International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

DEFECTCNN: Improved Discriminative Convolution Neural Network Towards Instantaneous Automatic Detection and Classification of Complex Defect in Fabrics

P. Banumathi[1], Dr.P.R.Tamilselvi[2]
[1]Assistant Professor, Department of Computer Science, Cherran College for Women, Tirupur, Tamil Nadu, India.
[2] Assistant Professor, Department of Computer Science, Government arts and Science College, Komarapalayam, Tamil Nadu, India.
Address for Correspondence
[1]Assistant Professor, Department of Computer Science, Cherran College for Women, Tirupur, Tamil Nadu, India.

Abstract

Due to enormous growth of textile industries has increased demand for the automatic fabric defect detection and classification system to the fabric material as it plays a crucial role in maintaining the quality of the services. Machine learning model has employed as automatic defect detection system to identify the material quality. Despite of several advantageous of the machine learning model, those models faces several challenges on handling the complex and uncertainty of varied texture and structural patterns. Further it is complex to process the boundaries and features with high degree of intra class variation and low degree of interclass variations. On leveraging and exploiting the deep learning architecture, the over lapping and varied texture patterns can be efficiently discriminated on defects. In this paper, a new deep learning architecture entitled as discriminative convolution neural model is proposed to detect and classify the defects in the fabric materials into various defect classes. Initially fabric image preprocessed on basis of the noise filtering through wiener filter and image enhancement through CLAHE technique. Enhanced image is segmented using image thresholding technique to segment it into the various regions on basis of pixel information's by grouping the neighbouring similar pixels intensity or textures to represent a mask. Segmented image regions are projected to the convolution neural network. Convolution layer of network is to extract the features from its composition containing kernels with different weights. It computes the high level features for different pixels based on surrounding and neighbouring pixel values on striding to produce the feature map containing gradient and edge of the images. ReLU activation function is applied to reduce the non linearity among the features in the feature map. Pooling layer of the model down-sample the convolved features to produce the activation map. Activation map is obtained using max pooling as it returns maximum value from the segment of the image processed using kernels. Activation map is transformed into tabular structure to perform the classification easily. In addition drop out layer is incorporated in the model to eliminate the overfitting issue during classification on reducing the correlation among the neurons. Fully connected layers of the model is used to learn the flattened features with weights and bias to classify the flatten features using softmax layer on basis of defect classes such as Hole , Color Spot, Thread Error and foreign body. Experimental analysis of the proposed architecture is carried out on TILDA dataset using cross fold validation to analyse the representation ability to discriminate the features with large variance between the different classes. From the results, it is confirming that proposed architecture exhibiting higher performance in classification accuracy of 98.43% in classifying the fabric defect on compared with conventional approaches

Keywords: Fabric material, Convolution Neural Network, Automatic Fabric Defect Detection, Defect Classification

1. Introduction

Fabric defect detection [1] is significant process in the textile manufacturing industries as fabric materials have complex and diverse texture patterns [2]. With periodic advancement and development of the flexible, efficient, reliable system for fabric production process in the textile manufacturing, occurrence of the fabric defects is also increasing. In order to eliminate the fabric defects and to increase the production quality, automatic fabric defect system has to be integrated with the production process to classify the fabric material into first quality and second

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

quality. However it is becomes mandatory process to maintain the quality of the services.

Traditionally, Machine learning model has employed as automatic defect detection system to identify the material quality. Machine learning model such as statistical based methods [3] Spectral analysis based method [4], model based method [5], dictionary based method [6] and motif based method [7] are flexible only the simple fabric structure and to precise alignment for template matching. However those models face several challenges on handling the complex and uncertainty of varied texture and structural patterns. On leveraging and exploiting the deep learning architecture, the over lapping and varied texture patterns can be efficiently discriminated on defects.

In this paper, a new deep learning architecture entitled as improved discriminative convolution neural model is proposed to localize, detect and classify the defects in the fabric materials into various defect classes with excellent performance. Initially fabric image preprocessed on basis of the noise filtering through wiener filter [8] and image enhancement through CLAHE technique [9]. Enhanced image is segmented using image thresholding technique and low rank decomposition model[10] to segment it into the various regions on basis of pixel information's by grouping the neighbouring similar pixels intensity or textures to represent a mask as low rank and sparse. The non-defective regions of fabric images are macro-homogeneous and highly redundant, and they can be treated as the low-rank subspace. Remaining defect segmented is projected to the convolution neural network.

Convolution layer of network is highly effective in discriminating the features. It abstracts the semantic features from its composition containing kernels with different weights. It computes the high level features for different pixels based on surrounding and neighbouring pixel values on striding to produce the feature map with different characteristics containing gradient and edge of the images. ReLU activation function is applied to reduce the non linearity among the features in the feature map. Pooling layer of the model down-sample the convolved features to produce the activation map. Activation map is obtained using max pooling as it returns maximum value from the segment of the image processed using kernels.

Activation map is transformed into tabular structure to perform the classification easily. In addition drop out layer is incorporated in the model to eliminate the overfitting issue during classification on reducing the correlation among the neurons. Fully connected layers of the model acts as versatile inference system to learn the flattened features with weights and bias to classify the flatten features using softmax layer on basis of defect classes such as Hole , Color Spot, Thread Error and foreign body.

The remainder of the article is organized as follows, section 2 represents different machine learning and deep learning architectures that have been widely employed for defect detection classification has been analysed. Section 3 deals with methodology of improved discriminative convolution neural network for instantaneous automatic defect detection. Experimental and performance analysis of the proposed architecture against conventional approaches has been detailed and evaluated with accuracy measure in the section 4. Finally article is concluded with future suggestions in section 5.

2. Related work

In this section , various conventional approaches behind automatic fabric defect detection towards employing both deep learning and machine learning model to various fabric based dataset has been discussed in detail on various aspects is as follows

2.1. Automatic fabric defect detection using learning-based local textural distributions in the contourlet domain

In this literature, automatic detection of the fabric defects is carried out on basis of statistical representation of fabric patterns using redundant contourlet transform. Initially preprocessing of the image is applied to detect the basic size of the image decomposition. Signature of the computed and these signatures is differentiated using bayes classifier. Transform contains the contour coefficient is modelled using Gaussian distribution. Gaussian distribution is distinguished against defective and defect free fabric images[11].

2.2. Visual saliency detection based on multiscale deep CNN features

In this literature, Visual Saliency model is used to localize and detect the defects in the fabric images. Saliency model learns the multiscale features extracted using convolution neural network. Convolution layer of the network extract the feature on different scales. Each layer of the model contains the discriminative high-level feature vector for saliency detection. High level feature vector represented as deep contrast feature. Saliency model contains the pixel-wise saliency annotations to the features[12].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

3. Proposed model

In this section, Improved Discriminative Convolution Neural Network using fabric images has been designed extensively with preprocessing and feature extraction steps to exploit the complex and diverse features to increase the classification of the defects in the fabric.

3.1. Image Preprocessing

Image preprocessing, fabric image preprocessed on basis of the noise filtering through wiener filter and image enhancement through CLAHE technique. Processing of those mechanism is as follows

3.1.1. Wiener Filter - Noise Filtering

Weiner filter is employed to noise reduction in the greyscale format of the fabric image. Weiner filter processes the contrast events which have less variation among pixels in the neighbourhood. It is considered as restoration and smoothing technique. It is optimal in terms of the mean square error. Smoothing is achieved by minimizing the mean square error and increase the linearity among the neighbouring pixels [16]. Weiner filter is represented in Fourier transform the fabric image

$$W(f1,f2)=\frac{H(f1,f2)S_{xx}(f1,f2)}{H(f1,f2)S_{xx}(f1,f2)+S_{\delta}(f1,f2)} \text{..........Eq.1}$$

Where $S_{xx}(f1,f2)$ represent the power spectra, $S_{\delta}(f1,f2)$ is additive noise and $H(f1,f2)$ represents filter. Weiner filter removes the noise using the compression technique.

3.1.2. Contrast Limited Adaptive Histogram Equalization(CLAHE)

CLAHE is employed to amplify the contrast of the noise removed image. Amplification of the contrast in image is carried out on partitioning the image into small definite non overlapping regions of equal sizes. It is represented as tiles. Partitioning is carried out on basis of interpolation of neighbouring pixels. Neighbouring pixel is combined to remove artifacts in the image.

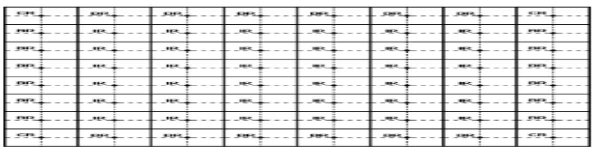


Figure 2: Partition of the Input Image using CLAHE technique

For an instance, the fabric image partition is represented in figure 2. This output partition in three varied clusters of regions termed as corner region which contains four sides, border region contains 24 regions and finally inner regions contains the 36 regions.

- **Histogram Computation On basis of Clip Limit**

Clip limit is parameter for enhancing the contrast of image regions on computing the histogram. Histogram is computed on basis of the clip limit. Histogram is redistributed to entire region with a condition that height should exceed beyond the clip limit. Further number of pixel has to be computed for each region which represented with grid size.

- **Cumulative Distribution Functions**

Cumulative Distribution Function is employed for contrast enhancement and for grayscale mapping. Cumulative Distribution function transforms each region into uniform density function with histogram equalization mechanism. In this part, pixel mapping is carried on merging the pixel of the various regions together.

No of grey scale pixels in each regions are represented as M

$H_{ij}(n)$ is the histogram of the image region

If $h_{ij}(n)$ > Clip limit

Enhance the contrast of the image

Else

Select next region for contrast enhancement

Compute CDF for mapping of contrast similar regions

$$CDF_{i,j}(n) = \frac{1}{M}\sum_{k=0}^{n} xh_{i,j}(n) \text{ .....Eq.2}$$

It combines the corner regions and border regions as initially and it propagates to inner regions to increase the image quality

3.2. Image Segmentation – Low Rank Decomposition Model

Image segmentation is carried out on the contrast enhanced image using global thresholding and low rank decomposition model. It segment it into the various regions on basis of pixel information's by grouping the neighbouring similar pixels intensity or textures to represent a mask as low rank and sparse on basis of the threshold[17]. The non-defective regions of fabric images are macro-homogeneous

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

---

and highly redundant, and they can be treated as the low-rank subspace. Contrast enhanced image is represented in matrix form towards segmentation.

Compute threshold

$$\text{Threshold} = E\sum_{i=0}^{n} p(I) \text{ ...Eq.3}$$

Segments of the image is

$$o(r,c)=\begin{cases} pI(r,c) > threshold \\ pI(r,c) < threshold \end{cases}$$

Where r represent the row and c represent column

Low rank segment considered as background or redundant pixels of the image is considered as low rank subspace. Sparse matrix is considered as foremost region of the image which is considered as defect part of the fabric material. Low rank decomposition model eliminate the low rank segments. Decomposition of the low rank segments follows the convex relaxation theory. Convex relation theory is formulated on patterns. Low rank decomposition is given as

$$\text{Convex relaxation} = \text{Min (rank (A)} + \boldsymbol{\delta}\ \|E\| \text{ ....Eq.4}$$

Where A is the low rank matrix and E is the sparse matrix containing defect region.

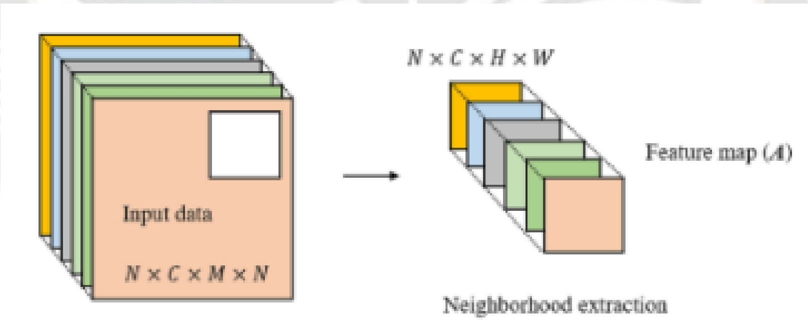
3.3. Improved Discriminant Convolution Neural Network

Defect segment of the image is processed using the DefectCNN which considered as improved discriminative connected convolution neural network. Discriminative Convolution Neural Network composed of the several layers such as Convolution layer, Max Pooling layers, Activation Layer, Dense Layers, Fully connected layer, Softmax layer and loss layer. It is employed for deep feature extraction and feature classification. Deep feature vector of the defect region considered as sparse matrix.

- **Convolution Layer**

Convolution layer is capable of learning hierarchical and representative features[13]. The convolution layer composed of multiple filter or kernel to convolve with complex texture of the defect segment to abstract the versatile features to derive the feature map which is termed as activation map. Convolution is mathematical operation is represented as multiplication of the image matrix and multiple filter to extract deep features with semantic properties as it capable of locating the salient region. It contains the texture details which help to locate the boundaries.

Feature matrix of fabric defect segment 5*5 is multiplied with kernel 3*3 matrix to provide convolution matrix or feature map. Convoluted of the sparse feature is represented as saliency map.



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

=

1	0	1
0	1	0
1	0	1

4	3	4
2	4	3
2	3	4

Feature Matrix **Kernel Matrix** **Feature Map**

The convolution layer provides the feature map on the convolution operations by concatenating activations. Convergence of the feature map is carried out using epoch and it increase the feature generation on normalization of the activation function represented as ReLu to obtain the linear

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

feature map on certain convolution layer. Distance among the feature is computed employing cosine distance measure

Cosine distance of the features in the feature map is evaluated as

$$C_f = y(m^t f^t + c)$$

- **Pooling layer**

Pooling layer further reduces the sparse features of the image or region segmented. Hence it is considered as max pooling of the high level features of the defect segment. It is also termed as down sampling of spatial features on decreasing the dimension of the defect feature on retaining only selected weighted features. Selected weighted feature has greatest pixel value. Feature pooling of the convoluted matrix is presented as

4	3	4
2	4	3
2	3	4

=

4	3
3	4

Convoluted feature **Max pool Features**

Max Pooling layer connects the texture features into small patches on account of the pixel values. Max pooling is used to estimate the greatest no of the features to the each subset. It further enhances the model generalization [13].

- **Fully Connected Layer**

Fully connected layer of the CNN is organized as fully connected layer with multiple constraints to process the feature map. Activation map is obtained using max pooling as it returns maximum value from the segment of the image processed using kernels. Activation map is transformed into tabular structure to perform the classification easily. In addition drop out layer is incorporated in the model to eliminate the overfitting issue during classification on reducing the correlation among the neurons.

Fully connected layers of the model is used to learn the flattened features with weights and bias to classify the flatten features using softmax layer on basis of defect classes such as Hole , Color Spot, Thread Error and foreign body. Discriminative feature map is composed of the pixel features. Fully connected layer uses the activation function to process feature normalization or feature flattening as layer to eliminate the non-linearity and over fitting issues in the feature. Fully connected representation of the feature extraction and classification is represented in the figure below

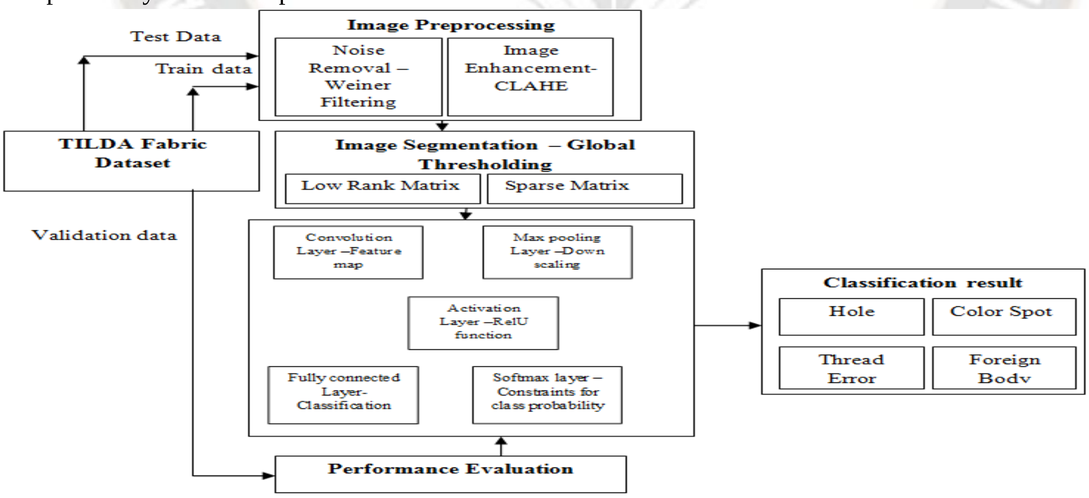


Figure 3 : Architecture Diagram of the proposed model

Softmax layer is employed in the fully connected layer to generate the defect classes by deducing the feature vector into defect class vector. It is to verify the reliability of the model. Further loss layer is incorporated in fully connected layer to minimize the feature variance on the classes of the features. The closest approximation of the testing sample may be from various classes, which represents that the minimal residual may be derived from numerous

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

classes. The finial classification result is generated by integrating the results based on the voting rule.

The class coefficients for the saliency feature interpretation is given by class objective function as

$$Y = \beta_0 + \beta_1 X$$

Where the class coefficients are represented as

$$\beta_1 = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2}$$

The integral derivates of the class objective function with respect to the class coefficients has been extracted on estimation of Error Sum of Square (SSE). Softmax layer which follows delta rule is given by loss function of the hyper parameters. It is to determine multiple linear weights of pixel features. In addition, feature weight can be computed through iterations.

$$\Delta W_i = C(t\text{-net})x_i$$

where ***'c'*** is the learning rate

'x' is input for that weight

On the objective of minimizing the SSE and solving loss of the classifier, Delta rule will be updated. Algorithm 1 explains the working of the proposed fabric defect classification model

Algorithm 1: Defect Classification

Input : TILDA Image Dataset

Output : Fabric Defect Classes

Process
Preprocess
Image Denoising ()
W= Weiner Filter(matrix(Input Images))
Image Contrast Enhancement ()
Normalized Image N = CLAHE (W)
Histogram ()
Clip Limit ()
Cumulative Distribution Function ()
Image Segmentation
Segment S= Global Thresholding (N)
Compute Signature of the each pixel)
For (Pixel length [i]!=0) &(Pixel length >0) & (Pixel length ++)
If (Pixel value of the pixel 1= Pixel value of pixel 2)
Merge Both pixel and group the pixel and mask it with boundary
Else If (Pixel value of the pixel 1= Pixel value of the pixel 3)
Merge both pixel and group the pixel and mask it with boundary
Segment S= (Sparse Segment, Low rank Segment)
Feature Extraction and Classification ()
DefectCNN()
Convolution Layer () abstract the high level feature
Kernel () with different weights and bias
Striding = Feature
Activation function (feature) = Feature map
Pooling layer () reduces the higher level feature
Max_pooling() gathers maximum value feature to produces activation map
Fully connected Layer ()
Drop layer ()
Eliminate the feature overfitting on estimating the correlation () of the features
Flatten layer () normalizes the image features
Softmaxlayer classifiers the features into defect classes
Loss layer minimizes the feature variance in class generated
Output layer () generates the defect classes
Output = {Hole, Color Spot, Thread Error, Foreign Body}

Algorithm explains the processing of the images towards classification of the fabric defect into multiple classes on basis of the complex and diverse feature processing in the unique discriminative convolution neural network.

4. Experimental Results

In this section, performance analysis of the experimental outcomes has been computed and evaluated on cross fold validation to TILDA dataset [14]. Performance analysis of architecture is exhibited on the optimal parameters for the proposed architecture for fabric defect classification. The architecture is simulated in matlab tool. The dataset containing fabric defect images was classified into training set, testing set and validation set.

In this 80% of images is employed to train the proposed learning architecture and 20% was employed to test the proposed architecture. On 80% training images, it further classified into 60% for training the architecture and 20% to validate the trained model. 5 fold cross validation has been used to enhance the accuracy of the proposed architecture in defect classification [10]. DCNN training parameter has been illustrated in the table 1

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

Table 1: DCNN training parameters

Parameter	Value
Activation Function	ReLu
Learning rate	10^{-6}
Loss Function	Cross Entropy
Batch size	10
Drop Out	0.4
Max epoch	100

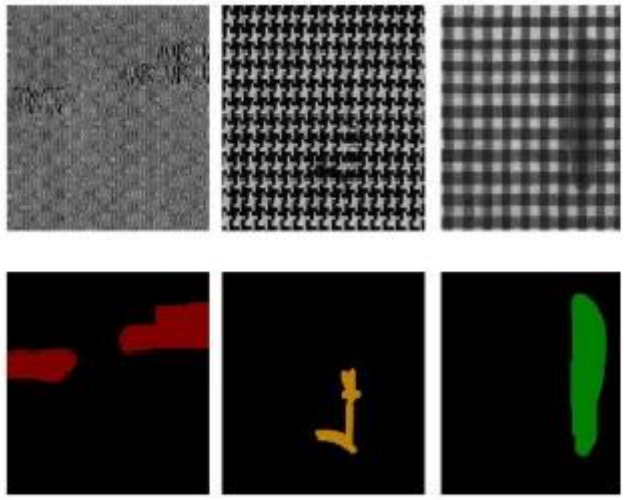


Figure 4: Defect Detection

The fabric defect images taken for processing of the defect classes will measure the variation in the fabric defect type and its values in terms of ground truth value from TILDA dataset. Fabric defect feature on texture patterns is measured effectively using the pixel value of the defect region. Figure 4 illustrates the model results of the defect classification of the fabric on employing the proposed architecture.

Figure 4 illustrates the evaluation of learning models with respects to the precision [15]. In this model, defect feature produce high accuracy in the classification of the fabric defect on the processing fabric.

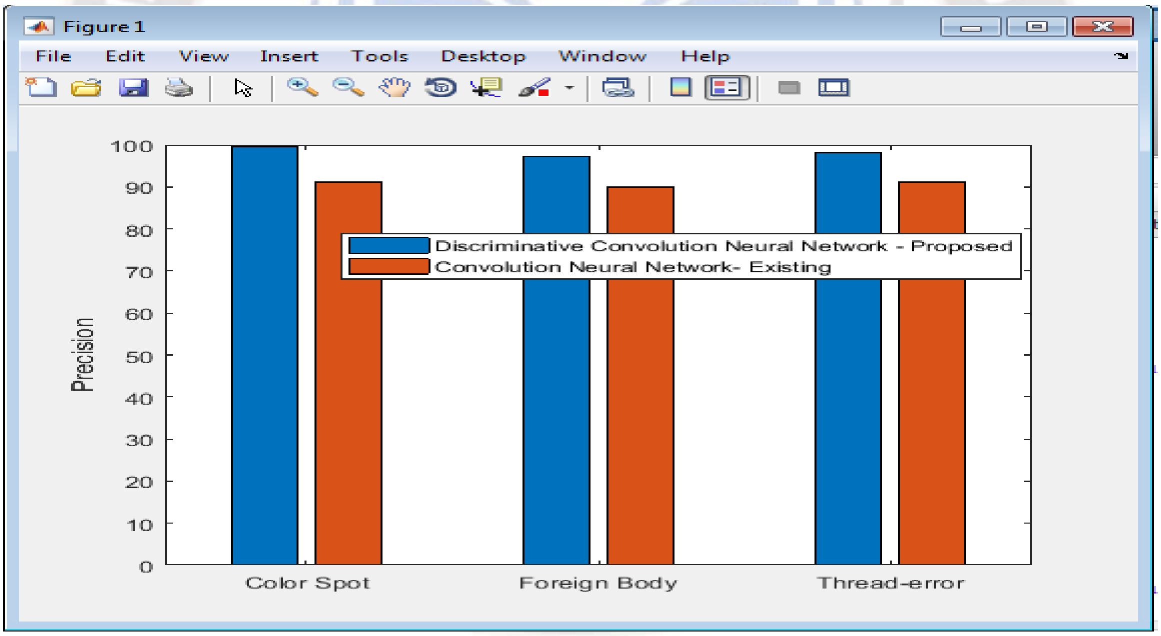


Figure 5: Evaluation of Fabric Defect Classification Architecture with respect to precision

The precision, recall has be calculated using confusion matrix with parameters like true positive, false positive, false negative and true negative. Performance values have been extracted from on different instances of classes to determine the performance accuracy on the defect pixel value at different sparse region of the model and it is compared with conventional approaches for defect classification.

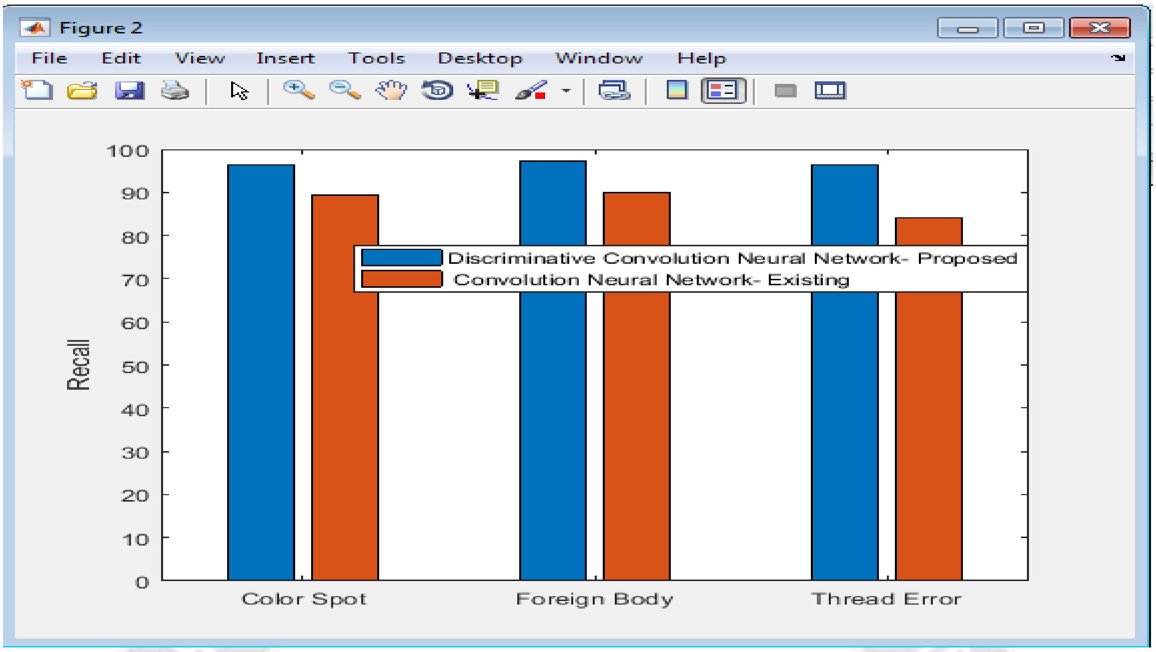


Figure 6 : Evaluation of Fabric Defect Classification Architecture with respect to Recall

Figure 6 illustrates the performance of the proposed architecture towards classification of the fabric defect images in terms of recall on the defect class's results with reduced high level features of the convolution layers. On analysis, it produces the effective results on true positive values computation. Figure 7 provides the performance results of the f measure on results of classes containing fabric defect types.

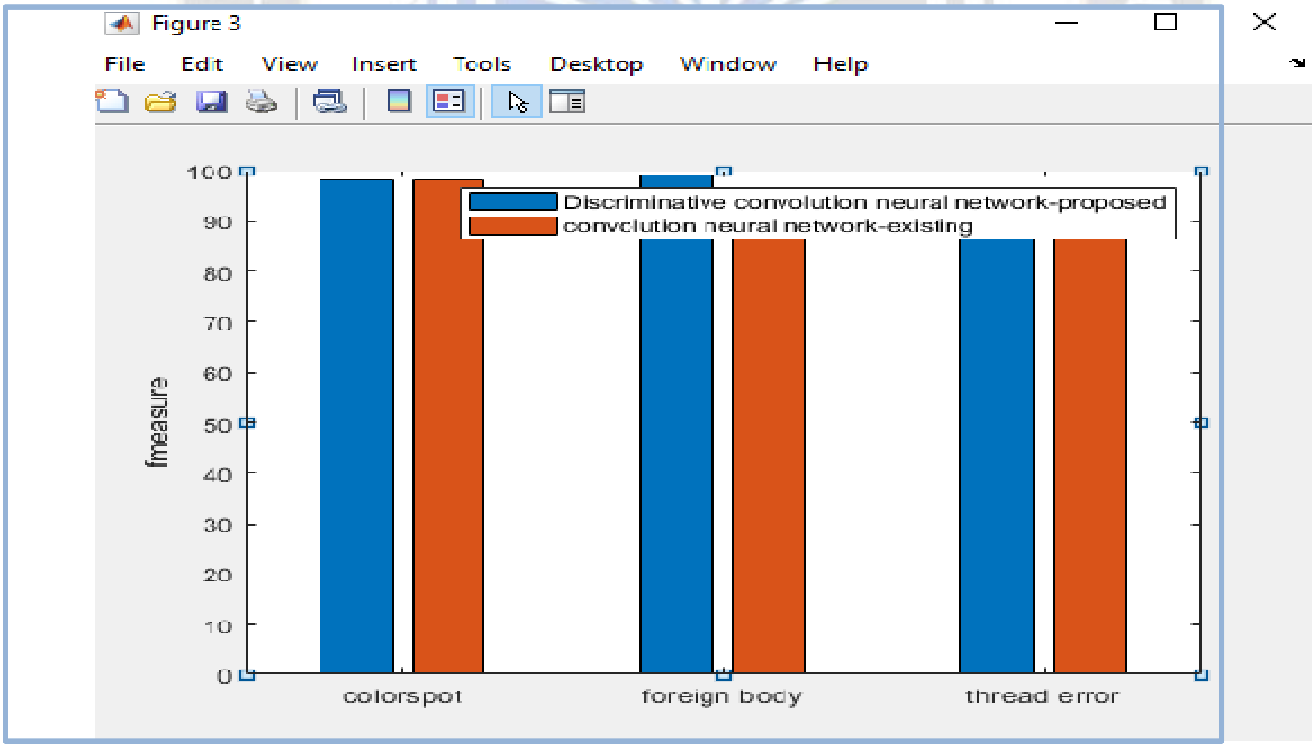


Figure 7 : Evaluation of Fabric Defect Classification Architecture with respect to F measure

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
Article Received: *10 September 2023* ***Revised:*** *20 October 2023* ***Accepted:*** *30 October 2023*

It is interesting that the accuracy values of the proposed model are high in the classification of fabric defect images on multiobjective activation functions of the defect CNN classifiers. It classifies the discrete feature texture. This paradigm can be applicable to any type dataset of fabric defect images [18]. Table 2 represents the performance of the classification accuracy on proposed classifier against conventional approach.

Table 2: Performance computation of proposed architecture on Fabric Defect Classification

Techniques	Classes	Precision	Recall	F measure
Proposed Technique – Improved Discriminant Convolution Neural Network	Color Spot	0.997	0.914	0.981
	Foreign Body	0.978	0.904	0.981
	Thread Error	0.987	0.912	0.989
Existing Technique- Convolution Neural Network	Color Spot	0.947	0.891	0.963
	Foreign Body	0.937	0.921	0.942
	Thread Error	0.947	0.901	0.954

Performance of the proposed approach produces the classification maps with high classification accuracy [10]. Proposed model can highly minimize the data redundancy and enhances classification efficiency on basis of the dataset. Finally proposed model is high capable in producing high accuracy on capturing the distinctive features and information between various fabric defect classes across various fabric image dataset.

Conclusion

Improved discriminative convolution neural model for locating, detecting and classify of the defects in the fabric materials has been designed and implemented. Initially fabric image preprocessed on basis of the noise filtering through wiener filter and image enhancement through CLAHE technique. Enhanced image is segmented using image threshold technique to segment it into the low rank and sparse region. Segmented sparse regions representing the defects are projected to the convolution neural network. Convolution layer of network is to extract the high level features from its composition containing kernels with different weights on striding to produce the feature map containing gradient and edge of the images. ReLU activation function is applied to reduce the non linearity among the features in the feature map. Pooling layer of the model down-sample the convolved features to produce the activation map. Activation map is transformed into tabular structure to perform the classification easily. In addition drop out layer is incorporated in the model to eliminate the overfitting issue during classification on reducing the correlation among the neurons. Fully connected layers of the model is used to learn the flattened features with weights and bias to classify the flatten features using softmax layer on basis of defect classes such as Hole , Color Spot, Thread Error and foreign body. Experimental analysis of the proposed architecture is carried out on TILDA dataset using cross fold validation to analyse the representation ability to discriminate the features with large variance between the different classes.

References

[1] D. Yapi, M. Allili, and N. Baaziz, ``Automatic fabric defect detection using learning-based local textural distributions in the contourlet domain," IEEE Trans. Autom. Sci. Eng., vol. 15, no. 3, pp. 1014_1026, May 2017.

[2] S. Ozdemir and A. Ercil, ``Markov random _elds and karhunen-loeve transforms for defect inspection of textile products," in Proc. IEEE Conf. Emerg. Technol. Factory Automat. (ETFA), 2002, pp. 697_703.

[3] S. Susan and M. Sharma, ``Automatic texture defect detection using Gaussian mixture entropy modeling," Neurocomputing, vol. 239, pp. 232_237, May 2017.

[4] J. Zou, M. Shen, Y. Zhang, H. Li, G. Liu, and S. Ding, ``Total variation denoising with non-convex regularizers," IEEE Access, vol. 7, pp. 4422_4431, 2019.

[5] C. Li, C. Liu, G. Gao, Z. Liu, and Y. Wang, ``Robust low-rank decomposition of multi-channel feature matrices for fabric defect detection," Multimedia Tools Appl., vol. 78, no. 6, pp. 7321_7339, Mar. 2019.

[6] C. Li, G. Gao, Z. Liu, Q. Liu, andW. Li, ``Fabric defect detection algorithm based on histogram of oriented gradient and low-rank decomposition," J. Textile Res., vol. 38, no. 3, pp. 153_158, 2017.

[7] L. Tong, W. K. Wong, and C. K. Kwong, ``Fabric defect detection for apparel industry: A nonlocal sparse representation approach," IEEE Access, vol. 5, pp. 5947_5964, 2017.

[8] O. G. Sezer, A. Ercil, and A. Ertuzun, ``Using perceptual relation of regularity and anisotropy in the texture with independent component model for defect detection," Pattern Recognit., vol. 40, no. 1, pp. 121_133, Jan. 2007.
[9] C. S. C. Tsang, H. Y. T. Ngan, and G. K. H. Pang, ``Fabric inspection based on the elo rating method," Pattern Recognit., vol. 51, pp. 378_394, Mar. 2016.
[10] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, ``Patterned fabric defect detection using a motif-based approach," in Proc. IEEE Int. Conf. Image Process., Sep./Oct. 2007, pp. II-33_II-36.
[11] J. Jing, X. Fan, and P. Li, ``Patterned fabric defect detection via convolutional matching pursuit dual-dictionary," Opt. Eng., vol. 55, no. 5, May 2016, Art. no. 053109.
[12] P. Li, J. Liang, X. Shen, M. Zhao, and L. Sui, ``Textile fabric defect detection based on low-rank representation," Multimedia Tools Appl., vol. 78, no. 1, pp. 99_124, 2019.
[13] J. Cao, J. Zhang, Z. Wen, N. Wang, and X. Liu, ``Fabric defect inspection using prior knowledge guided least squares regression," Multimedia Tools Appl., vol. 76, no. 3, pp. 4141_4157, Feb. 2017.
[14] C. Li, G. Gao, Z. Liu, M. Yu, and D. Huang, ``Fabric defect detection based on biological vision modeling," IEEE Access, vol. 6, pp. 27659_27670, 2018.
[15] C. Li, G. Gao, Z. Liu, D. Huang, and J. Xi, ``Defect detection for patterned fabric images based on GHOG and low-rank decomposition," IEEE Access, vol. 7, pp. 83962_83973, 2019.
[16] Dr.P.R.Tamilselvi and P.Banumathi "Fabric Deconvolution Wiener Filter and Feature Extraction Regionprops for Locating Defects" International Journal of Recent Technology and Engineering (IJRTE)",volume 8 Issue 3 September 2019.ISSN:2277-3878.Page No 7519-7525.
[17] Dr.P.R.Tamilselvi and P.Banumathi "Fabric Deconvolution Wiener Filter with Smoothness Feature Extraction For Projecting Directional Defects" International Journal of Food and Nutritional Sciences Volume 11.5 and Issue 3 December 2022 PAGE NO: 1272-1286 ISSN: 2319 1775 Online 2320 7876.
[18] Dr.P.R.Tamilselvi and P.Banumathi "An Exploration an Fabric Defect Detection system" IEEE Conference Proceedings December 2017 ICCIC PAGE NO: 208-211 ISBN:978-1-5090