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Fabric Defect Classification Using Combination of Deep Learning and Machine Learning

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Abstract

Automatic systems can be used in many areas, such as the production stage in factories, country defense, and traffic control. They provide the opportunity to reach results faster with higher success rates thanks to human-computer vision cooperation. In this study, it is aimed to develop an intelligent system that automatically detects and classifies defects in fabrics. Thanks to the developed system, the cause of the malfunction is eliminated, and the recurrence of the malfunction is prevented. Using deep learning methods in fabric defect classification studies has a disadvantage compared to other methods. Multiple layers in deep learning cause a time-consuming process. Therefore, a combination of Deep Learning and Support Vector Machines (SVM) has been used in this study. The success of the provided system has been compared with other deep learning algorithms in terms of time and accuracy.

Keywords: Convolutional neural network; fabric defect classification; machine learning.

1. Introduction

Fabrics, which differ according to their usage areas, constitute one of the most basic needs of people. Textile is becoming increasingly popular sector with the increase in online shopping. High customer satisfaction, especially due to scoring in online shopping, causes more demand for the product sold. When the customer is satisfied with the product, it provides more profit to the businesses by not returning the product they bought. Customer satisfaction depends on fabric quality, sewing quality, and whether the fabric is defective or not. Since fabric defects affect the gain, it is necessary to find the defects on the fabric produced and take the necessary measures. There are many types of fabric defects. ISO standards [1] indicate that there are 130 different fabric defects. There are some reasons for the occurrence of these defects like raw materials, machines, or humans [2]. It is important to identify and correct the cause of any defect so that the defect does not happen again. Many studies have been carried out to automate the fabric control traditionally done by human power. While some of the studies distinguish fabrics as defected or non-defected, other studies also classify fabric defects detected. It is meaningless not to classify the defect on the fabric in terms of making necessary corrections.

Zhu et al. [3] optimize DenseNet, which is a CNN (Convolutional Neural Network) algorithm. They combine the new method with new hardware for fabric defect detection. Huang et al. [4] perform segmentation and detection based on neural networks. Huang determined the location of the fault as well as the fault detection. Karlekar et al. [5] use wavelet decomposition and different preprocessing operations to obtain segmented defects. Chang et al. [6] develop a new method for patterned fabrics. Fabrics are divided into lattices, including periodic patterns. Then, the lattice containing the defect is detected. Wei et al. [7] make a combination of compressive sampling theorem with CNN. This new method is more effective compared to traditional methods and performs well in small data sets. Studies on the Tilda data set, also used in our study, were examined in detail. Başıbüyük et al. [8] have achieved 97% success by applying particle filtering in some parts of the Tilda dataset (c1-r1, c1-r3). Sezer et al. [9] apply independent component analysis (ICA) for defect detection. They use the parts of c1-r1, c1-r3, c2-r2, c2-r3 of the Tilda dataset. Bissi et al. [10] use Gabor filter bank and principal component analysis (PCA) and test the performance using the parts of c1-r1 and c1-r3 of Tilda. This study, with more than 98% success, is more effective than the study of Başıbüyük et al. [8]. Jing et al. [11] combine the Gabor filter and genetic algorithm in their study. When the performance of Local Homogeneity Analysis (LHA) is compared with Wavelet transform and Gabor Transform, it is seen that LHA gives the highest accuracy rate (96.40%) in the study of Kure et al. [12]. After partitioning the images into blocks, feature vectors extracted from each block are used in a regression-based method named PG-LSR in the study of Cao et al. [13]. Liu et al. [14] use ELM (Extreme Learning Machine) method after extracting the features from segmented defects in fabrics. The accuracy of the system they provided is 94.5%. Jing et al. [15] use a convolutional neural network (CNN) after division the images into patches. Tilda is one of the databases used to test the proposed method. In this database, 97.48% classification

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accuracy rate has been achieved with Tilda dataset. Jeyeraj et al. [16] use a transfer learning-based CNN algorithm called AlexNet. They obtain a high accuracy rate (96.55%). Cuifang et al. [17] extract features using pyramid histogram of oriented gradients (PHOG) and perform classification using support vector machine (SVM) in their study. The performance of PHOG is superior to the performances of scale-invariant feature transform (SIFT) and histogram of oriented gradients (HOG). It is seen that machine learning-based methods are used in most of the studies using the Tilda dataset. There are very few studies in the literature that test the performance of deep learning algorithms on the Tilda dataset.

The common feature of the algorithms used in this study is that the input images to be classified must have dimensions of 224x224x3. Therefore, the images in the dataset were pre-processed. In the pre-processing step, the performances of different color maps used to make the images three-dimensional were also examined. The performances of ResNet18 and GoogLeNet have been investigated using the three-dimensional version of the Tilda dataset. Then, the used deep learning algorithms are combined with SVM to decrease the response times of deep learning algorithms.

2. Methodology

2.1. Dataset

Tilda data has 12 different groups. Not all of these groups are available for use. Only eight groups (c1-r1, c1-r3, c2-r2, c2-r3, c3-r1, c3-r3, c4-r1, c4-r3) can be accessed. The groups of c1-r1, c1-r3, c2-r2, c2-r3 (groups with the names beginning with c1 and c2) consist of un-patterned fabric samples, while the other four groups (groups with the names beginning with c3 and c4) consist of patterned fabric samples. There are eight different classes (e0, e1, e2, e3, e4, e5, e6, e7) in each group. Each group contains a total of 400 images, with 50 images of each class. Table 1 contains un-defective fabric samples belonging to e0 classes of groups for each group.

2.2. Preprocessing Operations

Tilda dataset has images of sizes 768×512, and all of them are gray levels (Figure 1). Deep learning algorithms to be used are trained with RGB images. It is not known whether these images in the Tilda dataset are gray level to reduce the space needed on the Ram or Hard disk, but they must be RGB to be processed in deep learning. Therefore, the images are converted into three dimensions using two different color maps (HSV and gray). Images ready to be used in deep learning algorithms are 224×224×3 in size (Figure 2). Converting the images from one dimensional to three dimensional will result in loss of information. Lack of knowledge in the processes will affect the performance of all methods. For this reason, performance comparisons between the methods were made in our study. Without the lack of knowledge, the success of the methods will be higher than expected.

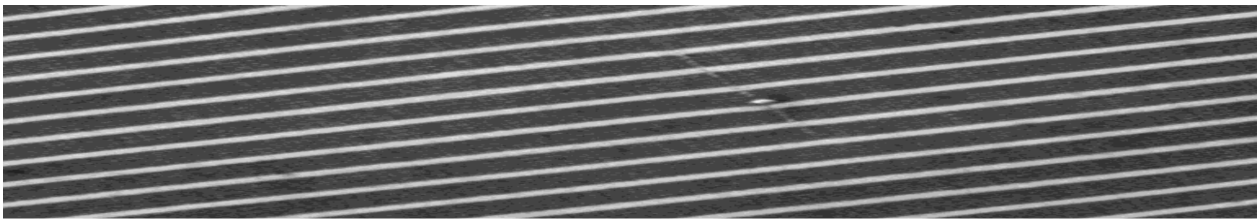
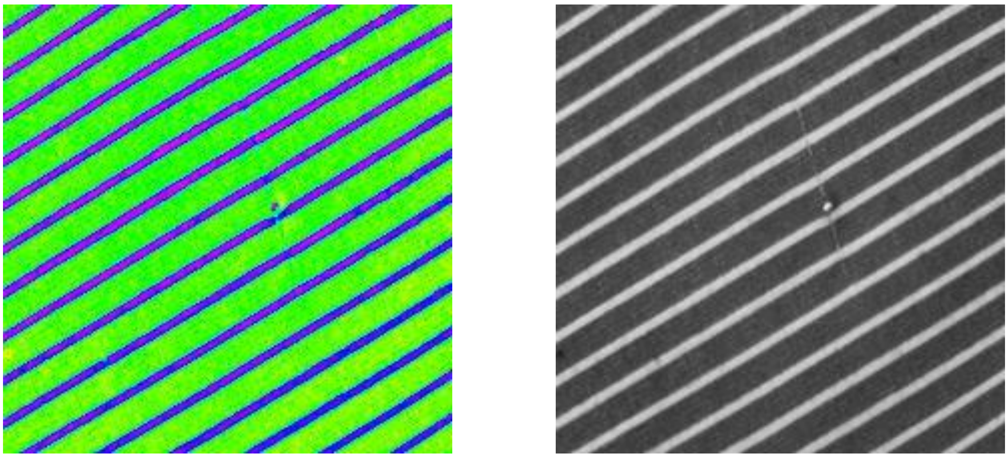


Figure 1. *Image before preprocessing (c3-r3)*



(a) *(b)*

Figure 2. *Image after preprocessing (a) using hsv colormap (b) using a gray colormap*

2.3 Deep learning & Machine Learning

Deep learning is an improved version of artificial neural networks. Many studies are using deep learning in the literature. Deep learning is used in various fields such as image processing, video processing, signal processing, object recognition, defense industry, and robotics. Deep learning uses many layers of nonlinear processing units for feature extraction and conversion. The output from each previous layer is used by each subsequent layer as input.

There are many different types of deep learning architectures established by increasing the number of layers in artificial neural networks. CNN is one of these architectures. It is used in image processing. Two of the most widely used CNN models, which are ResNet and GoogLeNet, have been compared in this study. The structure of the ResNet, which is the first network with 34 layers, consists of residual blocks. It is a model designed deeper than all architectural structures. The GoogLeNet model, which consists of the combination of Inception modules, has a complex structure.

A large number of layers in CNN algorithms causes a waste of time. In this study, a new method has been developed to eliminate this disadvantage. This study consists of two basic parts: feature extraction and classification. The features extracted by CNN have been inserted into the Support Vector Machines (SVM) classifier. Thanks to the SVM classifier, it is found whether there is a defect in the fabric. If there is a defect in the fabric, it is found out what this type of defect is.

3. Results

In the experimental phase of this study, the methods have been compared in terms of accuracy and execution time. They have been tested in a personal computer (Intel (R) Core (TM) i7- 6700HQ CPU @2.60 GHz). Table 1 and Table 3 contain the results obtained using color maps of HSV and gray, respectively. In Table 1, the accuracy rate of the ResNet18 algorithm is up to 87.5% (for the group of c3-r1). The classification accuracy of GoogLeNet is a maximum of 81.67% (for the group of c2-r2). The maximum accuracy rates from combinations with SVM are close to the maximum accuracy rate of ResNet18 (SVM & ResNet18, SVM & GoogLeNet). Looking at the average accuracy rates of the methods, it is seen that ResNet18 is again the most successful method (76.98%). Considering the accuracy rates of the groups, it is seen that c1-r1 is classified with the highest performance (78.54%). In Table 3, the maximum accuracy rate is obtained when using the ResNet18 algorithm (84.17%). C1-r1 is the set with the highest accuracy rate for all methods.

On the other hand, ResNet18 is the method with the highest accuracy rate. However, it is observed that there are problems in the classification of the c4-r1 and c4-r3. All methods have very low accuracy rates for these groups. In Table 1 and Table 3, it is seen that close results are obtained that support each other when two different color maps are used. Here, it can be concluded that when using any of the color maps of HSV and gray, similar results are obtained unless different processes such as filtering and morphological processing are applied.

Table 1. *Accuracy rates for hsv colormap*

	c1		c2		c3		c4		Average
	r1	**r3**	**r2**	**r3**	**r1**	**r3**	**r1**	**r3**	
ResNet18	85.83%	81.67%	76.67%	81.67%	87.5%	75%	61.67%	65.8%	76.98%
GoogLeNet	63.33%	72.5%	81.67%	71.67%	83.33%	71.67%	46.67%	53.3%	68.02%
SVM & ResNet18	86.67%	76.67%	77.5%	69.17%	78.33%	67.50%	60.83%	55%	71.46%
SVM & GoogLeNet	85%	69.17%	68.33%	70%	72.5%	69.17%	52.5%	55%	67.71%
Average	78.54%	73.96%	76.04%	73.13%	77.71%	70.84%	55.42%	57.28%	

Table 2 and Table 4 contain time comparisons for the methods. The completion times of ResNet18 and GoogLeNet are given in minutes, and the completion times of SVM-based methods are given in seconds. Deep learning-based methods give results in a longer time (28.13 minutes). On the other hand, classification with SVM gives results in a very short time (about 30 seconds). As it can be understood from here, deep learning-based methods respond about sixty times longer than SVM-based methods. This method will be better than deep learning-based methods in terms of time and performance when the performance of SVM-based Resnet18 is improved.

Table 2. *Time comparison for hsv colormap*

	c1		c2		c3		c4		Average
	r1	**r3**	**r2**	**r3**	**r1**	**r3**	**r1**	**r3**	
ResNet18	29.15 min	30.92 min	29.35 min	28.27 min	29.42 min	28.92 min	31.33 min	30.0 min	29.36 min
GoogLeNet	27.03 min	26.85 min	29.22 min	27.42 min	32.42 min	31.18 min	29.37 min	28.93 min	
SVM & ResNet18	27 sec	26 sec	28 sec	28 sec	28 sec	27 sec	27 sec	29 sec	30 sec
SVM & GoogLeNet	32 sec	32 sec	32 sec	31 sec	32 sec	33 sec	32 sec	32 sec	

Table 3. *Accuracy rates for gray colormap*

	c1		c2		c3		c4		Average
	r1	**r3**	**r2**	**r3**	**r1**	**r3**	**r1**	**r3**	
ResNet18	84.17%	80.0%	82.5%	80%	80%	76.7%	62.5%	60.0%	75.73%
GoogLeNet	80.83%	72.5%	77.5%	70.00%	75.83%	65%	49.17%	41.67%	66.56%
SVM & ResNet18	77.50%	74.17%	70.00%	68.33%	74.17%	65.83%	65.83%	55.00%	68.85%
SVM & GoogLeNet	74.17%	63.33%	62.50%	74.17%	70.83%	58.33%	50.00%	47.50%	62.60%
Average	79.17%	72.5%	73.13%	73.13%	75.21%	66.47%	56.88%	51.04%	

Table 4. *Time comparison for gray colormap*

	c1		c2		c3		c4		Average
	r1	r3	r2	r3	r1	r3	r1	r3	
ResNet18	26.62 min	27.65 min	27.18 min	27.4 min	26.43 min	26.72 min	27.32 min	27.32 min	26.89 min
GoogLeNet	26.03 min	29.27 min	26.23 min	26.25 min	26.88 min	26.55 min	26.43 min	25.87 min	
SVM & ResNet18	29 sec	28 sec	23 sec	28 sec	27 sec	27 sec	28 sec	27 sec	29 sec
SVM & GoogLeNet	30 sec	31 sec	33 sec	31 sec	31 sec	30 sec	30 sec	31 sec	

Some parts of the Tilda dataset consist of non-patterned fabrics, and the other part of it consists of patterned fabric samples. Table 5 shows the performances of the methods according to the un-patterned/patterned fabrics. While all methods are more successful in classifying defects in non-patterned fabrics (75.29%), they show less success in classifying patterned fabric defects (64.19%).

Table 5. *Average accuracy rates for un-patterned/patterned fabrics*

Method	Un-Patterned Fabrics	Patterned Fabrics
ResNet18	81.56%	71.15%
GoogLeNet	73.75%	60.83%
SVM & ResNet18	75.00%	65.31%
SVM & GoogLeNet	70.83%	59.48%
Average	75.29%	64.19%

4. Conclusion

Deep learning is one of the most popular concepts in recent years. The loss of time caused by deep learning algorithms has been eliminated with the system proposed in this study. What distinguishes deep learning from artificial neural networks is the high number of layers. This feature provides higher success when using deep learning. However, the disadvantage of deep learning is that it is a time-consuming process. Deep learning may not be preferred in areas where speed is important, as its algorithms take a long time to produce results. In this study, the combination of deep learning with SVM has been carried out to eliminate this disadvantage of deep learning. After extracting the features using deep learning methods, the classification has been performed in the SVM algorithm.

When looking at the performance comparisons of the methods, it is seen that SVM-based methods give results about 60 times shorter than deep learning-based methods. Looking at the accuracy rates, it is seen that ResNet18 is the most successful method in classification. The second most successful method after ResNet18 is the combination of SVM and ResNet18. The time advantage of the SVM & ResNet18 combination avoids the disadvantage of having low classification success.

The failure of the methods in the groups of c4-r1 and c4-r3 where there are fabric images with mixed patterns indicates that these methods should take extra precautions for such fabrics. The process of detecting defects on patterned fabrics requires different pre-processing operations than detecting non-patterned fabric defects. The results obtained in this study also reveal the necessity of this.

Tilda dataset, a data set used in previous studies, has been used in this study. Only a portion of this dataset is public. For this reason, tests have been carried out on the public part. Additionally, this data set is one dimensional. Data loss occurs during the conversion of images from one dimensional to three dimensional. For this reason, the system performance seems to be lower than the performances of the studies in the literature. The success of this preliminary study will be increased by adding innovations to the preprocessing step.

Declaration of Interest

The authors declare that there is no conflict of interest.

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