning rate is 0.001.

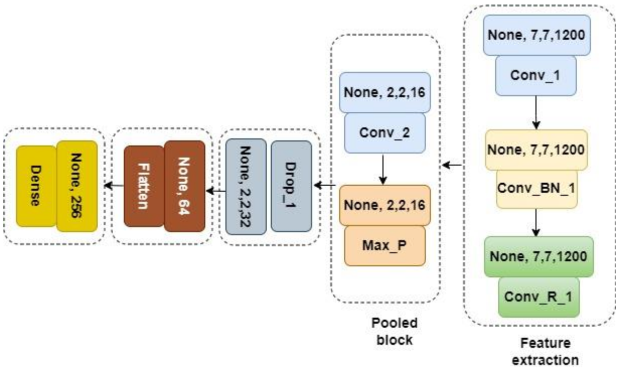


Figure 2. The block structure map of fine-tuning approach

4. EXPERIMENTAL RESULTS

In this section, the results of the fine-tuned MobileNetV2 architecture on a fabric database containing circular knitting fabric defects are presented. Firstly, some general explanations about the fabric database have been given. Then, the experimental results obtained are discussed.

4.1. Fabric Dataset

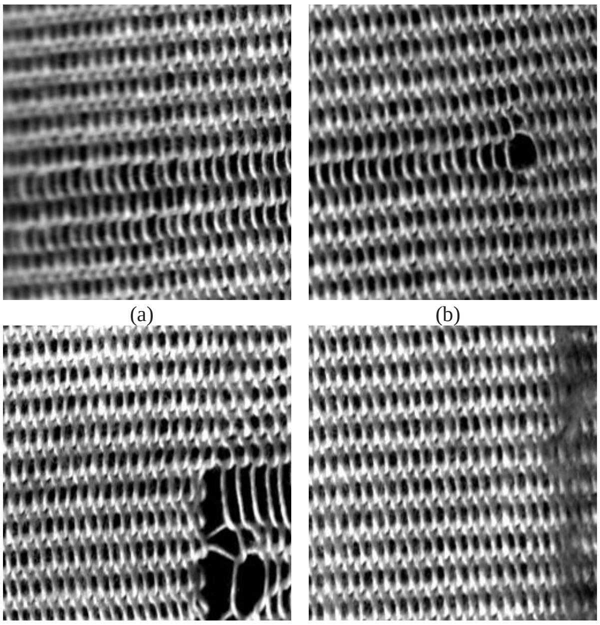
The dataset used in the study was created on a knitting machine in a textile factory [24]. Fabric production was monitored by installing a line scanning camera and a line light system on the circular knitting machine. Table 3 present information about the fabric dataset.

Table 2. Fabric defect classes and number of image in fabric dataset

Defect types				Defect-free
Needle breakages	Holes/tear	Press-off	Gout	
2493	219	243	45	10820

There are the most common circular knitting fabric defects, including needle breakages, hole, press-off and gout. There are 13820 images in the database. The size of images is 256x250. Figure 3 shows some representative defect samples.

Images in this dataset contain a lack of contrast and noise. Therefore, a pre-processing step was applied. In this paper, gaussian smoothing is used to pre-processing step for denoising fabric images. Gaussian filtering is applied to improve visual quality at various scales. As a result of the preprocessing, the defective pixel regions were better highlighted. Also, the performance of deep learning algorithms is improved by minimizing the noise components.



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

Figure 3. The representative defected samples of the fabric dataset: (a) needle breakages, (b) holes/tear, (c) press-off, (d) gout

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4.2. Defect Detection Results

The proposed MobileNetV2 model is compared with InceptionV3 [25] and Xception [26] architectures. Accuracy, precision, recall and F1-score are used as comparison metrics. Thus, comparisons could be performed within the framework of different parameters. The methods used in the comparison have been tested and trained with optimal values. Xception is version of a well-known Inception module. There are some differences between Inception and Xception models. Readers can be read these differences from their original papers.

Deep models were trained using circular knitting fabrics. In experimental works, the circular knitting dataset was split into 90% and 10% for training and testing, respectively. With the use of this method, training data that won't be used in testing can be provided. Validation set was 10% of the training image set. Hyperparameters of deep models were determined on the basis of the validation set. Experimental results were obtained 5 times and the average classification results were reported.

The first experiment has been performed in the form of binary classification of fabric images defected and defect-free. Therefore, it does not include classification results among four different defect types. The classification results of the deep architectures are given in Table 3. As can be seen from these results, the proposed fine-tuned MobileNetV3 model produced the highest results. The original MobileNetV2 model produced poor results in fabric defect detection [18]. However, the feature extraction capacity of this deep model has been improved with the fine-tuned MobileNetV2 version. In addition, the images in the fabric database were pre-processed before the classification process. Thus, noise and brightness changes in the images are reduced. This has positively affected the performance of the fine-tuned MobileNetV2 model. The obtained results encouraged the use of deep learning-based methods to detect circular knit fabric defects.

The feature extraction and pooling layer structure in fine-tuned blocks are arranged for fabric defect detection. This had a positive effect on the performance of the MobileNetV2. The performances of the Inception and Xception models can be improved with some adjustments to these models. Especially in the inception connection model, the number of convolution operations and kernel sizes can be rearranged. The Xception model, which was developed on the basis of the Inception model, can be re-designed in a similar way. In addition, all models can be trained with a larger number of fabric images to improve their performance.

Table 3. Overall classification results InceptionV3, Xception and fine-tuned MobileNetV2 models on fabric dataset

	Accuracy	precision	recall	F1-score
InceptionV3	78.30	78.32	78.29	78.14
Xception	80.45	80.38	80.47	80.24
Fine-tuned MobileNetV2	92.13	92.15	92.19	91.96

The second experiment has been carried out to distinguish between 4 different fabric defect in the dataset. Classification result are given in Table 4. The proposed fine-tuned MobileNetV2 architecture achieves effective results. In particular, needle breakages and hole fabric defects, which have similar visual characteristics, are effectively distinguished. It has been understood that existing architectures should be configured according to error types. With fine-tuned block, it is clear that MobileNetV2 has a strong ability to find the four most prevalent fabric defects. Of the four defect kinds, the needle breakages defect has the lowest detection accuracy. The most important reason for this is that the defected region resembles a defect-free image pattern. InceptionV3 and Xception models obtain lower classification results. When the results between Table 3 and Table 4 are compared, it is seen that the success of the methods in distinguishing 4 different classes is partially lower. The main reason for this is both the high number of classes and the low number of faulty examples in the database.

Table 4. Classification accuracies of InceptionV3, Xception and fine-tuned MobileNetV2 models on 4 fabric defects

	Needle breakages	Holes/tear	Press-off	Gout
InceptionV3	74.23	76.27	76.72	75.53
Xception	73.49	77.13	76.41	76.81
Fine-tuned MobileNetV2	89.28	91.24	90.43	90.17

5. CONCLUSION

In this paper, fine-tuned MobileNetV2 architecture is proposed to detect the most common fabric defects in circular knitting fabrics. Considering the fabric database used, MobileNetV2 architecture is used for the first time to detect circular knitting fabric defects. Pre-processing steps have been performed to the images in the fabric database. Thus, improvements have been made against undesired situations such as lack of contrast, noise and blurring. Fine-tuned blocks have been added to the MobileNetV3 architecture to detect types of circular knitting fabric defects. Thus, the feature extraction capacity of the model is improved. Convolution and pooling kernels in blocks are determined by experimental testing.

The proposed model produced better results than Inception and Xception models. The proposed model contains fewer hyperparameters than the other two models. Therefore, the model requires less time to train and test. Future research will lead to the development of hybrid deep learning models. Thus, more powerful methods will be developed in detecting circular knitting fabric defects.

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