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A Novel Industrial Application of CNN Approach: Real Time Fabric Inspection and Defect Classification on Circular Knitting Machine

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ABSTRACT

Fabric Automatic Visual Inspection (FAVI) system provides reliable performance on fabric defects inspection. This study presents a machine vision system developed to adapt in circular knitting machines where fabric defects can be automatically controlled and detected defects can be classified. The knitted fabric surface are detected during real-time manufacturing. For the classification process, three different transfer learning architectures (ResNet-50, AlexNet, GoogLeNet) have been applied. The five common knitted fabric defects were recognized with the artificial intelligence-based software and classified with an average success rate of 98% using ResNet-50 architecture. The success rates of the trained networks were compared.

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KEYWORDS

Circular knitting machine, Knitted fabric, Defect detection, Deep learning, Convolutional neural network (CNNs)

1. INTRODUCTION

The knowledge of human brain, statistics and applied mathematics is needed to machine learning based on deep learning that has seen tremendous growth in its popularity and usefulness. Luckily these are achieved by using powerful computers, larger datasets and techniques used to train networks. Challenges and opportunities are ready to improve deep learning even further in coming years [1]. Dramatic improvements have been seen in computer vision; medical image analysis, text analysis, speech recognition, computer games, cyber security for example. The evolution of neural networks with more neurons, connecting layers/neurons in different way and automatic feature extraction are interpreted with deep learning resulting in more computing power indeed [2].

Developments in Industry 4.0 have incorporated concepts and technologies such as the internet of things, artificial intelligence, and smart factories into our lives. Especially as use of artificial intelligence and computer vision technologies together, different methods are developed using smart vision systems instead of production stages and quality control processes that are followed, controlled, and decided by humans. Considering the production process in

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the textile sector, both in production stages and post-production quality evaluations are mostly decided by human monitoring and evaluation by following a labour-intensive method.

In the current technology, fabric defects are checked by the workers on the illuminated surface after production. The fabric structure can be composed with different methods such as knitting, weaving and the nonwoven texture property. Considering the knitting fabric production, common defects are seen such as hole/cracks, loops/drop stitches, lycra missing, knots [3-7]. These defect types are defined on the knitted fabric roll after production prosess. Improvements on defect detection technology reduces production cost by also improving product quality. Many attempts have been performed to automatically perform this process. Different systems and algorithm parameters must be used for each fabric formation method.

Many studies have been found using image processing techniques such as histogram-based, color-based, image segmentation-based, frequency domain operations, texture-based defect detection, sparse feature-based processing, image morphology, and deep learning. Deep learning methods are given and analysed with their characteristics and shortcomings [8]. Several research studies were performed to detect defects automatically in circular knitting machines. Some of them are taken to get a background. Saeidi et al. developed a visual inspection system for a circular knitting machine, which comprised a CMOS (Complimentary Metal Oxide Semiconductor) camera using the Garbor wavelet as the detection algorithm [9]. Hemdan et al. have achieved image analysis using a fabric evaluation system for knitted fabrics. Different texture recognition methods: thresholding analysis, radon transform, a discrete Fourier transform, and neural network are applied [10]. Marmaralı et al. have developed a system determining eight different knitting fabric defects; hole, broken needle, colored yarn, thick yarn, thin yarn, cloth fall out, vertical-horizontal lubricant stains on circular knitting machine [11]. Yundang et al. have proposed a system for automatic inspection using smart visual sensors. Defect detection rate is seen 98% on warp knitting machines during actual factory operation as well [12]. Şeker et al. have applied autoencoder deep learning algorithm to detect fabric defects [13]. Takeuchi et al. have offered a simple analysing system for vertical line defects by fixing a camera on the circular knitting machine [14]. Wang et al. have presented and compared defect detection method and deep-learning defect detection techniques. They have used the average brightness of Wale direction successive pixels [15]. Hanbay et al. have introduced a computer vision-based detection system for circular knitting fabrics using shearlet transform [16].

When the knitted fabric production capacity of Turkey is considered, the importance of an automatic fabric insepetion system for knitted fabric can be well understood. The total annual production capacity of 949 circular knitting manufacturers operating in Turkey is 740.6 thousand tons. This corresponds to 3rd rank after China and India with a share of 3.8% [20]. Within the scope of the study, the most common defect types and the frequency of these defects were determined by interviewing with 10 different knitted fabric manufacturers. Table 1 summarizes the scale of the knitted fabric manufacturer according to gathered information. The annual rate of the most common types of defects in a knitted fabric enterprise is as shown in Table 1. It can be clearly revealed that approximately 27.4 tons of defective fabrics are producted in a year. This defective fabric amount will change according to the production capacity of the mill. The difference between raw fabric defects and 2nd quality sales is 40,000 Euros/Year for one knitted fabric enterprise. When the total capacity of Turkey with 949 circular knitting manufacturers is considered, it is estimated that 37.96 million Euros loss will occur annually. Minimizing this loss is very critical in terms of sustainability. These losses can be intervened quickly to prevent a loss of 40,000 Euros/Year in an operation.

Table 1. Annual amount of defective knitted fabrics

	Defect Types	**Defective Fabric Amount (Kg/year)**
1	Knots	908,4
2	Lycra missing	11.606,4
3	Drop stitches	10.522,8
4	Loops/Drop	4.057,8
5	Hole/cracks	301,8
	Total	**27.397,2**

The proposed study presents a machine vision system designed for circular knitting machines to inspect fabric defects during the knitting process. The design of the proposed FAVI system made the fabric inspection possible requiring no modifications to the circular knitting machine and without reducing the production efficiency. The computers in the factory can follow the automatic fabric control process. The knitted fabric surface is detected in real time during manufacturing. In many real-time studies in the literature, fabric defects have been detected using different image processing techniques and classified by artificial neural network methods. In this study, deep learning architectures, which offer more robust and effective solutions to pattern recognition and classification problems, are used. Since these network models are trained with at least one thousand data, they have very high accuracy rates. The growth of data and reaching more meaningful information from the data necessitate optimization of feature estimations. With a classical Neural Network model, the connections between neurons and layers and the learning parameters pose enormous computational difficulties. Therefore, deep learning algorithms can be used as an important solution to obtain faster and safer results in real-time industrial applications.

This study develops an innovative solution and test the performance of deep learning algorithms on a real-time fabric defect detection system.

2. MATERIAL AND METHOD

2.1 Material

Knitted single jersey elastic fabrics are normally produced by plating of lycra (spandex) combine with cotton yarn in a circular knitting machine. This type of fabrics and their cloths have a great response and gain their original size and shape due to physical extension by any part of human body. In the study, single jersey fabric was produced from 30/1 ring combed yarn with a density of 35 stitch/inch. Pilottelli circular knitting machine was used to build the vision system. Technical specifications of the industrial circular knitting machine were 30 inches cylinder diameter, 28 needles/inch number of feeder and 300 rpm production speed. Videos taken with common defects are classified for training. Classifications are performed for 5 defects; **double yarn, holes, drop stitches, oil lines,** and **lycra missing**. Recognizing difficulties of defects are changing according to their type. Image frames are taken on circular knitting machine with camera system in holder are given in Figure 1. The resolution of the image was set to 248 pixels/line, and the size of the image frame were selected as 2048x638 pixels. Since the difficulty level of the defects created in the circular knitting machine is different, the number of images of some defects could not be equalized. The class with the minimum number of defects considered to ensure that the number of images is equal in other defect types.

2.2 Machine vision system design

The machine vision system was designed in accordance with the circular knitting machine structure and operating system. The system consists of camera attachment unit, the lightening unit, an encoder, and a desktop computer. The camera system and the lighting unit should see the fabric surface properly. Appropriate locations were determined for the machine vision system so that it can be easily adapted on the circular knitting machine, does not interfere with the operation of the knitting machine, and does not affect the production performance.

Suitable apparatus and mechanical parts were designed for connecting the cameras to these positions. A camera holder designed to operate with the machine in Figure 2. This holder includes a lighting unit, an encoder and camera together with a holder. Lighting unit includes 12 LED’s providing 6 V white light source. LED has placed on the circumference of fiberglass plate covering camera lens. Since the diameter of the camera holder apparatus is 6.5 cm, 12 LED light sources with a diameter of 0.8 cm were placed on the fiberglass plate at equal intervals. The number of light sources used are sufficient in terms of the sensitivity and resolution of industrial cameras being quite good. Morover uniform lighting is needed to get clear images with homogeneous light conditions. The image acquisition system captures high resolution and vibration free images. Thus, synchronization is necessary while taking video images of knitted fabric. For this aim, encoder pulses are being sent to camera input. “BASLER 105993 raL2048-48gm-basler racer” camera was mounted into the knitting machine. The sampling rate of the camera was determined as 51 kHz (51000 lines/sec). Images followed by BASLER GUI named PYLON and the image acqusion parameters adjusted. Having designed the machine vision system and its position in the circular knitting machine, a connection made with the computer in the quality control room. Communication between the circular knitting machine and the computer is provided by ethernet cable in the quality control room of the production mill.

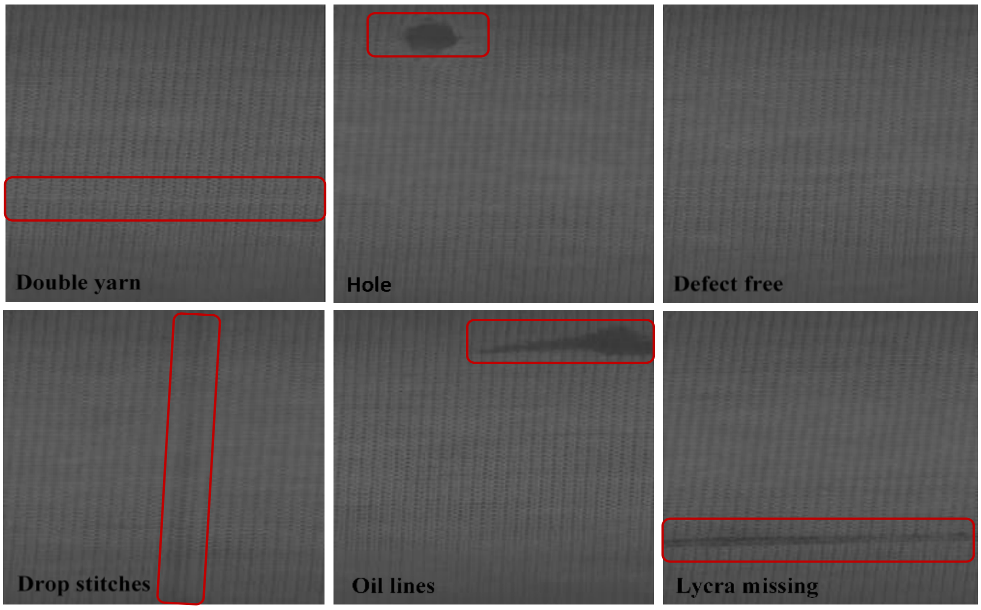

Figure 1. Images taken by the machine vision system

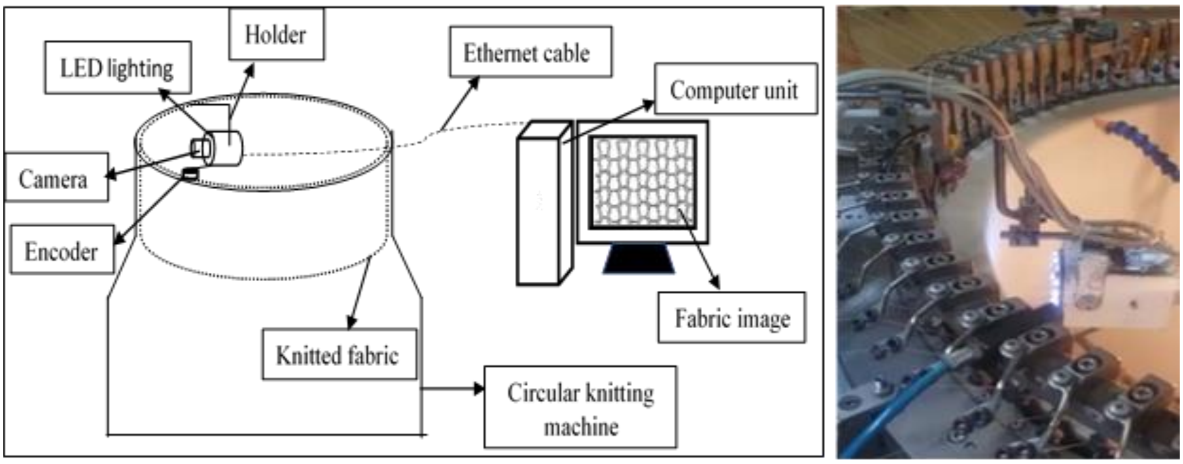

Figure 2. Machine vision system-The circular knitting machine

2.3 Method - convolution neural networks (CNNs)

CNNs are a sub-branch of deep learning used in analyzing visual information. Deep learning goes to the neuroscientific perspective of classification problems. It addresses a more general principle of learning multiple composition levels that can be applied in machine learning frameworks [1]. CNNs take the neural network techniques of the previous generation. They then add advanced automatic feature extraction to make it easier to answer computationally difficult questions about complex data with great reliability in applications. Automatic feature extraction is another one of the great advantages that CNNs has over traditional machine learning algorithms [2]. The target of a CNN is to learn higher-order features in the data via convolutions. They are well suited to object recognition with images and consistently top image classification competitions. They can identify faces, individuals, street signs, vehicles, objects, and many other aspects of visual data. CNNs have been shown to learn general visually generic features on the first few layers and then gradually build up dataset-specific features on later layers. These early layer features are similar to Gabor filters and color blobs.

The system consists of image acquisition hardware and pattern recognition software. Image Acqusition Toolbox and Deep Learning Toolbox have studied in MATLAB®2019 in two stages. Initially, the image frames captured by using the machine vision system for offline training phase. The testing process then performed on the images taken while the knitting machine was running in real-time application. Total 250 defective images, with 50 image frames for each of the 5 different defect classes, were compiled for use in CNNs. Along with the determination of the defect classes, 1600 frames of defect-free fabric images were included in the data set so that the trained convolution neural network could distinguish the fabric without defect. Transfer learning architectures: ResNet-50, AlexNet and GoogLeNet networks were trained using with 1850 image frames in total. While training networks; 70 % of database is utilized for training and remaining is for (30%) validation. The information obtained from the literature, it was observed that the most frequently changed parameters during transfer learning applications were "**Learning Rate**", "**Mini Batch Size**" and "**Number of Epoch**". Meanwhile, during training network, many different values applied for these parameters and the best network training result was obtained.

(i) <u>ResNet</u>

The original architecture of ResNet consists of 152 layers. ResNet has a deeper structure than previous architectures. ResNet, which has a different logic than its predecessors, where the network model is beginning to deepen; It is formed by adding the residual block to the model, which feeds residual values to the next layers. With this feature, ResNet ceases to be a classic model (Figure 3) [17].

ResNet-50 that is a smaller version of ResNet 152 used as a starting point for transfer learning. This model consists of 5 stages each with a convolution and identity block (Figure 4). Each convolution block has 3 convolution layers, and each identity block also has 3 convolution layers. The ResNet-50 has over 23 million trainable parameters.

The fc (fully connected) layer in the last layer in ResNet network has been changed to suit our own data. The parameters are taken during training network; Learning Rate=0,0001, Mini Batch Size=32 and Number of Epoch=50. The success percentage of the artificial neural network trained with the entered parameters was obtained as 96.58%.

(ii) <u>AlexNet</u>

AlexNet consists of eight layers, the first five of which are convolutional, and the last three are fully connected layers (Figure 5). Among these layers, there are also "pooling" and "activation" layers. The designed network used for classification with 1000 possible categories [19].

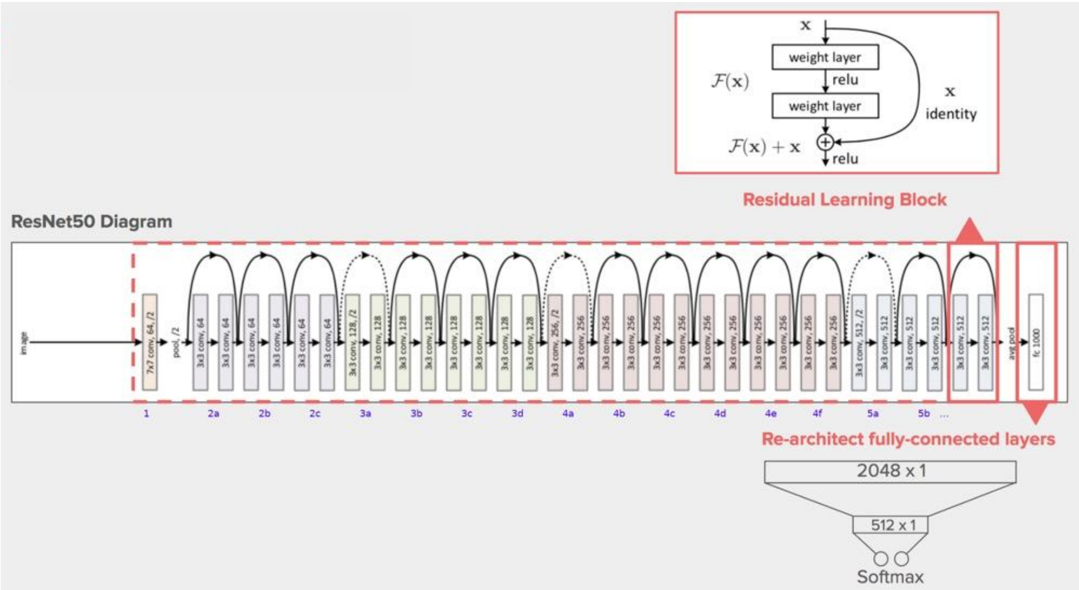

Figure 3. ResNet architecture [18]

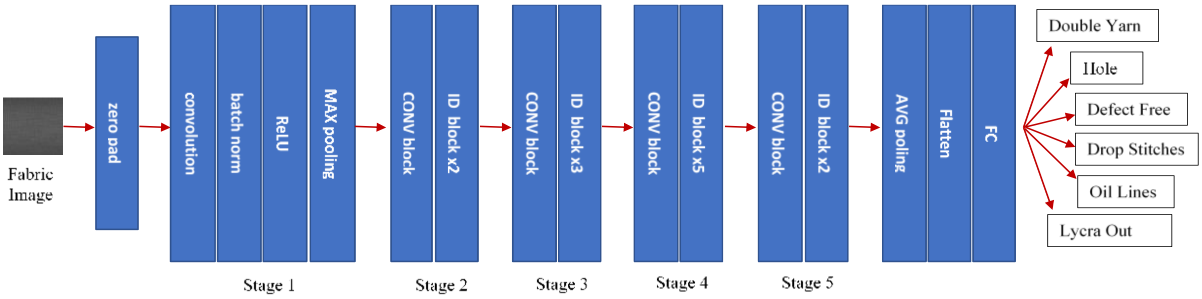

Figure 4. ResNet-50 architect

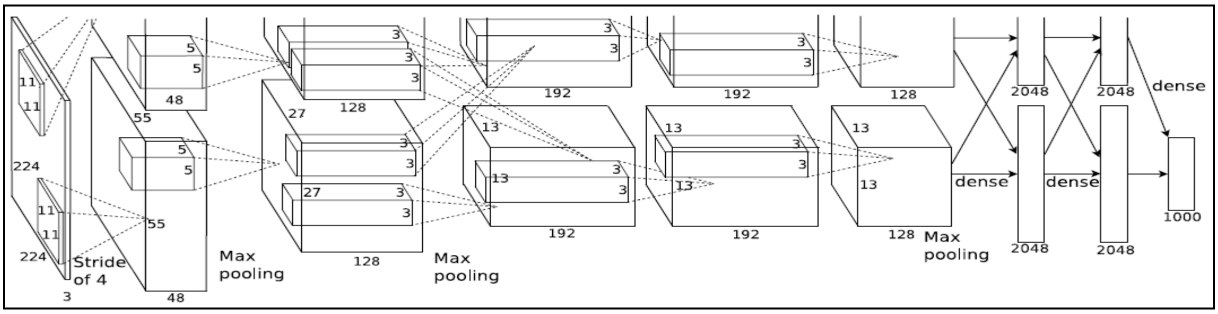

Figure 5. AlexNet Architecture [18]

AlexNet architecture was adapted to the dataset which used in knitted fabric defect control by changing the last three fully connected layers (fc6, fc7 and fc8) before training. By changing the output layer in the last, the training analysis stage was started. During the AlexNet network training, the training process parameter was used by entering Learning Rate=0.001, Mini Batch Size=32 value, and Number of Epoch=50. 40 iterations were performed in each Epoch with the number of images in the data set and the entered Mini Batch Size value. The success percentage of the artificial neural network trained with the entered parameters was obtained as 91.89%.

(iii) ***<u>GoogLeNet</u>***

GoogLeNet consists of a complex structure created from 'Inception' modules (Figure 6). Unlike previous studies, the depth and width of the network prepared were increased while the calculation cost was kept low. Architecture consists of 22 layers. Architectural decisions based on the Hebbian principle and the intuition of multi-scale processing to optimize quality. It is different and difficult to understand from the network models mentioned so far [20].

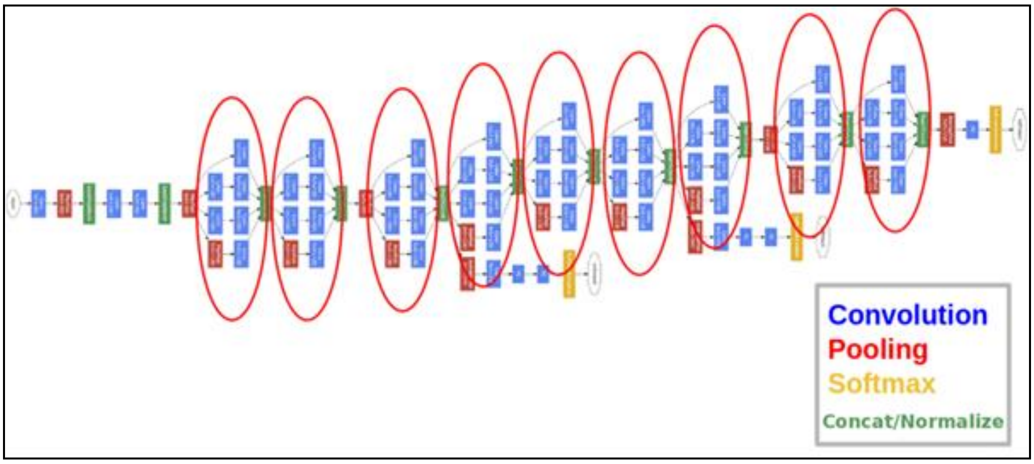

Figure 6. GoogLeNet architecture [19]

Before the model was trained, the output layer was changed by adapting the fully connected (fc) layer to our own data set. While training GoogLeNet network, the parameters are taken as Learning Rate= 0,001, Mini Batch Size=32 and Number of Epoch= 30. After 40 iterations were completed, the success rate with 94,23 % was obtained.

2.4 Confusion matrix

Cross Validation is a technique used in model selection. The error of a test performed is predicted in a machine learning model. After placing a model in training data, its performance is measured against each new validation set and then how the model performs when trying to predict new observations. Confusion matrix is a table used to measure the performance of a classification model on a set of test data for which actual values are known (Table 2). The confusion matrix gives very fruitful information about the predicted performance of the estimator or model that use in machine learning. The whole data set is randomly divided into two parts as training set and test set. The trainer is used to select the most suitable model parameters using cross validation, and the test set is used only to measure the performance (accuracy) of the most suitable model. Classification accuracy is evaluated by the percentage of data samples classified as correct by the algorithm. Actual values are true binary values “0” and”1" [22,23].

Table 2. Confusion matrix

		Predicted	
		Positive	Negative
Actual	**Positive**	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

True Positives (TP) are the examples where the real data value is 1 and the predicted value is 1. True Negative (TN) refers the examples where the real value is 0 and the predicted value is 0. False Positive (FP) are the **e**xamples where the real value is 0 and the predicted value is 1. False Negative (FN) are the examples where the real value is 1, and the predicted value is 0. In other words, if the output of the correctly predicted value is false, it will be FN. Accuracy Rate is a measure of how often the classifier method makes correct estimates. Predicted values are found by dividing the sum as in Equation 1. Precision is based on true positive values only out of all positive values. It is a measure of how accurately you are predicted (Equation 2). It takes a value between 0 and 1, it should be as high as possible **Recall (Sensitivity)** shows how successfully positive situations are predicted. The best value is 1, the worst value is 0 (Equation 3). **F-Score** is difficult to compare two models with low precision and high recall or vice versa. F-score helps to measure Recall and Precision at the same time.

$$Accuracy = (TP + TN)/ (TP + TN + FP + FN) \quad (1)$$

$$Precision = TP/ (TP + FP) \quad (2)$$

$$Recall = TP/ (TP + FN) \quad (3)$$

$$F - Score = 2 \times Recall \times \frac{Precision}{Recall} + Precision \quad (4)$$

Having trained the CNN models, CM (confusion matrix) analysis was performed with 20 fabric images from each class for validation. A total of 120 fabric images used for testing. The images used for testing phase were taken during knitted fabric production in real time with the machine vision system placed on the circular knitting machine.

3. RESULTS AND DISCUSSION

3.1 The results of resnet-50 cnn algorithm

After creating a confusion matrix chart from the true labels and the predicted labels, TP and FP rates in the row summary were displayed as sensitivity and specificity. Also, specify column summary as displayed the positive predictive rates and false predictive rates as precision and negative predictive value. Figure 7 shows CM (confusion matrix) of fabric defects on the circular knitting machine and the evaluation of the CNNs algorithm in six classes such as (1) double yarn, (2) hole, (3) defect free, (4) drop stitches, (5) oil lines and (6) lycra missing respectively.

According to the ResNet-50 analysis made on the obtained images, the success rate which called sensitivity for each class were given in Figure 7. An average accuracy of 98.31% were achieved. According to ResNet's classification results, there were actually 20 hole defects, but only 18 of these 20 defects were correctly predicted. One of the hole defects is classified as defect free and the other one hole defect is labeled as oil lines. The remaining images in classes double yarn, defect free, drop stitches, oil lines, and lycra missing are all classified with 100% accuracy as can be seen in the Figure 7. This ratio is a very good result for determining the defect class on the knitted fabric. When the knitted fabric defect, which are evaluated manually in the fabric production line by the experienced employees, the success rate is acceptable.

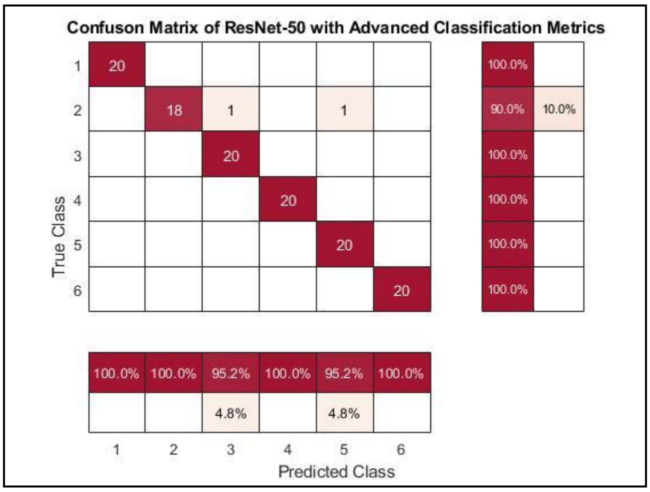

Figure 7. ResNet-50 classification results

3.2 The results of alexnet cnn algorithm

According to the AlexNet results the success rate for each class were obtained as Figure 8. An average accuracy of 95% were achieved. When AlexNet's classification results were examined, it can be observed that 20 of 18 double yarn defects were correctly predicted. One of the double yarn defects labeled as defect free and the other one as drop stitches. Looking at the hole defect, 2 of them were classified as defect free and 1 as a drop stitch. Finally, trained network classified one of the 20 oil lines as hole defects. Thus, defect free, drop stitches, and lycra missing classes labeled with 100% accuracy.

3.3 The results of googlenet cnn algorithm

According to the GoogLeNet results of the analysis made on the obtained images the success rate, which called sensitivity for each class were obtained (Figure 9). An average accuracy of 94.17% were achieved. When GoogLeNet's classification results were examined, there were actually 20 hole defects, but only 18 of these 20 defects were correctly predicted. Two of the hole defects were predicted as as a defect free class. From the third row, it can be seen that one of the defect free class was classified as drop stitch and one as a hole defect. The last one, trained network classified one of the 20 oil lines as lycra missing and two of them were classified as hole defects.

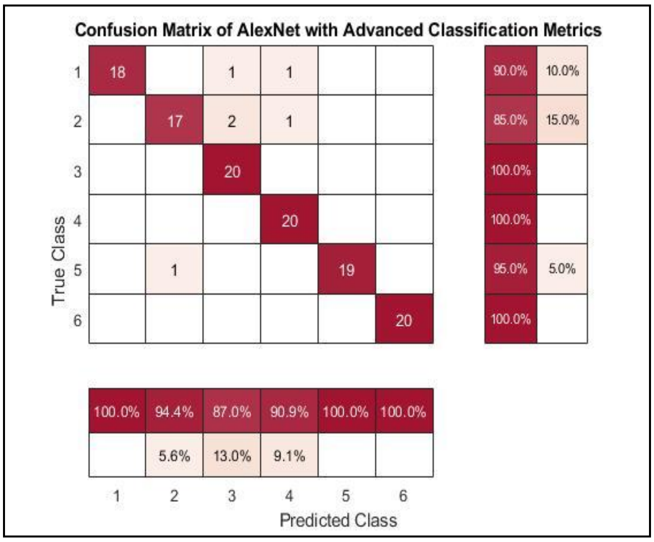

Figure 8. AlexNet classification results

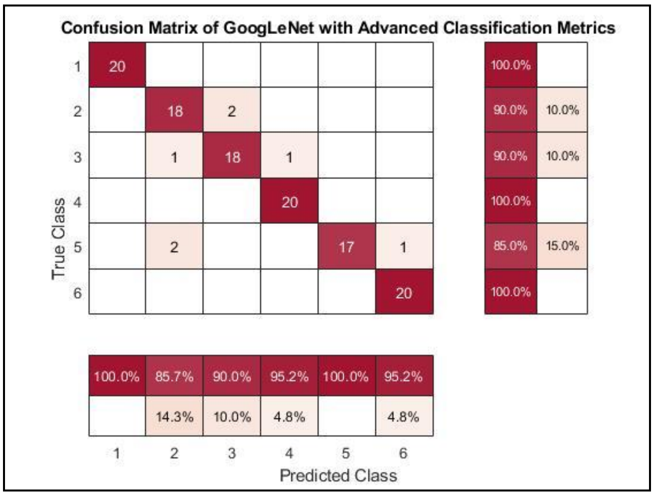

Figure 9. GoogLeNet classification results

All three of the CNNs architectures trained with transfer learning for real-time defect classification on the circular knitting machine were tested. According to the comparison of the methods (Figure 10), it was revealed that all of three method achieved high classification success rate. According to the average accuracy rates, ResNet-50 network achieved the highest success rate of these three architectures. According to F-score; double yarn defects were classified with the highest 100% success rate for two networks (ResNet-50 and GoogLeNet), while the lowest 94.5% was achieved using AlexNet. Hole defect is labeled with a 94.7%, 89.5%, 87.8% success rates respectively for the three trained networks. A classification success rate was achieved between 90% and 97.5% for the defect free fabric. While ResNet-50 showed a 100% success rate in the drop stitches defect, the other two trained networks also achieved a success rate over 95%. In the oil lines class, an overall success rate of over 90% was observed with three networks. Finally, while the GoogLeNet network completed the classification process with a successs rate of 97.5%, other two the networks had a success rate of 100%. When the images obtained by the machine vision system placed on a circular knitting machine are evaluated, the classification obtained results are mostly acceptable. Consequently, using deep learning technique for real-time defect inspection is highly reliable and applicable for industrial application. All the deep learning architectures applied within the scope of the study showed a success of over 94%. Among these architectures, the highest success was obtained with ResNet50. It is theoretically thought that the success will increase as the number of layers increases in a network model. However, this is not the case in reality. Based on this, the ResNet model was created. According to the new created theory (ResNet), thanks to the residual value feed, the new output equation optimizes the learning error with the residual value from the two previous layers even if the current weight is 0. Thus, faster, and more reliable success rates are obtained by using residual values [17]. The ResNet50 model gives a better result due to its feedback feature.

4. CONCLUSION

The textile sector aims to produce fabrics with high quality standards together with high production capacity. Customer demands and expectations from the product are increasing and changing day by day. This situation makes competition conditions difficult. Textile enterprises get attention importance to technologies and developments. These will provide speed and flexibility in production, reduce costs, improve product quality, and improve their functions. When the defect detection studies are examined, it is seen that not only image filter applications are sufficient for real-time industrial applications, but also machine learning or deep learning methods are used together with different filter applications. Image processing methods are used in surface feature extraction, and defect detection and classification processes are performed by artificial intelligence methods (CNNs).

A machine vision system has been developed on circular knitting machines where fabric defects can be automatically controlled and detected defects can be classified. The five most common knitted fabric defects; double yarn, holes, drop stitches, oil lines, and lycra missing were detected and classified with the prepared CNN based artificial intelligence software with an average success rate of 98%. Although there are many studies on fabric defect detection by using image processing algorithms in the literature, any study has not been encountered that use CNNs technique with a machine vision system adaped on an industrial circular knitting machine. In this study, real-time knitted fabric inspection proces was achieved during the fabric production via a program user interface based on CNN algorithm. The use of such a machine vision system in knitted fabric enterprises will bring great economic gains to companies. When the analyzes are evaluated, the annual cost of defective fabrics sold as second quality is quite high. Therefore, the usega of this system is expected to increase the production of knitted fabric enterprises, while it is expected to significantly reduce the company reclamation due to defective fabrics.

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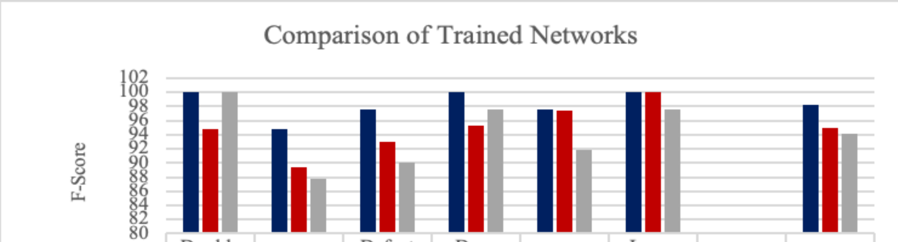

	Double Yarn	Hole	Defect Free	Drop Stitches	Oil Lines	Lycra Out		Average
ResNet-50	100,0	94,7	97,5	100,0	97,5	100,0		98,3
AlexNet	94,7	89,5	93,0	95,2	97,4	100,0		95,0
GoogLeNet	100,0	87,8	90,0	97,5	91,9	97,5		94,1

Fabric Defect Classification

Figure 10. Comparison of the CNNs architectures

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