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Detection and classification of fabric defects using deep learning algorithms

Derin öğrenme algoritmalarını kullanarak kumaş kusurlarının tespiti ve sınıflandırılması

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Detection and Classification of Fabric Defects Using Deep Learning Algorithms

Highlights

- *A novel Deep Learning-based model is proposed for detection of different types of fabric defects.*
- *Numerous models have tested and compared in the study in terms of both time and accuracy. ResNet50 and KNN outperform other models in fabric defect detection.*
- *Fabric defect detection is a critical issue in the textile industry. Deep Learning based systems are expected to reduce defect detection times with high accuracy potential.*

Graphical Abstract

The proposed method for detecting defective fabrics consists of four steps; the dataset is loaded, resized, given as input to pre-trained models and classified as defective or no defect.

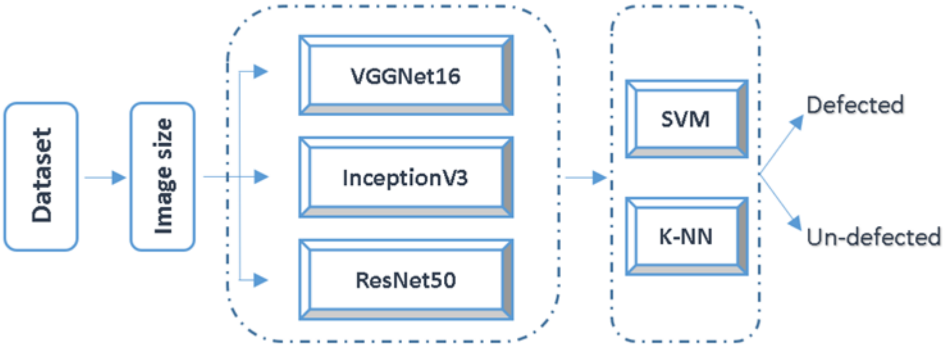

Figure. Proposed method

Aim

In this study, we focus on a novel deep learning method, employing cutting-edge methods like image processing, deep learning, and artificial intelligence to autonomously identify imperfections in fabrics.

Design & Methodology

The research can be divided into two primary sections: firstly, assembling the dataset, and secondly, devising and educating various models to identify, categorize, and assess the effectiveness of detecting chosen defects in fabrics. In the study, we tested and compared the most widely used deep learning algorithms, namely, CNN, VGG16, InceptionV3 and Resnet50. Results reveal that the Resnet50 model gives higher accuracy than the other models.

Originality

A novel deep learning model has been implemented which can be applied on all fabric types and all motifs (patterned, unpatterned).

Findings

Our findings indicate that the ResNet50 model paired with KNN classification outperforms other methods in fabric defect detection, with the potential to significantly enhance computer-aided diagnosis in textiles once fast computing becomes more accessible.

Conclusion

The study concludes that the ResNet50 model, in combination with the KNN classifier, excels in fabric defect detection despite time inefficiencies, suggesting significant potential for computer-aided diagnosis in the textile industry..

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Detection and Classification of Fabric Defects Using Deep Learning Algorithms

Research Article / Araştırma Makalesi

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ABSTRACT

The textile industry primarily relies on fabric as a crucial raw material, the production of which involves multiple complex stages. Due to the multitude and complexity of these stages, fabric defects can frequently occur. The rapid pace of production and the substantial market share of the sector mean that relying on human inspection for error detection can lead to significant time losses and can reduce the accuracy of defect detection to around 60%. Consequently, recent years have seen a shift towards the development of intelligent systems for fabric defect detection in parallel with technological advancements. With the rapid progression of artificial intelligence, the application of image processing techniques has commenced in this field. This study has developed a real-time defect detection system for fabrics using deep learning techniques. Initially, a network model was created using an open-source neural network library, Convolutional Neural Networks (CNN), achieving very low accuracy. Subsequent implementations using the VGGNet16 and InceptionV3 architectures reached accuracies of 86% and 90%, respectively. ResNet50 has shown that it has a much more successful performance than CNN with an accuracy rate of approximately 95%. This allows fabric defects to be found more consistently.

Keywords: Image processing, fabric defect detection, deep learning, textile.

Derin Öğrenme Algoritmalarını Kullanarak Kumaş Kusurlarının Tespiti ve Sınıflandırılması

ÖZ

Tekstil sektörünün en önemli ham maddesi olan kumaşın üretimi birçok aşamadan meydana gelmektedir. Bu üretim aşamalarının fazlalığı ve karmaşıklığından dolayı kumaşlarda bazı hatalar meydana gelebilmektedir. Günümüzde kumaş üretim süreci neredeyse tamamen otomasyon ile olduğundan ve kumaş üzerinde oluşan hata çeşitliliğinin fazlalığından dolayı kumaş üzerinde oluşabilecek hataları tespit etmek oldukça zordur. Hataların tespit edilmesinde; sektörün pazar payının büyüklüğü ve üretimin çok hızlı olmasının nedeniyle insan kontrolü ile tespit etmek hem zaman kaybına hem de hata tespit oranının %60 seviyelerine kadar düşmesine neden olmaktadır. Bundan dolayı son yıllarda teknolojinin gelişmesiyle paralel kumaşların hata tespitinde daha çok akıllı sistemler geliştirilmeye başlanmıştır. Günümüzde yapay zekâ teknolojisinin hızla gelişmesiyle bu sektörde de görüntü işleme teknikleri uygulamalar başlamıştır. Bu çalışmada derin öğrenme teknikleri kullanarak kumaş üzerinde gerçek zamanlı hata tespit sistemi geliştirilmiştir. Yapılan çalışmada ilk olarak açık kaynaklı bir sinir ağı kütüphanesi olan CNN ile bir ağ modeli oluşturulmuş ve bu yöntemle %89 doğruluk elde edilmiştir. Sonra VGG16 mimarisi ile %89 ve IneptionV3mimarisi ile %86 oranında doğruluğa ulaşılmıştır. Çalışmayı daha iyi hale getirmek için kumaşları hatalı ve hatasız başlığı altında iki sınıfta sınıflandırıp önceden eğitilmiş Evrişimsel Sinir Ağları modellerinden olan ResNet50-v2 özellik çıkarıcı olarak kullanılmıştır. Bu şekilde yaklaşık %95 doğruluk elde edilmiştir.

Anahtar Kelimeler: Görüntü işleme, kumaş hatası tespiti, tekstil, derin öğrenme.

1. INTRODUCTION

Fabric quality is of paramount importance in the textile and ready-to-wear clothing sectors. The fabrics used in these sectors directly affect the quality, durability, aesthetics, and comfort of the final product. In the study on brand value creation and apparel, Gezer [1]. states that "Fabric quality holds critical importance for customer satisfaction and the brand value of the company. It directly influences the durability, comfort, aesthetics, and service life of products.". It is imperative for companies operating in the textile and ready-to-wear industries to ensure the quality of the fabrics used in their products and to offer high-quality items to their customers. This is considered to be a crucial factor that can increase customer satisfaction, enhance the brand value of the companies, and provide a competitive advantage in the industry.

Detection of fabric quality is feasible through the accurate identification of fabric defects. Fabric defects encompass any flaw or imperfection in the texture, pattern, or color of the fabric. These defects can occur during the production process, as well as during storage, transport, or cutting stages. Approximately 200 types of fabric defects and their possible causes are documented in the literature. Due to the large number of defects and the complexity of these defects, it is impossible to detect

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one defect at a time with a detection system [2]. However, only about 50 of these are typically recorded in the quality control charts by textile professionals [3]. In his study, Ala has documented statistical data of fabric defects in a factory, identifying a total of 3211 defects and classifying them by type of error. The top five categories of defects identified in this study are presented in Table 1. Looking at the numerical data for defects identified to date, the top five most common errors account for approximately 85% of the total defects. Consequently, in our study, we have compiled the defective product folder prioritizing from most to least frequent defects as follows: "warp break," "stop mark," "warp streak," "weft streak," and "half weft defect."

Table 1. Observed defects and their quantities in fabrics

Defects	Number of Defects	Fault Rate
Warp Break	1542	48.0 %
Stop Mark	492	15.3 %
Warp Streak	279	8.7 %
Weft Streak	221	6.9 %
Half Weft Defect	191	6.0 %
Miscellaneous Defects	486	15.1 %
Total	3211	100 %

To enhance manufacturing quality, it is essential to detect fabric defects during the production phase swiftly and accurately. Currently, in Turkey, the detection of faults and defects in fabrics is predominantly conducted through visual inspection by human operators. In the era prior to industrial automation, production volumes were smaller, making defect detection considerably simpler. Today, nearly all fabric production is automated, and products move rapidly along conveyor belts, which complicates the identification of defects through human visual inspection. Moreover, a quality control inspector's maximum concentration span during the inspection of fabric quality is approximately 30 minutes [4]. Fabric defects account for about 85% of the total defects within the textile industry [5].

With the advancement of computer programs, numerous software applications have been developed for the detection of fabric defects. Until the 2020s, most software could detect defects to a degree comparable to human vision (approximately 60%). However, computer-assisted equipment has been considered successful because it can detect faults much faster than the human eye. As we approach the present, significant developments have occurred in the field of artificial intelligence, including machine learning, image processing, and deep learning. These advances have resulted in numerous algorithmic methods that have achieved considerable success in image processing. Libraries that interpret images and identify their defects and imperfections have begun to emerge. Indeed, it has become possible to detect defects in an image with an accuracy rate exceeding 90%.

Motivation. The motivation behind the study can be inferred as follows:

Industrial Application: There is a clear aim to develop a practical solution that can be used in the textile industry to identify fabric defects, which can save time and reduce waste, ultimately leading to more efficient production processes.

Advancement in Automated Inspection: The research seeks to advance the capabilities of automatic visual inspection systems, an area that is of growing importance as industries move towards automation.

Utilization of Accessible Technologies: By using a standard PC and integrated webcam for the detection system, the researchers are motivated by creating a solution that can be easily implemented without the need for specialized or expensive hardware.

Improving Computational Efficiency: There is a motivation to find the optimal balance between the accuracy of defect detection and the computational resources required, making the solution more accessible for real-world applications with potential hardware constraints.

Filling a Research Gap: The study may be motivated by a lack of comprehensive research comparing the performance of different models in fabric defect detection, especially in using real-time detection and classification.

Novality. The novelty of the study is embedded in the following aspects:

Real-time Textual Display of Defects: A significant novel feature of this study is the implementation of a program that can display fabric defects in real-time as textual information when images are presented to a webcam. This bridges the gap between image recognition and practical, actionable output, which is valuable in industrial settings.

Comparative Model Analysis: The study provides a comparison of several machine learning models using different architectures (CNN, VGG16, InceptionV3, ResNet50) to detect fabric defects. It's possible that the specific combination or comparison of these models in this context is novel.

Integration of SVM and K-NN for Classification: The research incorporates the use of SVM and K-NN algorithms specifically for the classification of fabric defects, which might be a novel approach within this particular application area.

This paper is organized as follows: Introduction outlines the research problem and the innovative approach taken and summarizes the related studies in the literature. Section II Material and Methods is the that discusses the practical application of these models for real-time defect detection. Results provide a performance comparison of different neural network architectures, leading to the selection of the most efficient model. Conclusion section encapsulates the study's contributions and its potential industry impact.

The investigation into fabric defects holds a significant position in enhancing production quality and reducing costs within the textile industry. Below are examples of pivotal studies conducted in this domain:

In the study by Shumin Ding [6] in 2012, an approach based on Gabor filters and Principal Component Analysis (PCA) for fabric defect detection is examined. The study elucidates the application of Gabor filters in pinpointing various characteristics of defects on fabric surfaces, based on patterns with distinct orientations and frequencies. The PCA algorithm is employed to analyze these characteristics, with the authors noting this approach yields more accurate results compared to traditional methods and is suitable for real-time applications. They emphasize the reduced need for human intervention in detecting fabric defects using this approach, demonstrating the effectiveness of a Gabor filter and PCA-based methodology in fabric defect detection.

Zhang Hu's work [7] tackles an enhanced Support Vector Machine (SVM) algorithm for textile defect detection. The study proposes a novel method for feature extraction and SVM classification. During feature extraction, a feature vector is formulated using different characteristics of patterns on the fabric surface. For SVM classification, the improved algorithm adopts an approach that requires fewer training samples for classifying instances than its predecessors. The authors report that this enhanced SVM algorithm exhibits superior performance in detecting fabric defects and underscore its suitability for real-time applications, showcasing that an improved SVM algorithm can deliver better performance with a less training-data-intensive approach.

The research by Gupta Mishra [8], focuses on analyzing fabric defects for automatic inspection systems. The authors highlight the importance of quality control during the fabric production process and identify the detection of fabric defects using automatic inspection systems as a crucial step. The paper discusses various image processing and feature extraction techniques for defect detection on fabric surfaces, including morphological operations, Gabor filters, color-based features, and wavelet transforms.

The study by Zhoufeng Xianghui [9], evaluates the use of deep convolutional neural networks and presents an application example for fabric defect detection in the textile industry. The authors argue that the application of deep learning methods can automate and increase the accuracy of the human process of detecting fabric defects, thereby saving time and costs. A deep convolutional neural network is employed to extract features from fabric surface images.

In the article published by Mei Wang [10] in 2018, a method for fabric defect detection is presented. The method uses an enhanced CNN, which utilizes deep learning features to detect defects in fabric images. The developed CNN model operates through a three-stage process comprising feature extraction, feature matching, and classification. The method's performance is tested using two different datasets, with results indicating higher accuracy rates compared to other methods.

The study in 2022 by Talu Hanbay [11] discusses the use of a CNN based on an ESA for detecting fabric defects. The study indicates that the ESA-based CNN method achieves a higher accuracy rate and is effective in detecting fabric defects.

Devrim Soyaslan's work [12] examines the application of computer vision techniques for fabric defect detection. The authors argue that traditional methods fall short in detecting fabric defects, hence computer vision techniques provide more accurate results. Several different image processing methods are utilized to extract features from fabric surface images, including color space transformation, contrast enhancement, histogram equalization, edge detection, and morphological operations. The authors note that combining these methods enables accurate defect detection and draws attention to the time and cost savings in the production process.

In the study by Çıklaçandır [13], different approaches using four CNN-based models, namely ResNet18, ResNet50, GoogLeNet and AlexNet, were used in the feature extraction step, while EL, KNN and SVM were used in the classification step. In this study, unlike other studies, feature fusion method was used for feature extraction.

To date, the studies carried out to detect fabric defects have been done with the existing computer hardware in mind. Therefore, models that tire the system and take a long time to produce results have been eliminated. However, it should be known that technology is developing very fast and hardware is becoming more and more powerful. Especially the developments in quantum technology will shorten this process much more. On the other hand, these studies are of great importance for automatic fabric quality control and fast and accurate detection of defects.

2. MATERIAL AND METHOD

The study conducted consists of two primary sections. The initial part involves the creation of the dataset, followed by the development and training of different models to enable the system to recognize selected fabric defects, as well as the classification and evaluation of their performance. The final stage aims to implement a program that allows the real-time textual display on the screen of images presented to a computer-connected webcam.

2.1. Data Set

The dataset we used is a dataset developed by the "Automatic Visual Inspection of Technical Objects" working group of DFG (Deutsche Forschungsgemeinschaft), which contains 8 different classifications, 7 different fabric defects and 1 non-defective classification [14]. Tilda dataset consists of 3200 images of 768 × 512 pixels in total. The dataset is divided into 12 folders. The folders starting with Cd1 are composed of unpatterned fabric prefixes and the folders starting with Cd2 are composed of patterned fabric samples (Figure 2). Each folder consists of 8 subdirectories (e0, e1, e2, e3, e4, e5, e6, e7) and each directory contains 50 samples (Figure 1). Non-defective samples are located in index e0. The other indexes contain defective fabric samples.

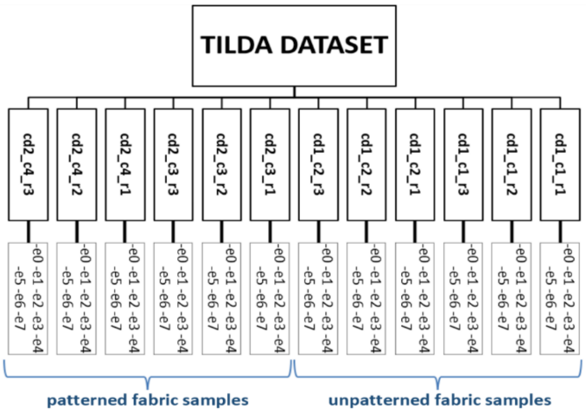

Figure 1. Tilda dataset

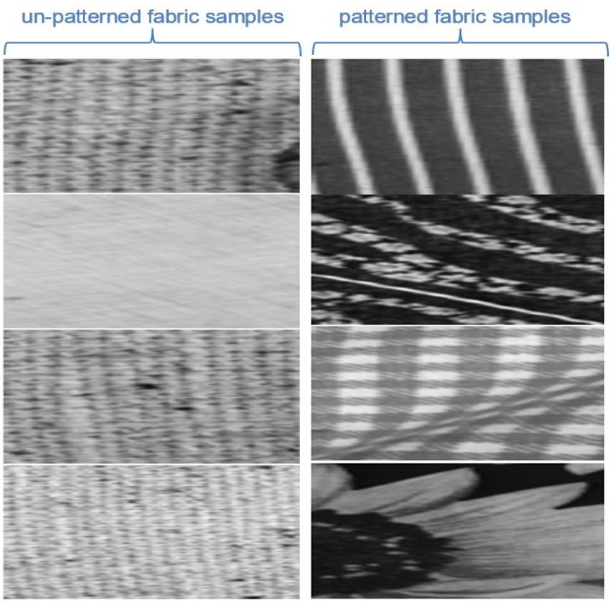

Figure 2. Fabric samples

2.2. Algorithm

CNN is a deep learning algorithm that is mostly used in image processing and takes visual objects as input [15]. In addition, CNN is a multilayer ANN (Artificial Neural Network) model developed specifically for computer vision applications. It is an approach that provides higher performance than other classification methods. On the other hand, the disadvantage of CNN is the need for powerful hardware resources [13]. The traditional CNN architecture consists of five main layers. These are input, convolution, pooling, fully-connected and output layers. The convolutional layer detects the features of the image coming from the input layer without processing, filters them and outputs a new feature map. The pooling layer prevents over-learning and improves computational cost by reducing the size of the model. The Fully-connected layer optimizes class scores and is located near the end of the CNN architecture. The output layer is the classification layer and has as many values as the number of classes [16]. From these layers, many different CNN architectures can be created by changing the number of convolutional layers, pooling layers and fully-connected layers [17].

There are many different models that can be designed for CNN. Model selection is considered as an important factor in solving the problem. There are many models designed and proven to be successful for the discrimination of 2D images. Pre-trained models are expected to learn faster or be more successful than untrained models. In this study, VGGNET16, InceptionV3 and ResNet50 models with different architectures are used for classification. Table 2 shows the main parameters of these models.

VGGNet16 is a CNN architecture used to win the ILSVR (Imagenet) competition in 2014. It has 16 layers and a very uniform structure. It is architecturally similar to AlexNet and is considered to be one of the most perfect vision model architectures among the architectures produced to date. The network consists of approximately 138 million parameters and has convection layers of 3x3 filters in a single step instead of a large number of hyperparameters. In the VGGNet16 structure, the convolution and maximum pooling layers are consistently used throughout the entire architecture, with the same padding and maximum pooling layer being used as in the 2-step 2 x 2 filters. In the last layer, 2 fully connected layers are used, followed by a Softmax for the output. Recognition and classification learning of a 224 x 224 image is achieved by pixel segmentation and network training. In this way, our network learns the classification and the accuracy of the network in learning increases in image analysis.

Table 2. Main parameters of models [18]

Model	Input size	Mini community value	Learning rate
VggNet16	224 x 224 x 3	64	0.00005
InceptionV3	299 x 299 x 3	32	0.001
ResNet50	224 x 224 x 3	32	0.001

The InceptionV3 architecture developed by the Google team won the ImageNet competition in 2014. The Inception architecture uses layers connected in parallel.

The model consists of building blocks including convolution, average pooling, maximum pooling and fully connected layers. Using a Softmax function for the output, this model consists of 42 layers in total and receives an image of 299 x 299 pixels on input.

The ResNet50 architecture, which won the 2015 ImageNet competition, has 152 layers and around 23 million parameters. Widely used in image detection and classification, the ResNet50 architecture resembles an updated neural network in its structure and works on the principle of feeding the input as a "residual" to the output of the next two-layer convolution.

2.3. Classification

SVM are a learning algorithm utilized for classification detection [19]. The concept relies on identifying a high-dimensional hyperplane that separates different classes at an optimal level. SVM operates by finding the hyperplane that maintains the maximum margin or distance between the nearest data points of each class. The data points closest to the hyperplane are referred to as support vectors and are used to define the hyperplane [20].

The K-NN algorithm, on the other hand, is a type of lazy learning algorithm. It does not learn from the training data but memorizes it. When a prediction is required, the algorithm searches for the closest neighbors within the entire dataset [21]. In the operation of the algorithm, a K value is determined, which denotes the number of elements to consider. When a new value is presented, the distance between this value and the nearest K elements is calculated. The Euclidean function is commonly employed for distance calculation, although alternative functions such as Manhattan, Minkowski, and Hamming can also be utilized [22]. After the distances are calculated, they are sorted, and the new value is assigned to the appropriate class [23].

2.4. System Specifications

The system information of the computer used for the project software is shown in Table 3. In the created system, Python language was selected and the software was implemented using the keras library in the Jupyter Notebook environment. Keras supports a wide range of export options for wide adoption, beyond ease of learning and ease of model building. It also runs models seamlessly on CPU and GPU.

Table 3. System configuration employed in the research

System Configuration	Features
CPU	AMD Ryzen5 3400G 3,70 GHz.
RAM	16 GB.
GPU	AMD Radeon RX Vega 11 Graphics 2 GB + 7 GB
Operating System	MS Windows 10 Professional x64
Camera Model	Front- Facing 720p
Camera Resolution	1 MP

This research comprises code written on a personal desktop and a webcam integrated into the device. In the executed study, images randomly selected from the downloaded dataset were only displayed to the camera during the final part, where screen captures were obtained. These images were utilized to represent fabric defects such as warp and weft errors, hole errors, and stained or unstained fabric imperfections. The objective within the scope of this work was to accurately recognize fabric defects and subsequently, through a PC camera, match the displayed fabric to one of the predefined error classes and transcribe it into text form using a Python program written for this purpose.

2.5. Proposed System

The proposed method for detecting defective fabrics consists of four steps. First, the dataset is loaded and then the fabric samples are preprocessed and resized. The fabric images are then given as input to the pre-trained models. As pre-trained deep learning models, VGGNet16, InceptionV3 and ResNet50 are used as feature extractors. SVM and KNN algorithms were used as classifiers to classify the fabric samples as defective or perfect. The proposed method is given in Figure 4.

2.6. Loading The Data Set

The dataset we used in this study is the Tilda dataset that we introduced earlier. This dataset consists of 200 non-defective, 1400 defective, 1600 non-patterned fabric samples and 200 non-defective, 1400 defective, 1600 patterned fabric samples. The defective samples, totaling 2800, were categorized into 7 different folders (e1, e2, e3, e4, e5, e6 and e7) according to the type of defects. At the end of our study, since only the binary classification of defective and non-defective will be used, the samples in folders e1, e2, e3, e4, e5, e6 and e7 are gathered under a single index named "e10". In this way, fabric images were categorized into two basic categories as defective or perfect. In addition, patterned and unpatterned fabric samples were brought together in a single folder. The final version of the dataset folder is shown in Figure 3.

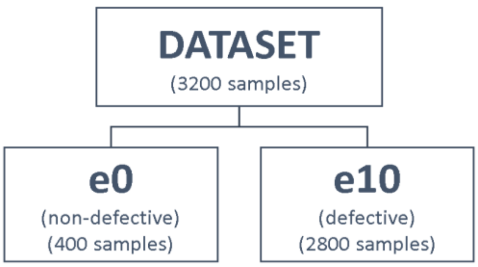

Figure 3. Dataset

2.7. Resizing

Since the image input is different for different models, the fabric samples were resized. For the InceptionV3 model, the images were set to 299 x 299 pixels, for the VGGNet16 model the images were set to 224 x 224 pixels and for the ResNet50 model the images were set to 224 x 224 pixels [24].

2.8. Feature Extraction From Pre-Trained Models

In this study, three pre-trained deep learning models with good results in image processing are used for fabric defect detection. Basically, VGGNet, Inception and ResNet have convolutional and fully connected layers that can be used as feature extraction layers.

2.9. Classification

SVM and K-NN, the two most preferred algorithms for classification, were used in this study.

Images captured by the camera are filtered and then fed into the trained system. These filtered images are compared with the previously trained and classified model. If the system detects a discrepancy, it reports a fabric defect and may halt the system if necessary. Here, the importance lies in having high-performance computing hardware. Simultaneously, the detected fabric defects are added to the dataset to enrich it, facilitating easier detection of future defects models used was evaluated using different metrics such as Accuracy, Precision and F Score.

- False positives (FP): samples predicted as positive that are from the negative class.

- False negatives (FN): samples predicted as negative, whose true class is positive.

- True positives (TP): correctly predicted samples belonging to the positive class.

- True negatives (TN): examples correctly predicted as belonging to the negative class.

Accuracy is a metric that is widely used to measure the success of a model but is not sufficient on its own. The measurement of accuracy is given in Equation 1.

$$Accuracy = \frac{|TN| + |TP|}{|FN|+|FP|+|TN|+|TP|} \tag{1}$$

Precision is a measure that estimates the probability that a positive forecast is correct. The precision measure is

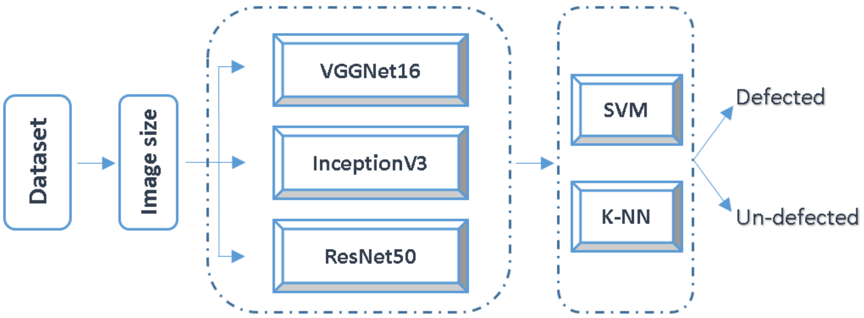

Figure 4. Proposed method

3. EXPERIMENTAL APPLICATIONS

The models were tested on a computer, the specifications of which are detailed in Table 3. Due to the limitations of our computer hardware, the batch size was set at 100. An epoch refers to one complete training cycle on the entire dataset. If the number of epochs is set too low, the model may not undergo sufficient training. Conversely, setting the epoch count too high can result in excessively prolonged model training times.

given in Equation 2.

$$Precision = \frac{|TP|}{|FP|+|TP|} \tag{2}$$

The F-score is a harmonized average of the positive prediction rate and sensitivity measures, calculated as shown in Equation 3.

$$F\ Score = \frac{2\ x|TP|}{2\ x\ |TP|+|FP|+|FN|} \tag{3}$$

Some of the randomly selected data from the datasets

Model	Image Size	Classifier	Accuracy	Precision	F Score
VGGNet16	224x224	SVM	81,11%	83.91%	82,51%
		KNN	86,82%	89.20%	88,01%
InceptionV3	299x299	SVM	86,55%	89.36%	87,95%
		KNN	90,18%	92.25%	91,56%
Resnet50	224x224	SVM	95,54%	96.36%	95,95%
		KNN	95,88%	96.25%	96,06%

3.1. Comparison of Methods

Within the scope of this study, a review of the extant literature on fabric defect detection reveals that the most prevalently utilized models include Convolutional Neural Networks (CNN), VGGNet16, Inception V3, and ResNet50 architectures. In this study, binary classification was performed and the performance of the were used for training and some for testing. Table 4 shows the classification results obtained. The highest accuracy of 95.88% was obtained with the Resnet50 model and KNN classifier; the lowest accuracy of 81.11% was obtained with the VGGNet16 model and SVM classifier. The results we obtained in this context are shown in Table 4

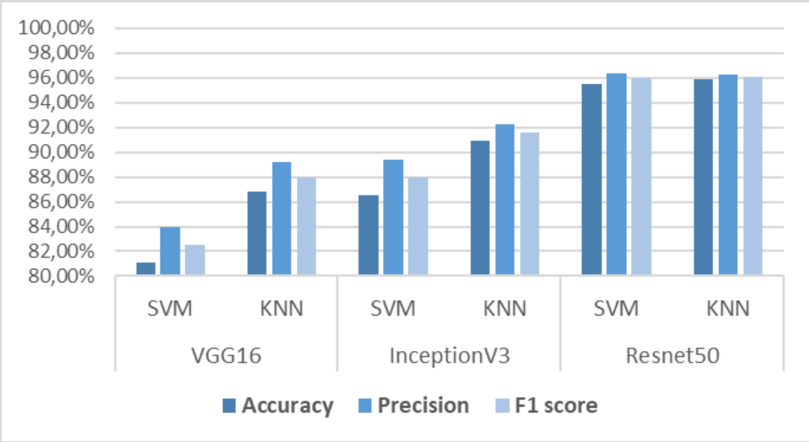

Figure 5. Performance comparison

As can be seen in Figure 5, the lower accuracy of the SVM classifier is related to the size of the dataset. Since the data set we used is large, it is not suitable for SVM. When we look at the results of the KNN algorithm, it is seen that the image size is not affected much, but it is more suitable than SVM in accuracy values. In addition, to look at the performance of the classifiers in terms of time, the results of feature selection using 100 randomly selected samples are shown in Table 5. These results show that the SVM classifier takes much longer than KNN. The average time of the SVM classifier is 36.07 seconds, while KNN takes 6.87 seconds. The fact that SVM takes so long for 100 samples is one of the major disadvantages of using it on large data sets.

Table 5. Classification times

Model	Classifier	Duration (sec)
VGGNet16	SVM	36,12
	KNN	6,21
InceptionV3	SVM	26,55
	KNN	7,08
Resnet50	SVM	45,54
	KNN	7,34
Ortalama	SVM	36,07
	KNN	6,87

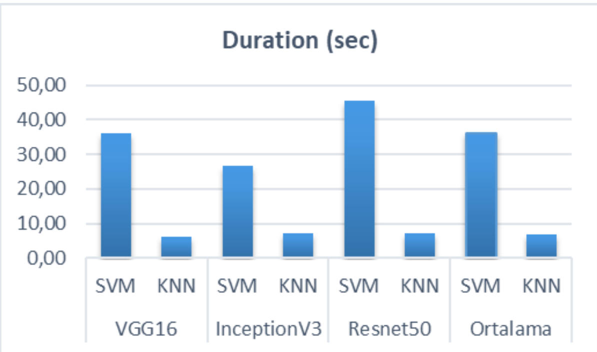

Figure 6. Classification times

4. CONCLUSION

The main objective of our study is to use state-of-the-art technologies to improve fabric quality by detecting defects in the fabric in the fastest and most accurate way. In recent years, there have been great advances in image processing techniques. However, the use of CNN-based models has become quite common in this field. In this study, the Tilda dataset consisting of 3200 publicly published fabric samples is used to test the methods. First, all images are dimensioned according to the model's features. Then, the features extracted by the pre-trained models in the feature extraction process were used for classification. Three different models, VGGNet16, InceptionV3 and ResNet50, were used in the feature extraction step, while SVM and KNN algorithms were used in the classification step. As a result of the experimental studies, ResNet50 model and KNN classifier gave the best results. In terms of accuracy, sharpness and F-score results, SVM and KNN classifiers were close to each other. However, when the time test was performed, the SVM algorithm performed very poorly. It can be concluded that SVM algorithm is not suitable for large data sets.

In this study, comparisons were made using the most widely employed deep learning algorithms, such as CNN, VGGNet16, InceptionV3, and ResNet50 models. The comparison results indicate that the ResNet50 model provides higher accuracy than the other models. However, it should not be forgotten that with current technology, a significant disadvantage of these models is the long time required to detect errors. Additionally, to shorten this duration, we are compelled to filter and downsize images from our database considerably. Although CNN algorithms are more time-efficient, in this era of rapid technological advancement we prefer the model that offers the highest accuracy. The ResNet50 architecture's achievement of approximately 95% accuracy within a relatively long duration may not be acceptable in terms of time. However, there is no doubt that with the imminent widespread adoption of high speed computer technologies, this duration will be reduced to reasonable values.

As a result, the ResNet50 model outperforms other pre-trained models and can be used effectively in fabric defect diagnosis. These findings show promise that computer-aided diagnosis systems can play an important role and make a valuable contribution in the field of textiles.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Recep Ali GEZE: Performed the experiments, analyzed the results and wrote the initial draft of the manuscript.

Ayhan AKBAŞ: Co-supervised the study, analyzed the results, and wrote the final manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study

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