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CNN-Based Fabric Defect Detection System on Loom Fabric Inspection

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ABSTRACT

Fabric defect detection is generally performed based on human visual inspection. This method is not effective and it has various difficulties such as eye delusion and labor cost. To deal with these problems, machine learning and computer vision-based intelligent systems have been developed. In this paper, a novel real-time fabric defect detection system is proposed. The proposed industrial vision system has been operated in real-time on a loom. Firstly, two fabric databases are constructed using real fabric images and new defective patch capture (DPC) algorithm. One of the main objectives in this study is to develop a CNN architecture that focuses only on fabric defect detection. One of the most unique aspects of the study is to detect defective pixel regions of fabric images with Fourier analysis on a patch-based and integrate it with deep learning. Thanks to the novel developed fast Fourier transform-based DPC algorithm, defective texture areas become visible and defect-free areas are suppressed, even on complex denim fabric textures. Secondly, an appropriate convolution neural networks (CNN) model is developed. Thus the new dataset dataset is refined using negative mining method and CNN model. However, traditional feature extraction and classification approaches are also used to compare classification performances of deep models and traditional models. Experimental results show that our proposed CNN model integrated with negative mining can classify the defected images with high accuracy. Also, the proposed CNN model has been tested in real-time on a loom, and it achieves 96.5% detection accuracy. The proposed model obtains better accuracy and speed performance in terms of detection accuracy with a much smaller model size.

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KEYWORDS

Computer vision, fabric defect detection, CNN, feature extraction

1. INTRODUCTION

It is a very important issue in the fabric industry to detect and classify defects during production. Traditionally, human-oriented defect detection is an approach that takes a lot of time and causes labor costs. In this approach, serious losses can occur in fabric production in cases such as operator distraction, eye fatigue, and distraction. For this reason, image processing and artificial intelligence-based automatic fabric control approaches are inevitable.

Automatic defect detection systems include two important stages: Obtaining clear images during fabric production and detecting whether there are errors in the images. Capturing non-blur and noise images clear fabric images is quite a challenge. This is because fabric looms produce high levels of noise, there is lint constantly floating around, the dimensions of looms exceeding 2m and they produce high vibrations. In addition, the small size of defect size of 1mm and the constant movement of the fabric are other factors that make the image acquisition process difficult. The aforementioned difficulties significantly prevent the spread of some error detection systems based on image processing and artificial intelligence, which have high error detection accuracy. From this point of view, the disadvantages of

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existing systems can be eliminated by examining the powerful feature extraction and machine learning methods in the literature.

Defect detection methods in the literature could classified [1] as structural [2], [3], statistical [4], spectral [5,6]-[7], model-based [8], learning-based [9] and hybrid methods [10]. In this study, a CNN-based defect detection architecture is proposed in contrast to the current approaches. However, the process of building a large fabric data-set containing different fabric defects is costly and challenging.

Defects in fabric images disrupt regular fabric texture and pattern. Therefore, the problem addressed while analyzing images can be defined as texture-based image analysis and classification. Thus, the problem can be moved to the field of image processing and machine learning, and texture features can be extracted with well-known texture analysis methods. Defective fabric production can be prevented by detecting the location and type of defect with the meaningful features obtained. [11]. Starting from this point, using statistical measurements and histogram information, defects are defined in images containing regular texture patterns. [12]. By using the Gabor wavelet network and morphological filters, fabric background and fabric defect regions were distinguished and common fabric defects were detected. [4]. In another study, fabric defects were detected with adaptive wavelet transform. [13]. Histogram thresholding was performed by successfully separating the background and error regions with specially designed low and high pass filters. In a study that classifies fabric defects such as horizontal and vertical missing thread defect, colored thread, spot, and gap, statistical properties of the images were calculated. [13]. The features obtained using the Bayesian classifier were classified and a 99.85% classification success was achieved. In a recent study, defect detection was performed on 247different fabric images containing repetitive textures. [14]. Considering the regular layout rule in the fabric images, the existing template and the regions in the fabric image were compared. The metric results were obtained and the existing template was analyzed for similarity. 5 different fabric defects that are common in fabrics containing 3 different texture types have been successfully detected. In addition, a comprehensive comparison with different feature methods was made and the error detection capacity of the method was highlighted. By analyzing the isotropic lattice structures in the fabric images, it can be understood whether the regular texture pattern is disrupted due to the error. For this process, fabric images are divided into non-overlapping sub-images and analyzed in a micro-level pattern. Jia and Liang [15] in their study, the image was divided into hundreds of lattice structures and focused on the error region without dealing with unrelated pixel regions. 5 different fabric defects were detected by pixel-based area calculation and histogram analysis of defective pixels in lattice regions. In a study examining the pattern regularity in fabric images with the autocorrelation function in polar coordinates, the changes in the pattern were also examined angularly and errors were detected [15]. With this method, both linear and blob-like defects were detected. Hole, oil stains, warp-lacking, and weft-lacking errors in plain white fabric images of 512×512 size obtained from the field scanning camera were detected and classified. [16]. Filtering and thresholding pre-processes are applied to the obtained images and given as input to the artificial neural network. Over 90% classification success was achieved in all defect types. Rotation-independent analysis methods are used to detect defects in fabric images containing regular and rotational states. With the versatile and multi-scale feature of the Gabor transform, the features of the images are extracted and the defect regions are segmented. [17]. Segmentation results are improved by filtering the obtained segmented image with a Gaussian low-pass filter. Fractal geometry has been used frequently in recent years to describe the natural irregularity of self-similar natural objects. Due to its success in detecting regularity, it has been used to detect errors that disrupt regularity in fabric images. [18]. By characterizing the roughness and complexity of fabric textures with fractal calculations, images were classified with support vector machines. In a study that can detect knit fabric defects in real-time, shearlet transform and artificial neural networks are used. [19]. The shearlet coefficients of the images obtained from the line scan camera in different scales and directions were calculated. The weights of the trained artificial neural network were recorded and real-time error control was performed on the knitting machine. Multi-scale local texture analysis was performed by calculating the singular value decomposition information of the fabric images converted to the CIE color channel. [20]. In addition, defected regions were determined by measuring the cosine similarity between the defected fabric modeling and the images analyzed with different scales. Yildiz et al. [21] detected different fabric defect using thermal camera. To extract important textural features, they used gray level co-occurrence matrix. To classify fleece fabric images, local binary patterns were used [22]. Firstly, local texture features were calculated. Then Naive Bayes and K-nearest neighbor classifier were used to classify fabric images. Yildiz et al. [23] developed thermal defect detection system to eliminate fabric defects. They benefit from thermal differences between defective and defect-free fabric regions. These differences are helpful in characterizing the defective region. In another hybrid method, wavelet transform and principal component analysis were used together to classify cashmere and denim lubric fabric images [24]. 95% success was achieved in the fabric images obtained with the thermal camera.

Although traditional methods of fabric defect detection give the desired results in most cases, most of these methods use hand-designed features such as filters, texture, and color. Although traditional methods can perform multi-scale and versatile feature calculations, they can perform limited analysis and calculations on the data. With the development of deep learning methods in recent years, the mentioned limitations have been removed. High-level inferences and decision-making processes are produced with deep learning algorithms. The main advantage of deep learning is to obtain high-level feature analysis of data with a well-designed convolutional neural network (CNN). Such a designed network has been built and accepted as a powerful feature calculator and has become a decision-making system that gives better results than traditional methods. Jing et al. [25] used the improved AlexNet architecture for CNN fabric defect classification. Network layers and convolution filters are optimized to detect yarn dye defects. Wang and Jing [26] on the other hand, classified fabric defects with a deep learning architecture, which they proposed a pyramid-based pooling layer, without using labeled training data. In a study with the Faster R-CNN model, the region of fabric defect was determined by using Region Proposal Networks (RPN) and Fast R-CNN models together [27]. The success and speed of the method have been increased with the constructed multi-scale feature pyramid and defected region boxes. Zhou et al. On the other hand, they updated the architecture of the Faster R-CNN model in the deep learning model they called FabricNet [28]. Especially by replacing the last part of the mesh with the Deformable Convolution (DC) block structure, the classification success for fabric defects has been increased. In another study, effective results were obtained on two different fabric datasets by using principal component analysis and deep feature extraction strategy together [29]. First of all, the features of the images were extracted with the VGG16 deep learning model. Then, by calculating the saliency maps of the images with principal component analysis, the final results in which the defects are segmented are obtained. In another CNN-based study with a visual long-short-term memory module integrated, a deep network modeling close to human visual perception was carried out [9]. Although this network model has more complex modules, it is designed as an architecture that can detect fabric defects between 95% and 97%. Mei et al. [30] proposed a multi-scale convolutional denoising autoencoder (MSCDAE) architecture to detect fabric defects of different sizes. In this model, which includes multiple convolutional denoising autoencoder layers, images are processed with the Gaussian pyramid method and image patches are produced. In the encoder and decoder layers of the network, these patches are extracted with convolution layers. During the test phase, residual maps were produced that clearly show the defected areas in the images. A variational automatic encoder was used in a study that detected 9 different fabric defects by real-time fabric defect detection [31]. Using the Structural similarity index measurement (SSIM) parameter, the similarity between 3 different parameters between the constructed image at the input and output of the autoencoder was measured. With the built layer architecture, the desired SSIM residual map is built, making it easier to distinguish defected regions. The high success rate in fabric defect detection studies based on deep learning is remarkable. Especially their classification success against many different fabric defect types is remarkable. With these aspects, deep learning methods have an edge over traditional feature extraction and machine learning methods.

Fabric defect detection studies have been carried out both with traditional methods and with deep learning methods, although a small number of them. The number of studies that can work in real-time, especially on knitting and weaving machines, is very limited. The methods cannot produce the desired results due to reasons such as noise, light change, and vibration from the knitting/weaving machine, especially in the industrial working environment. From this point of view, in this study, a new method that makes real-time fabric defect detection with deep learning methods on the weaving machine has been developed.

The main contributions are summarized as follows:

(1) To better classify the fabric textures, a novel CNN model with negative mining is proposed. This model improves the effectiveness and distinctiveness of the CNN model.

(2) Thanks to the novel developed fast Fourier transform-based DPC algorithm, defective texture areas become visible and defect-free areas are suppressed, even on complex denim fabric textures.

(3) The proposed model can meet the real-time requirements of defect detection on a loom.

The rest of this paper is arranged as follows. Section 2 briefly introduces the conventional defect detection systems and related feature extraction methods. Section 2 introduces our novel CNN-based defect detection method and gives details about the training, experimental setup of our defect detection system and fabric database. In Section 3, the classification results of the conventional feature extraction methods and our CNN model are provided to validate our method on a real fabric database. Section 4 presents real-time defect detection results on a loom. Finally, we conclude our study in Section 5.

2. MATERIAL AND METHOD

2.1 Material

2.1.1 Current Defect Detection Systems

Systems that can detect real-time defects in weaving looms can be divided into two according to the imaging approach: Still and systems using more than one camera, systems using mobile, and single camera. Figure 1.left shows an example defect detection system developed by Uster Technologies Vision [32] and includes 4 still cameras side by side. The most important advantage of using still cameras is the minimization of image degradation caused by vibration, resulting in a clear image. However, since a limited fabric area is seen with a single camera, it is necessary to use more than one camera side by side to view the entire fabric. More than one camera data is collected by the frame holder card. However, the increase in the number of cameras increases the cost of the system and makes defect detection management difficult.

To eliminate the high cost of still camera systems, some systems use a single mobile camera. The product named

Cyclops [33] from BMSvision company (see Figure 1.right) is relatively easy to manage. This German-origin product uses a rail mechanism that provides linear movement on the loom. This mechanism enables the display of the fabric surface produced by moving the camera on the horizontal axis. Cyclops transfer images to the server over the network and detect defects with the software on the server. Using blue-colored and flash lighting components, Cyclops can detect ten predefined fabric defects. The disadvantages of Cyclops are the server requirement and the ability to detect defects only on sparse fabrics. The embedded defect detection system suggested in this article eliminates the need for a server. In addition, thanks to the developed defect detection software, shallow fabric defects can be detected.

Both modern defect detection systems (Uster and Cyclops) mentioned having high costs. This negative situation significantly prevents the spread of these products with high defect detection accuracy in the market.

2.1.2 Defect detection algorithms

Existing defect detection algorithms transform fabric images into feature vectors and map these vectors to known classes with specific classification techniques (Nearest Neighbours (NN), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN)). The difference between algorithms is based on the difference in feature extraction approaches. In this study, a total of six different feature extraction approaches, three of which are in the spatial domain (Histogram of Oriented Gradient (HoG), Co-occurrence HOG (CoHoG) and Statistical), and three in the frequency domain (Fast Fourier Transform (FFT), Wavelet, and Shearlet), which are frequently used in the fabric defect detection literature, will be expressed.

2.1.2.1 HOG features

In the HOG method, the horizontal and vertical gradients of the image are calculated first. Then the pixel orientation matrix is obtained. Finally, the histogram of the orientation matrix is taken and the information obtained is used as attribute values [34]. Gradients and orientation matrix are calculated as follows:

2.1.2.2 CoHOG features

Gray Level Co-occurrence Matrix (GLCM) is frequently used in texture extraction studies. GLCM refers to the number of repetitions of pixel pairs in a particular direction [35]. Accordingly, the GLCM matrix of a gray level I image is calculated as follows:

Pixel values i and j; spatial coordinates x and y in the image; I (x, y) represent the brightness value in the image. The CoHOG method [36] calculates the density changes between pixels by scanning the image matrix according to different angle values. Unlike HoG, the image is analyzed by dividing the $M \times N$ region. GLCM is obtained by using the angle values (offsets) determined from each image region. A single feature vector is produced by combining the GLCMs obtained for all regions in the image (see Figure 2).

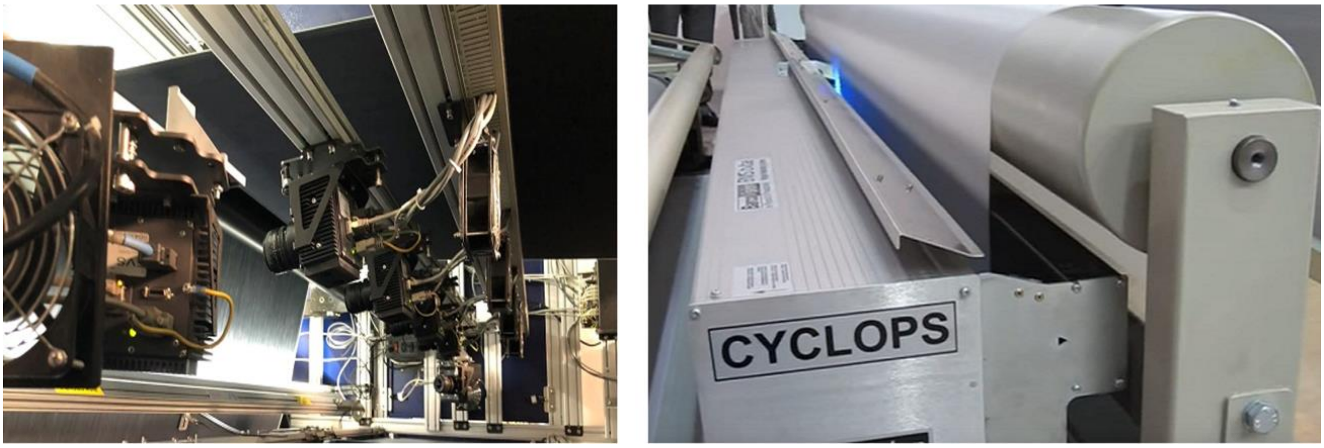


Figure 1. Current defect detection systems. (Left) Uster, (Right) Cyclops

$$f_x(x,y) = I(x+1,y) - I(x-1,y) \tag{1}$$

$$f_y(x,y) = I(x,y+1) - I(x,y-1) \tag{2}$$

$$\theta(x,y) = \tan^{-1}\left(\frac{f_y(x,y)}{f_x(x,y)}\right) \tag{3}$$

Where f_x and f_y, respectively are the horizontal and vertical gradients of the I image. θ express the orientation matrix.

$$C_{x,y}(i,j)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & if \quad I(p,q)=i \quad and \quad I(p+x,q+y)=j\\ 0, & otherwise\end{cases} \tag{4}$$

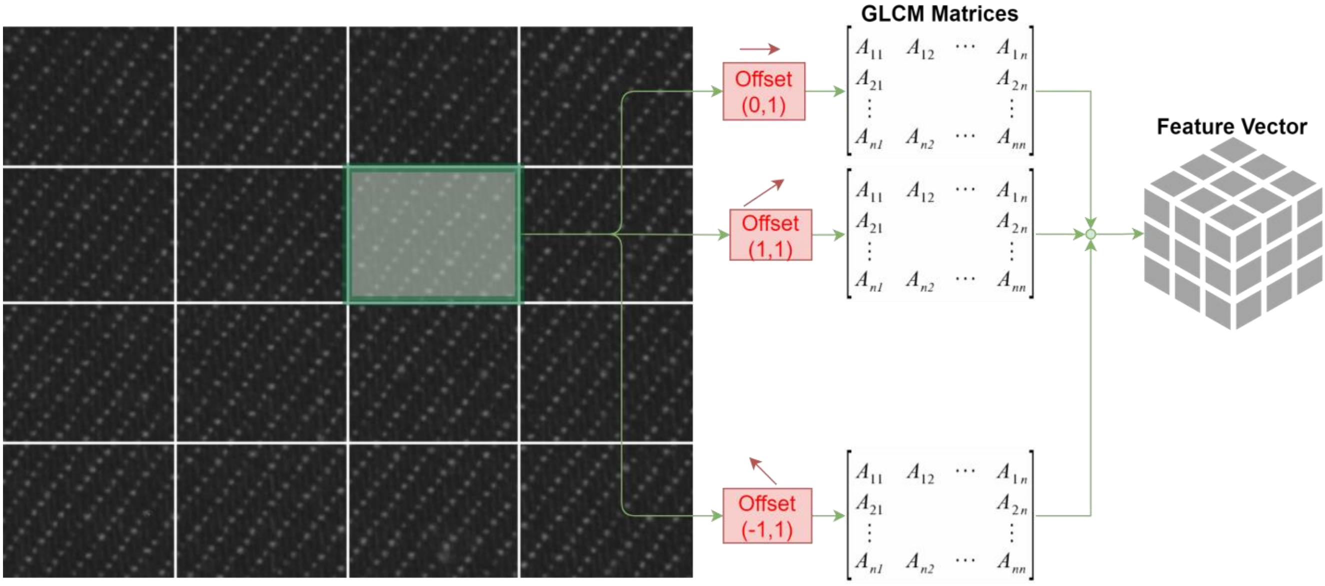


Figure 2. CoHog feature extraction

2.1.2.3 Statistical features

In the study [35], it is seen that four different statistical attributes (energy, contrast, correlation and homogeneity) of the gray co-formation matrix are obtained. These attributes are expressed as follows:

$$Energy=\sum_i\sum_j p(i,j)^2 \tag{5}$$

$$Contrast=\sum_i\sum_j |i-j|^2\, p(i,j) \tag{6}$$

$$Correlation=\sum_i\sum_j \frac{(i-\mu_i)(j-\mu_j)\,p(i,j)}{\sigma_i\sigma_j} \tag{7}$$

$$Homogeneity=\sum_i\sum_j \frac{p(i,j)}{1+|i-j|} \tag{8}$$

2.1.2.4 Fourier features

It is known that frequency domain techniques are used to detect texture/pattern differences in the image [6], [37]. In the study conducted in the article with reference no [37], the Central Spatial Frequency Spectrum of the image is obtained by using FFT, and 7 different statistical attributes are extracted from the spectrum visual.

$$P_1=|F(0,0)| \tag{9}$$

$$P_2=100\times\frac{F(f_{x1},0)}{F(0,0)} \tag{10}$$

$$P_3=f_{x1} \tag{11}$$

$$P_4=100\times\left(\sum_{f_{x1}=0}^{f_{x1}}\frac{F(f_{x1},0)}{F(0,0)}\right) \tag{12}$$

$$P_5=100\times\frac{F(0,f_{y1})}{F(0,0)} \tag{13}$$

$$P_6=f_{y1} \tag{14}$$

$$P_7=100\times\left(\sum_{f_{y1}=0}^{f_{y1}}\frac{F(0,f_{y1})}{F(0,0)}\right) \tag{15}$$

where P_1 expressing the mean spectral response, P_2, P_3 and P_4 represent the spectral changes in the horizontal axis. Spectral changes on the vertical axis are also represented with P_5, P_6, and P_7 variables.

2.1.2.5 Wavelet features

In this section, it is expressed how the feature vector is obtained from fabric images using the wavelet transform technique. Three-level wavelet transform is used in this study. Figure 3 shows the sub-band images obtained after the three-level transformation. Accordingly, a total of nine band images are obtained, including three sub-bands at each level.

In the study [38], it is shown that the luminance histograms in the lower band images show a symmetrical distribution, so they can be modeled with Normal Distribution. Thus, each sub-band image can be represented by the parameters of the Normal distribution (μ and σ). Since a total of 10 sub-band images are obtained after three-level transformation, the feature vector has 1×20 dimension.

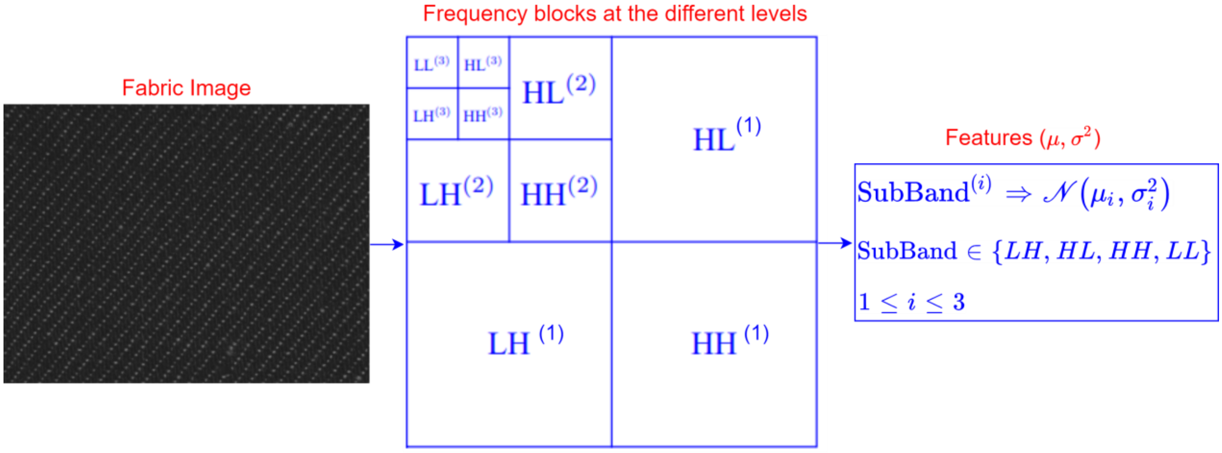


Figure 3. Wavelet feature extraction

2.1.2.6 Shearlet features

An important disadvantage of wavelet transform is that it can only obtain spectral responses of the image in horizontal and vertical directions. This limitation may cause pattern or texture features at different angles to be undetectable. The Shearlet transform has been developed to overcome this disadvantage of wavelet transform [39]. Accordingly, it enables multi-scale and multi-directional spectral analysis of the image. In this study, scale level 4 was determined, spectral responses of 10 degrees were calculated and features were obtained.

2.2 Method

In this study, a new product has been developed to be included in the mobile camera systems group. This product is very similar to Cyclops with its camera and linear motion system components. Its difference from Cyclops is that it can detect defects in shallow or sparsely woven fabrics and has embedded image processing capability. With this capability, it can instantly process images without transferring them to an additional server and reduces the system cost. With these features, it is thought that the proposed system will have a wide range of uses.

The prominent technical features of the proposed system when compared to its current counterparts are listed below:

1) Low cost (camera and loom machine synchronization is done through software and has no depended on multiple cameras to covering the whole fabric for data acquisition part.
2) An original and economical LED light apparatus was designed, produced and used.
3) A frequency-based approach specific to fabric types produced on looms is presented.
4) High accuracy values have been achieved because deep convolutional networks are used.
5) The proposed approach can work in real time.

2.2.1. Imaging hardware

In classical systems, the synchronization between the camera and the weaving loom is provided by hardware. Accordingly, a camera with a trigger output and a weaving loom with encoder connection are used. High-cost trigger cameras and encoder hardware increase the overall system cost. In the proposed system, the synchronization between the camera and the machine is software. For this, the production speed of the machine is determined by using the images obtained from the production before the recording process is made, and the camera movement speed and shooting speed parameters are updated accordingly. In this way, hardware requirements have been eliminated and an economical defect detection system has been produced.

The image recording module of the proposed system is shown in Figure 4. Accordingly, the image recording setup consists of the camera (FLIR Blackfly), lighting component, lens (Sony F-12mm), and linear system components. To obtain clear fabric images, attention has been paid to the fact that the camera has a "global shutter" feature and that the pixel size on the imaging sensor is high (5.86nm). The linear system has a length of 2m and allows the camera to move left and right on the loom. The camera table speed is fixed at approximately 18.8 cm/sec. Thus, a tour on the bench is completed at 11sec and the entire fabric surface produced can be viewed. Two different illumination apparatuses were designed and produced as samples to prevent the movement of the camera and fabric from blurring. In the first, 9 LEDs and lenses with a 50-degree angle were used. The lenses are used to prevent the light from spreading to the environment at a wide angle and provide focusing in a narrow area. In the other apparatus, 30 LEDs that can emit 4000K and 70 lumens light are used. Considering the quantum efficiency value of the imaging sensor, it has been ensured that the LEDs are at 525nm wavelength. Thus, the efficiency of the imaging sensor to convert light into electricity is maximized. The fabric images recorded with both illumination apparatuses were examined and high-quality fabric images were obtained with the second illumination apparatus. Thus, the second lighting apparatus was selected and the works started to create a fabric database.

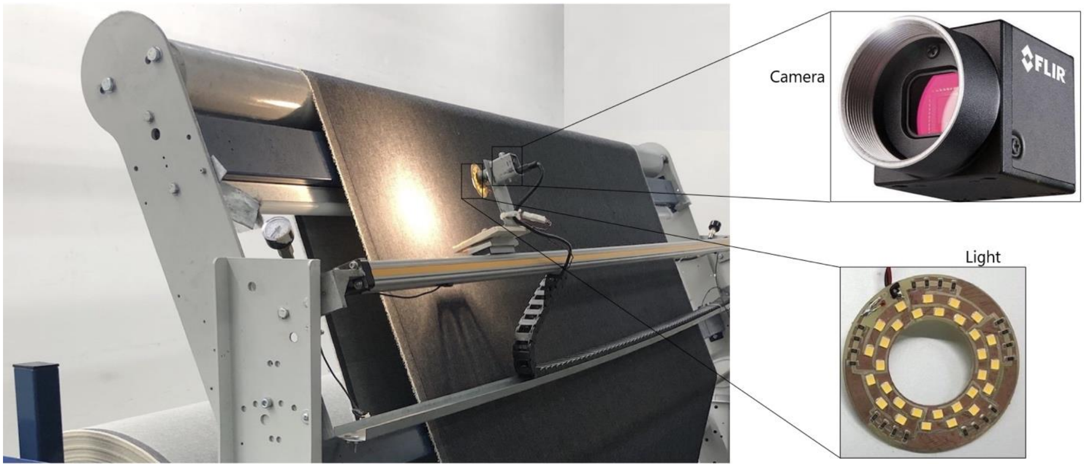


Figure 4. The proposed defect detection setup

2.2.2 Produced fabric databases

It should be emphasized that it is difficult to produce a sufficient number of different fabric defects due to the low probability of occurrence of defective fabrics in the fabric industry. This situation also leads to loss of production and labor in database construction. Therefore, this study focuses on detecting two different fabric defects. The first is the warp defect (H1), the second is the horizontal deformation defect (H2). Both types of defects were produced specially by the fabric operator and the defective fabric images were recorded. Accordingly, fabric images belonging to three classes without defect (14099 pieces), H1 (8936 pieces), and H2 (17289 pieces) were recorded in the DB1 database (see Figure 5). Produced dataset is available via this link https://github.com/MahdiHatami/denim-fabric-dataset.

The high size of the images in DB1 makes it difficult to detect small defect regions and causes memory insufficiency problems. Therefore, 1200×1920 DB1 images were saved in a new data set (DB2) in the form of 300×320 patches. The fabric images were divided into 6 equal parts and transferred to DB2. However, a patch must be taken from the defective parts of the H1 and H2 images. For this, the Defected Patch Capture (DPC) algorithm, whose stages are shown in Figure 6, is used.

The DPC algorithm developed within the scope of this study takes high-resolution defective images as input and only determines the center of the defective area (See Figure 7). Accordingly, the image in the spatial domain is transformed into a spectral image using the FFT transformation in the first step. Later, a special mask was designed to filter the main frequencies of weft and warp patterns in the fabric images. The two-level mask image contains five parallel ellipses. After the original spectral image is masked, reverse FFT conversion is made and a filtered fabric image is obtained. By filtering, defective areas became visible and defect-free areas were suppressed. A second process to make the defective areas more prominent is the power-law transformation. Finally, using a certain threshold (0.2), the image was reduced to a binary level. The two types of defects to be detected have a linear structure. For this reason, the longest striped region in the binary image was determined using Hough transform. The center of the detected line was set to be the center of the patch and 300×320 sized patches were taken from the defective area and recorded in DB2. As a result, a total of 31110 images (8265 H1, 5975 H2, and 16870 without defects) were recorded in the DB2 dataset.

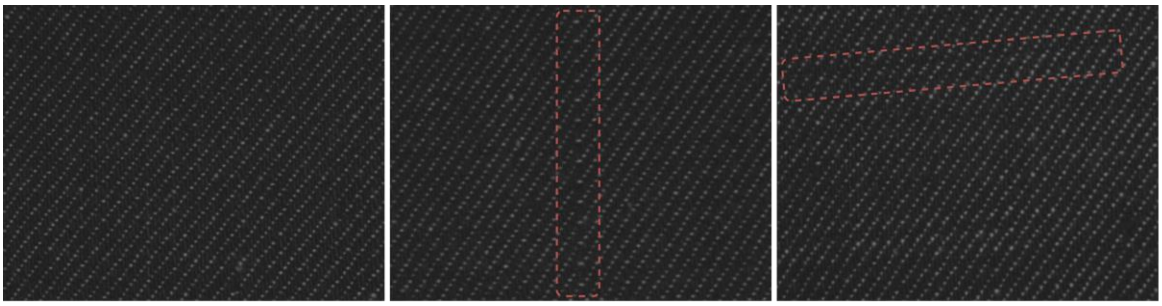


Figure 5. Fabric images. (left) without defect, (middle) warp defect-H1, (right) horizontal deformation defect-H2

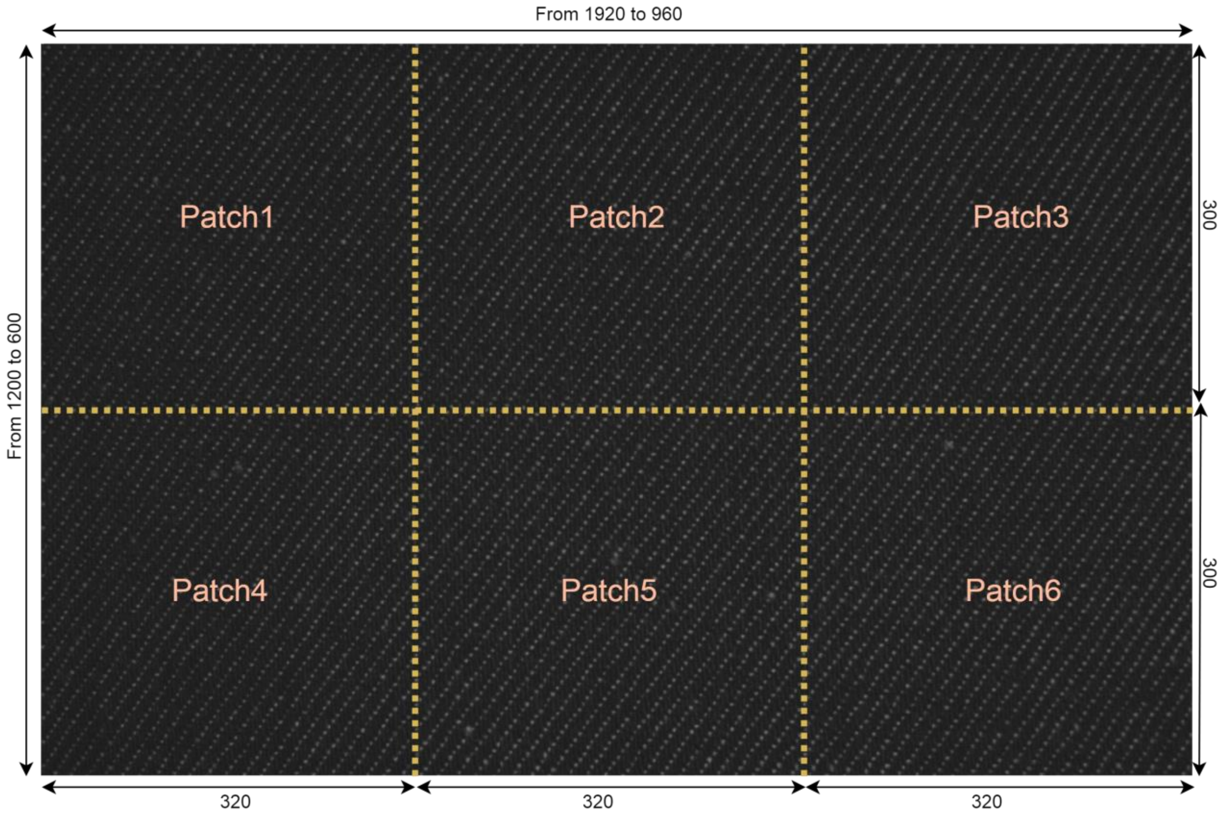


Figure 6. Splitting input image to patches

It should be emphasized that defeted fabric production is approximately 1-2% of the normal production. Therefore, the number of fabric defect images is very low compared to the none-defected fabric image. There is an imbalance in obtained high resolution raw fabric images. However, this imbalance was resolved by producing patches from defect fabric images. For this, firstly, the defect region was made clear in the frequency domain, then the patches that would include the relevant region were saved. In this way, the number of defect images has been brought closer to the number of none-defected images. Training and testing activities were carried out on an improved training set.

2.2.3 Determining the appropriate CNN architecture

In this section, the structure of the CNN architecture that provides the highest classification accuracy is investigated. For this purpose, four different CNN architectures with different layer depth, convolution mask number, and mask sizes were designed (see Table 1). Thus, the classification performances of a deeply structured architecture and a shallow architecture were evaluated. The parameters of the architectures used were set as epoch "10", optimizer "sgdm", package size "128", weight-decay "0.0005" and learning coefficient "0.001" and training/testing activities were carried out. For this, a server computer with 8GB GDDR5 GPU memory and Nvidia Quadro M4000 graphics card was used. 75% (~23322) of 31110 images in DB2 were used for training and 25% (~7778) for testing. As a result of the comparison, it was seen that the CNN network, whose architecture is clearly shown in Figure 8, provides the highest classification accuracy in training and test sets. This architecture number 4 which performs best amount other archtectures structure given in Table 2.

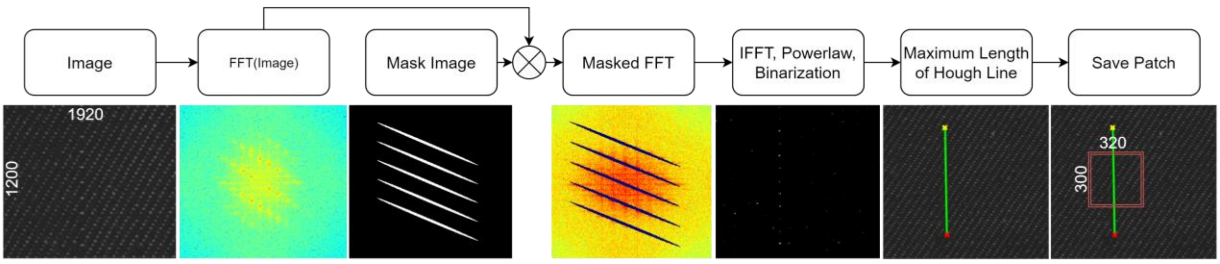


Figure 7. Stages of defected patch capture algorithm

Table 1. The CNN architectures

	Layer Number	Total parameters	Train Accuracy (%)	Test Accuracy (%)
CNN Architecture 1	11	75.243	93.44	93.28
CNN Architecture 2	16	7.773	93.44	93.64
CNN Architecture 3	11	160.173	91.09	90.28
CNN Architecture 4	19	4.325	97,6	97,3

Table 2. The CNN architectures 4 structures

	Layer	Output Size
Conv1	5 × 5, 10, stride(1,1)	300 × 320 × 10
Pool1	5 × 5, 10, stride(2,2)	150 × 160 × 10
Conv2	5 × 5, 7, stride(1,1)	150 × 160 × 7
Pool2	5 × 5, 7, stride(2,2)	75 × 80 × 7
Conv3	5 × 5, 7, stride(1,1)	75 × 80 × 7
Pool3	5 × 5, 7, stride(2,2)	37 × 40 × 7
Fully connected	10360	3

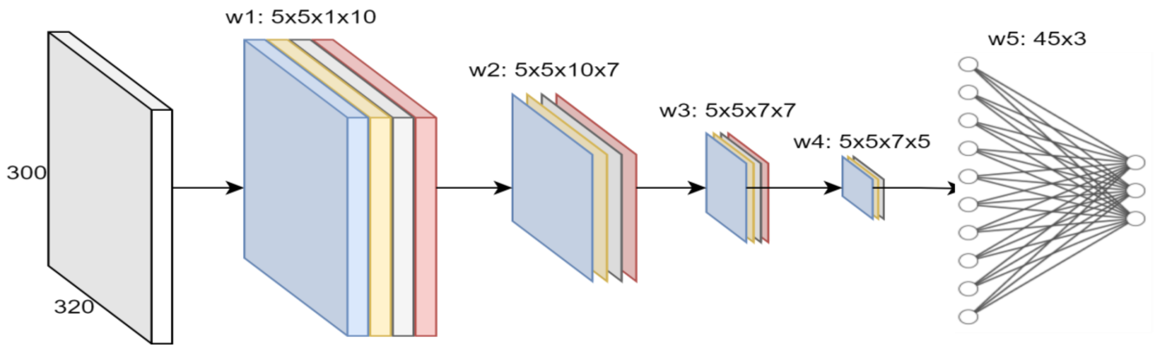
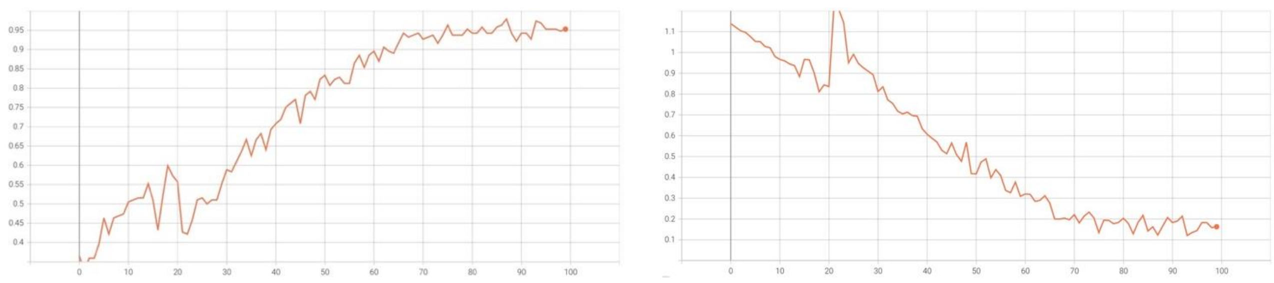


Figure 8. The proposed CNN architecture 4

3. RESULTS AND DISCUSSION

3.1 Comparison of Defect Detection Methods

In this section, the performance of defect detection methods is evaluated by considering the classification accuracy and working time. Before proceeding with the classification processes, the incorrectly classified images in the automatically generated DB2 data set were transferred to the correct classes. For this, the proposed CNN architecture has not been classified correctly and the images in the 5% incorrect portion have been examined by the fabric operator and transferred to the correct classes. The approach known as "negative mining" in the literature has been repeated three times and the data set has been updated. The results obtained by running the classical defect detection methods and the proposed CNN architecture on the updated DB2 dataset are presented in Table 3 also the validation accuracy and cross entropy loss presented in Figure 9 respectively.



a b

Figure 9. a) Classification accuracy b) Cross entropy loss

Table 3. Classification results of defect detection methods. (M: Million)

		Accuracy (%)		Time (sec)
Methods	Feature Numbers	Train	Test	For one image
Statistical	259	96.00	88.23	0.011
HOG	128	96.90	91.93	0.047
CoHOG	1536	95.31	87.52	0.312
Fourier	7	83.10	80.70	0.003
Wavelet	18	85.00	72.70	0.066
Shearlet	59	59.20	33.40	0.302
InceptionV3	6M	78.8	78,3	0.7
MobileNetV2	4.2M	65.5	63.5	0.65
Xception	22.8M	81.3	80.5	1.34
Self-Supervised	0.8M	94	94.2	0.88
Proposed model (Architecture 4)	4325	97.6	97.3	0.0061

When the results in Table 3 are examined, it is seen that the proposed CNN-based architecture has the highest classification accuracy. The reason for this is that CNN can extract low, medium, and high-level features from images thanks to its layered structure and can classify these features with high accuracy with the help of a fully connected layer. Also, the times of the methods to render a fabric image are given in the last column of the table. These time values were calculated by taking the arithmetic average of 100 image processing times. Accordingly, it is seen that the proposed CNN architecture works quite fast, so it is the most suitable method to use in real-time systems.

HOG and CoHOG methods calculate local and global features of fabric images based on gradient calculations. The light change in the fabric images and some non-defect noise information negatively affected the durability of the method. However, they have reached a better result than classical feature extraction methods in detecting fabric defects. Energy, contrast, correlation, and regularity used as statistical attributes seem to be successful in distinguishing fabric defects from the background. However, the success achieved in the training of the classifier is not at the desired level in the testing process of the classifier. Although the fabric images in the database have a regular pattern, this order is disrupted in the defect areas. The regularity parameter used is effective in capturing this situation. However, energy, correlation and contrast calculations were not sufficient to detect the defect with spatial pixel information. The reason for this is the insufficient local analysis of the fabric regions. Because the statistical calculations deal with the image as a whole, and therefore it is not possible to notice regional changes and reflect them on statistics. In other words, the statistical distribution in the pixel regions where the fabric defect occurs is lost among the pixel statistics of the whole image.

Fourier, shearlet, and wavelet transform methods that extract attributes by converting the image from the spatial domain to frequency domain failed to achieve the desired success in both the training and testing processes of the classifier. In particular, the Shearlet transformation method gave unsuccessful results in the type of woven fabric and its defects. In the Shearlet transformation applied in a multi-scale and angular direction, textural features of the fabric images in different levels and directions were obtained. However, defects expressing the distortion of regular fabric patterns could not be distinguished from the background and regular patterns. The most important reason for this is that the method is not resistant to situations such as noise and light changes. In addition, since the types of defects examined are similar to the regular structure in the fabric, the shearlet method together with the wavelet transform and Fourier transform methods did not reflect the defective regions strongly in the frequency spectrum. The sub-band images obtained in the wavelet transform method were modeled with the Gauss function. However, there is no special study to express the defective regions of the image with the parameters of the Gaussian function. In the method based on wavelet transform and Gaussian distribution, the frequency components of the defective regions are ignored and a spectrum or sub-band analysis to express the defect is not performed. In these methods, updates should be made to analyze and examine the defective area at the local level. In Fourier transform, defective regions are visibly apparent in the spectrum. However, this information was lost during the calculation of statistical 7 different feature information from this spectrum with a classical method. Therefore, it has been understood that the frequency spectrum needs to be analyzed with different methods. On the other hand, state-of-the-art methods that achieve better classification rate on much larger datasets. We have seen that it has worse results than the cnn architecture we designed for denim fabric dataset. In the proposed CNN-based fabric defect detection method, exactly this point was taken into consideration and the spectrum information of the Fourier transform was analyzed in a very different way. The frequencies of weft and warp patterns are filtered and the defective areas are made clear. In addition, the regions that do not contain defects are suppressed and the defect is brought to the fore.

3.2 Real-Time Defect Detection Application

Fabric defects are less likely to occur, making it difficult to perform a systematic comparison of the algorithm. Furthermore, it takes extra time and cost to change a loom’s warp beam, which limits the ability to quickly alter fabric materials for online evaluation. These reasons lead us to evaluate the accuracy of the system. To perform real-time defect detection, we used our trained CNN 4 deep network architecture, which is described in Section 3. The proposed embedded vision-based defect detection has mounted on the Picanol OptiMax loom (see Figure 10). Hardware and image acquisition strategies have been described in Section 3. NVIDIA's Nano card is chosen as the embedded platform. This low-cost card has a suitable hardware infrastructure to run CNN architectures. Software in Python programming language has been developed so that the images provided by the BlackFly camera can be stored and classified in Nano. This software transfers 5 images of 1920×1200 per second to Nano's RAM using the API of the camera.

The transferred images are first subjected to size reduction and then to patching. Finally, each patch is given as an input to the deep model which is loaded into the Nano and used the trained model to classify defects. The proposed framework has analyzed the denim fabric for about 24 hours and with images of over 30000. The majority of 98% of the captured frames are defect-free fabric images (i.e., approx. 600 images contain defects). After completing the real-time defect detection process, we compared the results of our detection system and quality control reports. Examining the results of the quality control unit gives us an overall overview of the two separate defect detection methods. Thus, an objective comparison has been conducted between our real-time system and quality control unit. Our proposed method can detect all of the defects labeled by the quality control unit which is 550 defects. In addition to this, our system can capture extra 29 defects which overlooked by the quality control unit. In case a defective image is detected, the defect type and information about the number of meters of the fabric roll are recorded in a separate database and defect reports are produced. The generated defect reports have been matched with the defect reports produced in the quality control unit and the detected defects have been verified. Classification results are given in Table (4).

4. CONCLUSION

In this paper, a real-time fabric defect detection system is proposed and implemented. The proposed defect detection system includes three main modules: vision system, CNN model, an embedded module. Firstly, a novel fabric database has been contracted by using an industrial vision system on a loom. Then, an effective CNN model with negative mining is proposed for fabric defect detection. In the proposed methodology, a novel defective patch capture algorithm based on fast Fourier transform is developed to suppress the background and highlight defect regions. This algorithm improves the effectiveness and distinctiveness of the CNN model. CNN model is trained using defective patch capture algorithm.

Real-time defect detection has been performed by moving the trained architecture to the embedded platform. The proposed model has some advantages such as the low computational cost and high detection rates. These advantages are the significant reasons for a detection system. Thus, real-time defect detection is performed, and high defect detection results have been obtained on a loom. However due to the environmental noise and loom machine vaibration our test classification results dropped by ~0.7%.

As noticed in the experiments, there are different defect types in fabric production. The constraints of camera and light source reduced the distinctiveness between foreground defects and fabric background texture in the obtained images. Therefore, in future work, we have planned to solve these problems. We will expand the fabric defect database in terms of the kinds of defects. Moreover, we also apply various learning algorithms to the fabric defect detection. To further real time defect detection, the design of learning algorithms will be investigated.

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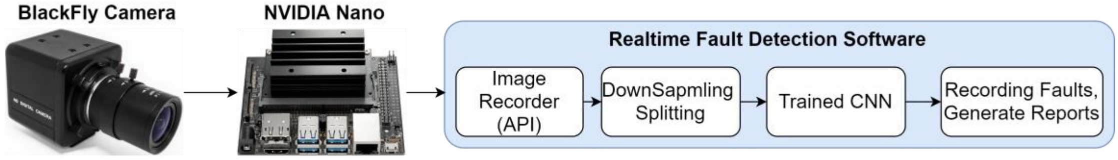

Figure 10. Real-time defect detection system.

Table 4. Real-time defect detection results

	Ground truth	Quality control unit	Our proposed method
Total images	30000	30000	30000
Defect-free	29400	27165	28371
Defected	600	550	579
	Classification results	~92.40%	~96.5%

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