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*Research Article*

# Ensemble learning application for textile defect detection

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ABSTRACT

Textile production has an important share in the Turkish economy. One of the common problems in textile factories in Turkey is fabric texture defects that may occur due to textile machinery. The faulty production of the fabric adversely affects the company's economy and prestige. Many methods have been developed to achieve high accuracy in detecting defects in fabric. The aim of this study is to compare the performance of the models using the new dataset and deep learning models. The findings have determined that the Seresnet152d model, which is one of the transfer learning models, can classify with 95.38% accuracy on the generated dataset. Moreover, the majority voting gives 95.58% accuracy rate. In order to achieve high accuracy in the future, it is planned to optimize the parameters of the models used in the study with the help of swarm-oriented optimization algorithms.



## 1. Introduction

People's lives are significantly impacted by the textiles and clothing they wear. The textile business is expanding at a quick rate, and with it comes a variety of new fabric models and design options. During the manufacturing process, the quality of the fabric must be carefully monitored and controlled using a variety of different strategies if the textile industry is to maintain its upward trajectory of expansion. The potential for defects in textile machinery is one of the aspects that might influence the quality of the fabric, and it is also one of the aspects that is among the most significant. The detection of machine-induced flaws has been the subject of the development of a great deal of practical methodology. On the other hand, in the most recent years, researchers have proposed investigations on the use of computer-aided methods to detect faults in fabric. Among them, approaches that are based on deep learning have recently seen a great deal of success in the areas of image identification, picture segmentation, and object detection over the past several years.

In the course of this research, a brand new dataset for the fabric was compiled, and it included both defects and non-defects classes. Using the recently compiled dataset, a variety of deep learning transfer models were put to use in order to establish whether or not the material in question was faulty. During the phase of testing, the Ensemble Learning method was chosen as the one to use. Estimation results were generated for this purpose based on the outcomes of the EfficientNetv2m, Seresnet152d, and Eca nfnet l0 models.

The remaining parts of the paper are structured as described below. The work that has been done to discover flaws in textiles is detailed in the second half of this article. In the third portion, both the data collection and the deep learning architecture that was utilized will be discussed. In the following section (section four), we will discuss the performance metrics, model training, and experimental findings. In the fifth segment, we address the overall evaluation, as well as the work that is planned for the future.

## 2. Related Works

Several recent research have been published that use deep learning to identify and categorize defects in materials. Researchers Wang and Lin have suggested a cutting-edge

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RCNN approach for detecting defects in fabrics. Using geometric and GAN-based techniques, the authors of this work created 2688 data points in order to simulate 100. Compared to the standard, faster RCNN, the proposed approach yielded considerable improvements in performance. The suggested faster multi-channel RCNN has an average accuracy of 90.05% on the larger dataset [16].

Separation Convolution UNet (SCUNet) is an algorithm that was proposed by Cheng, Chen, and Zhang as a model for the localization identification of fabric defects. They used the AITEX dataset, which has 106 different images of fabrics. They obtained an additional 1395 data points by using data augmentation techniques in order to supplement the limited data set. At the end of the research, they acquired an accuracy rate of 98.01% [5].

Chen and colleagues developed a model for the detection of damaged fabric in their research that was based on faster-RCNN. After inserting a Gabor kernel into the first layer of the faster-RCNN networks, the researchers utilized a genetic algorithm (GA) to determine which Gabor parameters produced the best results and then chose those values. In the study, a total of 6316 different fabric images were employed, and the mAP value at the conclusion of the training for the model was 94.57% [4].

Deep neural network technology was used by Liu et al. to construct a model that can detect defects on the surface of fabrics. The data are organized into two separate sets: dataset A contains 88,300 records, while dataset B contains 61,300 records. During the testing, it was determined that the detection accuracy was 99%, which makes it acceptable for production lines that have real-time needs [11].

Huang and Xiang proposed a semantic partitioning network, called RPDNet, which uses an iterative model analysis algorithm for pixel-level detection of fabric defects. They used FI and TILDA datasets for model training [8].

A lightweight CNN-based architecture was presented for the purpose of defect detection in fabric by Suryarasmi et al. The proposed architecture, FN-Net, can train anywhere from three to thirty-three times faster than the state-of-the-art architectures VGG16, MobileNetV2, EfficientNet, and DenseNet. Additionally, the proposed architecture requires less graphics processing unit and memory than the compared architectures. When it comes to class identification, FN-Net has a value of 0.86 for its F1 score on average, whereas VGG16 and EfficientNet, respectively, have the highest and lowest values of 0.81 and 0.50 among the base models [14].

In their research, Kahraman and Durmuşolu utilized Capsule Networks for the purpose of identifying fabric defects. For the training of the model, they utilized the TILDA dataset for experimental evaluation. This procedure was carried out in a variety of settings, and the results showed that it had an overall performance value of 98.7% [10].

Utilizing the AITEX dataset, Mohammed and Clarke constructed a brand new model in their research that could identify and categorize flaws in cloth. The U-Net deep learning model was used in this model to determine whether or not the fabric contains any defects. Following that, the VGG16 and Random Forest approaches were employed to classify the defects that were present in the fabric. The findings of the investigation showed that they were able to identify errors with a precision of 99.3 percent [12].

In order to differentiate between defective and non-defective fabric, Ashraf et al. utilized a CNN-based GoogleNet network. On the TILDA dataset, the performance of the proposed technique was examined, and a classification accuracy of 94.46% was obtained [1].

Biradar et al. conducted a new study called Competitive Cat Herd Optimization Algorithm (CCSO)-based Deep neuro-fuzzy network (DNFN) to effectively detect defects on the fabric surface. In the proposed CCSO-based DNFN model, 91.9% accuracy was achieved [2].

Biradar et al. In another study they carried out, they conducted a study on the classification of defects in fabrics with the Deep Convolutional Neural Networks (DCNN) model. They tested the proposed model on three data sets. When the findings obtained in the study were examined, it was seen that the accuracy was 99.06% in the TILDA dataset, 90.39% in the dataset consisting of patterned fabrics, and 98.33% in the dataset consisting of unpatterned fabrics [3].

Durmuşoğlu and Kahraman have worked on detecting defects on fabric surfaces using the VGG19 model and the TILDA data set. There are 682 sample data in the data set used in the study. However, due to the limited number of data in the data set, 38591 data were obtained by applying data augmentation techniques. At the end of the study, it was seen that 94.65% accuracy was obtained on the test data of the VGG19 model [6].

Jin and Niu developed the YOLOv5 object detection algorithm and detected faulty fabrics with this algorithm. The proposed method has been evaluated on the Tianchi AI and TILDA dataset. The results reveal the ability to detect and recognize certain fabric imperfections [9].

Zhou et al. proposed a method for error detection based on variational autoencoder (VAE) and Gaussian mixing model (GMM). The VAE model is trained for feature extraction and image reconstruction, while the GMM is used for density estimation. The proposed method has been validated in the AITEX and DAGM 2007 general dataset [17].

Rong-qiang et al. In this study, an improved convolutional neural network CU-Net is proposed for fabric defect detection. In this method, the classical U-Net network was developed. The publicly available AITEX defective fabric dataset was used as the test dataset. When the results of the study were examined, it was seen that the proposed method had an accuracy of 98.3% [13].

## 3. Material and Method

### *3.1. Dataset*

The details of our dataset are described in this section of the article. In the proposed research we will use two new datasets: one with defects and without defects. The faulty dataset includes goods that were damaged by the textile machine. The dataset includes a total of 2060 images of fabric, 1030 of which are defective and 1030 of which are not defective. The dimension of each image is 256 pixels by 256 pixels. Table 1 provides the total number of images in the dataset, which has been segmented into the three categories of training, validation, and test for the purposes of model training.

**Table 1.** The count of samples for train, validation and test sets.

| | Defective Textile | Non-Defective Textile |
|---|---|---|
| **Train** | 693 | 693 |
| **Validation** | 77 | 77 |
| **Test** | 260 | 260 |

### *3.2. Classification System*

This study focuses on the use of convolutional neural networks to identify defects affecting the textile industry in a more accurate and automated computer-aided manner without the need for human assistance. For this purpose, state-of-the-art EfficientNetv2m, Seresnet152d and Eca_nfnet_l0 models are used as the network architecture to obtain predictions based on the majority rule. The algorithms used in the study are briefly explained below.

EfficientNet network architecture, one of the models used, is based on scaling depth, width and resolution dimensions efficiently. The EfficientNet network architecture scales with the unified scaling method. Here, the scaling method is divided into two as composite scaling and traditional scaling. Composite scaling is a method based on scaling the depth, width, and resolution of meshes equally. Traditional scaling is a method based on scaling only one dimension of the network [15].

The Seresnet152 model was created by integrating Squeeze-and-Excitation (SE) blocks into the resnet152 model. The basic idea of the SE block is to improve performance by emphasizing the importance of feature maps that convolutional neural networks learn [7].

The ecanfnetl0 model is a variant of the NFNet model family. Unlike other models, this model uses Efficient Channel Attention (ECA). Also, in the model, SiLU activation functions are used instead of GELU activation functions. There is no normalization layer in this model. Instead it uses Weight Standardized convolutions with additional scaling values.

An overview of the proposed classification system is shown in Figure 1.

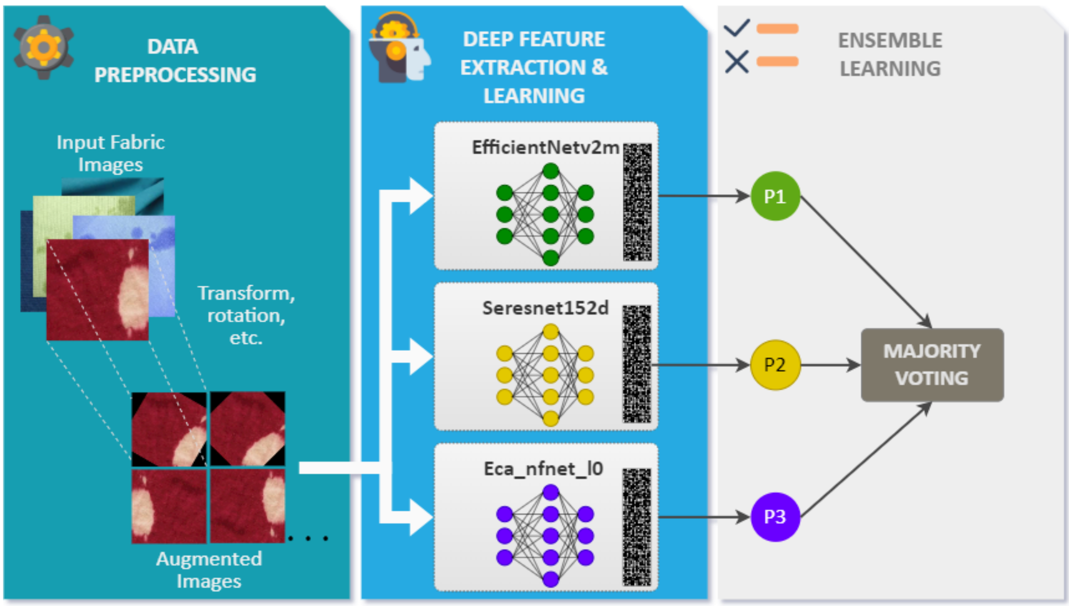



**Figure 1.** Overview of the proposed framework

Before each model can be trained, the data must be pre-processed through a series of smaller operations. As the input size of the model architectures is (224 224 3), the first step in the preparation section is to rescale the original photos. This is the first stage of the preprocessing phase. After that, the categorical variables are encoded using the one hot encoding approach so that they can be expressed in binary form. The samples were rotated with a probability of 0.5 in both the horizontal and the vertical planes for each dataset. This was done to acquire trustworthy validation results. For train procedure, the Python programming language and the Pytorch library were used. At the beginning of the phase where the model is being trained, the dataset is originally split into three sections: training, validation, and testing. We collected a total of 1386 data for the training phase, 154 for the validation phase, and 520 for the testing phase. In the training, the epoch value is set to 50 and the batch size value is set to 16. The Adam optimization function was chosen as the optimization algorithm of choice, and the learning rate was established at 0.001. The application of categorical cross entropy loss was done so that the appropriate error rates of the models could be determined. In addition, there is a possibility of overfitting occurring during the training phase as a consequence of utilizing a constrained number of classes in conjunction with deep CNN models. To avoid the models from becoming overly precise, data augmentation strategies and a dropout layer were incorporated into them.

## 4. Experimental Results

### *4.1. Performance Metrics*

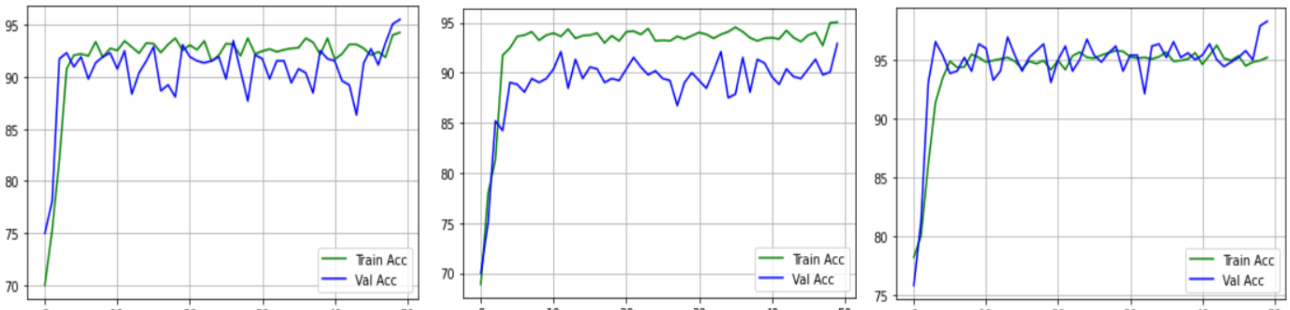
The classification accuracy of the models that were considered for this research was analyzed using performance measures that were based on confusion matrices. The confusion matrix offers an analysis of the connection that exists between the picture labels that are predicted by the model in the output layer and the image labels that are real present in the data. Accuracy, precision, recall, and F-score are the selected criteria used to demonstrate this connection. For the accuracy metric, it is anticipated that a successful model will have high TP and TN ratios.

### *4.2. Performance Evaluation*

This part provides a high-level overview of the output performance of the system as well as a summary of the most important conclusions from the study. Each deep learning model is trained in the Google Colab environment.

In the accuracy-loss graphs, the convergence of the model is said to be improved depending on how closely the validation curve follows the training curve. Figure 2 presents the success (accuracy) graphs that were obtained due to employing the Adam optimization function in the process of training the EfficientNetv2m, Eca nfnet l0, and Seresnet152d models. When the success graphs of the models are examined in greater depth, it is discovered that Seresnet152d performs better than the other models in terms of training and validation. In addition to this, the training graph of every model demonstrates a high accuracy score between the epochs of 48 and 50. However, there is a substantial gap between the training curve and the validation curve in the case of the Eca nfnet l0 model. The other models converge more successfully than this one does. Performing ensemble learning, it is hoped that the resulting models will allow for an improvement in performance when applied to the test dataset. The Majority Voting strategy, which is one of the ensemble learning strategies, was selected as the favored method in the model. A comprehensive examination of the samples that were classified using the complexity matrix of the model that was developed using the ensemble learning method is presented in Figure 3. When the findings are analyzed, it can be observed that the model determines that some instances of faultless are actually faultly. This is due to the fact that there is a positive link between certain cases belonging to the faultless class and certain instances belonging to the faultly class. The Seresnet152d model had the highest accuracy rate of the ones that were utilized, coming in at 95.38%, while the Eca nfnet l0 model remained at 88.08%. Nevertheless, using the Majority Vote approach brought the overall performance up to 95.58% of its potential. Although the EfficientNetv2 model had the highest TP value, this value was raised to 239 after receiving the majority vote. Similarly, the Seresnet152d model was the one that achieved the highest F-score value out of the three models at 95.16%. The results of the majority vote with regard to the other models indicated that this metric should be 95.41%.

In addition, the TILDA dataset was also used to evaluate the models. When Table 3 is examined, the SeresNet152d model obtained the highest accuracy with a rate of 91.69%. With the majority voting method, this rate increased to 93.41%. The proposed method appears to achieve high accuracy in both our dataset and TILDA dataset. In addition, the training times for both data sets are given in Table 4. Due to the large number of samples in our data set, the training of the models took a long time. The table also shows that the majority voting method achieves maximum accuracy in minimum time.




a) EfficientNetv2 b) Eca_nfnet_l0 c) Seresnet152d

**Figure 2.** Training and validation graphs of models with Adam optimizer

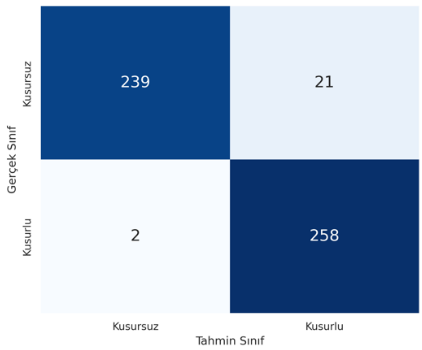



**Figure 3.** The complexity matrix obtained using the majority algorithm

**Table 2.** Statistical performance results

| Metrics | EfficientNetv2 | Eca_nfnet_l0 | Seresnet152d | Majority Voting |
|---|---|---|---|---|
| **Accuracy** | 92.12 | 88.08 | 95.38 | 95.58 |
| **TN** | 242 | 252 | 260 | 258 |
| **FP** | 18 | 8 | 0 | 2 |
| **FN** | 23 | 54 | 24 | 21 |
| **TP** | 237 | 206 | 236 | 239 |
| **Precision** | 92.94 | 96.26 | 95.38 | 99.17 |
| **Recall** | 91.15 | 79.23 | 90.77 | 91.92 |
| **F-score** | 92.04 | 86.92 | 95.16 | 95.41 |

**Table 3.** Accuracy parameter values of data sets

| Datasets | EfficientNetv2 | Eca_nfnet_l0 | Seresnet152d | Majority Voting |
|---|---|---|---|---|
| Our Dataset | 92.12 | 88.08 | 95.38 | 95.58 |
| TILDA | 87.06 | 71.64 | 91.69 | 93.41 |

**Table 4.** Training times of models (second)

| Datasets | EfficientNetv2 | Eca_nfnet_l0 | Seresnet152d | Majority Voting |
|---|---|---|---|---|
| Our Dataset | 2400 | 1200 | 2280 | 1920 |
| TILDA | 1383 | 840 | 1370 | 1020 |

## 5. Conclusions

In this research, we suggested and statistically analysed a computer-assisted system for detecting damaged fabric in the textile industry, one that performs feature extraction and deep learning. The proposed approach was developed with the primary goal of assessing the efficacy of current transfer learning models for defective fabric detection and enhancing their performance through ensemble learning. For the benefit of future academics working on this topic, a new open-source dataset has been produced. The results showed that the ensemble learning model had a 95.58% accuracy rate and an F-score of 95.41%. Average voting methods will be used in the future to fine-tune the models' performance for greater precision.

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