Grading of woven fabric defect in 4 point inspection system using convolutional neural network and multilayer perceptron network

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Abstract: Fabric inspection is important in the textile industry to produce good quality garment. Manual inspection system of fabric is popularly followed in apparel industry wherein the length, width and magnitude of the fabric can be assessed by the 4 point inspection system. However, the disadvantage is that it consumes more time and due to the nature of work eyes become tired from intense use, which leads to high inspection error. The automated inspection by machine can solve this problem. There are more advantages in applying automation technology for inspection system. The CNN and MLP neural network in deep learning is used for image processing. The woven cotton fabric defects were classified during inspection process and the penalty point 1, 2, 3 and 4 were awarded based on the intensity of the defects. The sample images were collected from Sky Cotex India Private Limited, Tirupur, India and were processed in Teachable machine for CNN and Anaconda python for MLP. The defects were assessed as the network input values and the defect classification was obtained as the output. The trained neural network was used to test the defective sample images to calculate the efficiency percentage which registered for CNN is 91.5%, 86.5%, 89.5%, and 90% and MLP is 90%, 80%, 80%, and 70% for the penalty point 1, 2, 3, and 4 respectively.

Keywords: *Woven fabric inspection, 4 point system, Convolutional Neural Network, Multilayer Perceptron Network, Teachable machine software, Anaconda Python software.*

1. Introduction:

The fabric is woven by using different techniques like hand loom, power loom (shuttle loom), and shuttle less loom. Every technology has the probability to generate fabric defects due to operational reason. Weaver can reduce the fabric defects up to maximum extent but he can't avoid the fabric defects to be occurred during weaving. Fabric grading is an important part in textile industry. Grading has been done based on the inspection system. In general, 4 point fabric inspection system has its acceptability worldwide [7]. The simplicity of this system makes it more popular among other woven fabric grading systems. This system is easily applicable in the fabric manufacturing. Identifying the defects in the fabrics is a very important process in the textile manufacturing industries as it affects the quality of the fabrics manufactured by the industries [16]. Usually fabric inspection in textile industries is done by human following subjective assessment .In textile industry; inspection of fabric defects plays on important role in the quality control. So here artificial neural network is used to replace the manual inspection system. The problems faced by humans working manually on quality system such as fatigue and tediousness. This process is time consuming. The best solution for this problem is to use Artificial Intelligence technique. The main drawbacks for manual system are time consuming and high accuracy is not achieved. Today, ANN is being applied to increasing number of real world problems of considerable complexity [8]. Convolutional Neural Network(CNN) and Multi-layer perceptron (MLP) in the deep learning are suitable for real time problems which is nonlinear in nature The neural networks can handle classification problems with high accuracy.

2. Main text:

2.1 The 4 point Inspection System:

The 4-Point Inspection System assigns 1, 2, 3 and 4 penalty points according to the dimensions, quality, and significance of the defect. No more than 4 penalty points were assigned for any single flaw. A defect can be measured either length or breadth direction; the system remains a similar. Only major errors were considered in this system. Classification of penalty points according to the dimensions of defect is shown in Table 1.

Table 1: 4 point inspection systems

Size of defect (Length in inches)	Penalty points
0-3	1
3-6	2
6-9	3
9 and above	4
Holes less than 1	2
Holes over 1 inches	4

2.1.1 Penalty point 1 for four point inspection system:

The images contain defects up to 3 inches are denoted as Penalty point 1. Images for penalty point 1 are shown in figure 1 (a) (b) and (c)

(a)Snarl **(b) Stains** **(c) Selvedge tails**

Figure 1(a) (b) (c) Images for penalty point 1

2.1.2 Penalty point 2 for four point inspection system:

The images contain defects up to 3-6 inches are denoted as penalty point 2. Holes containing 1 or less than 1 inch give penalty point 2. Images for penalty point 2 are shown in figure 2 (a) (b) (c) and (d).

 

(a) Snarl **(b) Stains**

 

(c)Selvedge tails **(d) Holes**

Figure 2(a) (b) (c) and (d) Images for penalty point 2

2.1.3 Penalty point 3 for four point inspection system:

The images contain defects up to 6-9 inches is denoted as Penalty point 3. Images for penalty point 3 are shown in figure 3 (a) and (b).

 

(a)Snaral **(b) Stains**

Figure 3(a) (b) Images for penalty point 3

2.1.4 Penalty point 4 for four point inspection system:

The images contain defects 9 and above inches it is denoted as penalty point 4. Holes containing over 1 inch gives penalty point 4. Images for penalty point 4 are shown in figure 4 (a) and (b).

(a)Holes (b) Selvedge tails

Figure 4(a) (b) Images for penalty point 4

2.2 Convolutional neural network:

A convolutional neural network (CNN) is a type of artificial neural network. The CNN is also known as the ConvNets. A neural network may be a system of hardware or software. CNN has one or more convolutional layers and are used mainly for image processing, image recognition, classification, and segmentation. CNNs are used for image classification and recognition because of its high accuracy. Layers are sparsely connected or partially connected rather than fully connected. Every node does not connect to every other node. It gives spatial information. CNN has multiple layers that operates and extract the features from the data. The layers like convolution layer, rectified linear unit layer, pooling layer and fully connected layer are present in the network. Structure of convolutional neural network is shown in figure 5.

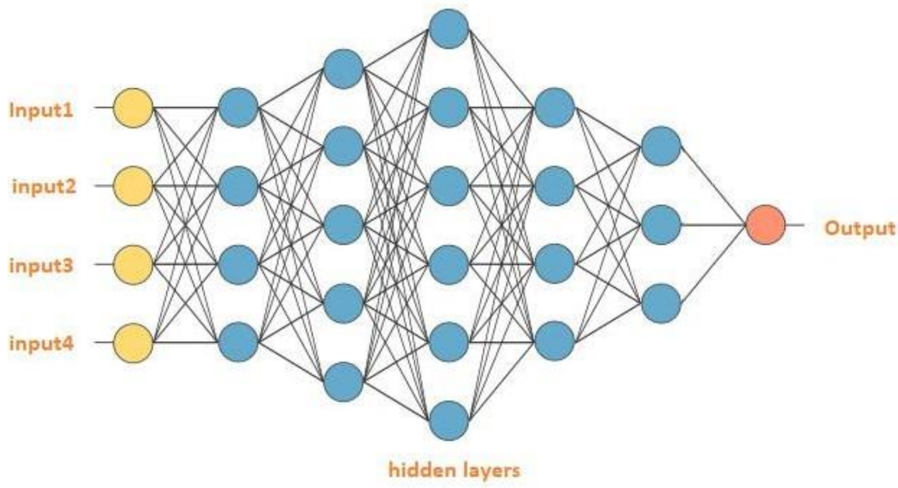

Figure 5: Convolutional Neural Network Structure

2.2.1 Methodology for CNN:

In this research, digital image processing technique was applied for testing the samples. Fabric defect images were collected from Sky Cotex India Private Ltd., Tirupur, Tamil Nadu, and India. Convolution Neural Network in deep learning had been used for training of neural network and then sample had been tested to calculate the efficiency. In this work image processing technique was applied for defective fabric. The various defective fabric images were captured by the digital camera and categorized into different defect groups to create a data set. The neural network had been trained with raw images. Then the trained network was used to classify the defects in the testing sample to calculate the accuracy. The training and testing was carried through the online portal Google's teachable machine software. The samples were uploaded in the cloud from the dataset and named as Penalty point 1, Penalty point 2, Penalty point 3 and Penalty point 4. The training was done using the uploaded dataset to create network. Once the training had been done successfully, each sample was tested one by one to get the results for classification. Data flow diagram of the process and flow process in training is shown in Figure 6 and 7.

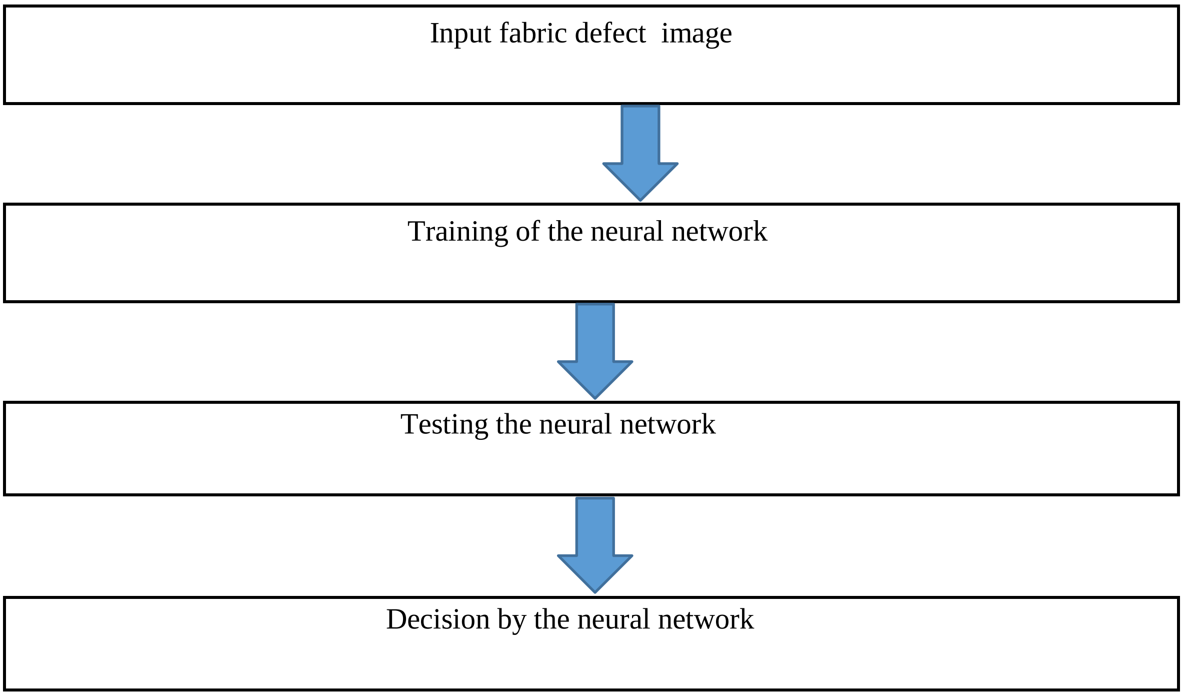

Figure 6: Data flow diagram of the process

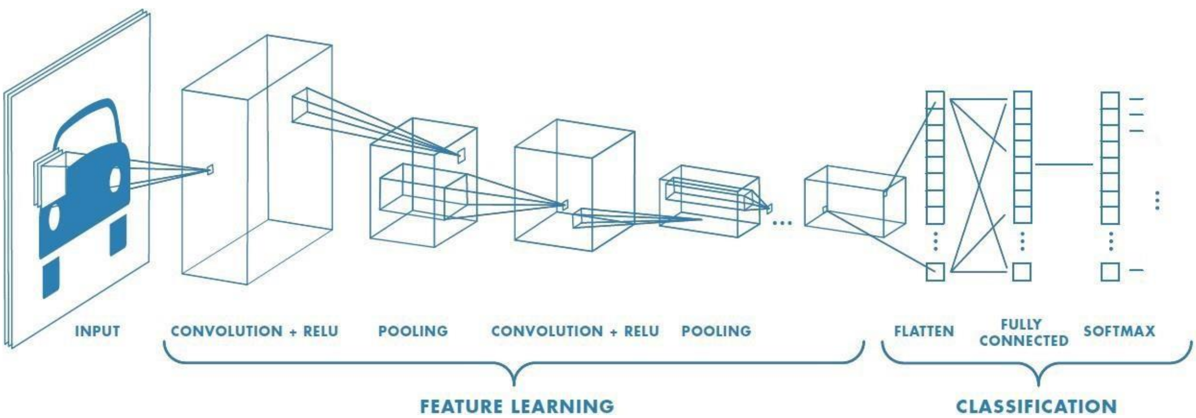

Figure 7: Flow process in Training

2.2.2 Input images

The images of the fabric defects were captured using the high quality image sensing device. The images were transferred from image sensing device to the computer system. A total of 440 images were collected through the image acquisition process, among these image 400 images were used for training and 40 images were used for testing. Figure 8 (a), (b), (c), (d) represents the image samples for the defects such as Snarl, Holes, Selvedge tails and Stains on the fabric respectively.

(a) Snarl

(b) Holes

(c) Selvedge tails

(d) stains

Figure 8 (a) (b) (c) and (d) Defect sample used for Training

2.2.3 Training of neural network

For training the neural network a total of 400 defective images were used. The convolutional neural network consists of input layer and hidden layers and output layer. The number of neurons in the input layers depends on the size of the input image. For training the neural network, the epochs and learning rate values had been adjusted to increase the efficiency of the process. One epoch means that each and every sample in the training dataset has been fed through the training model at least once. If epochs are set to 50, for example, it means that the model under training will work through the entire training dataset 50 times. Generally the larger the number, the better the model will learn to predict the data. The value of epoch used here is 50 and the learning rate is fixed as 0.001 for getting a good result. No of Images used for training and testing is shown in table 2.

Table 2: No of Images Used for training and testing

S.no	List	No of Image
1	Defect Images for Training	400
2	No of Images for Testing	40
3	Total No of Images	440

CNN parameters for training the network:

- Epochs- 100
- Batch Size- 16
- Learning Rate- 0.001 Time taken for Training CNN is 36 sec.

Mathematical calculation of CNN is shown below:

V[1, 0,0] = np.sum(X[2:7,:5,:] * W0) + b0

V[2,0,0] = np.sum(X[4:9,:5,:] * W0) + b0

V[3,0,0] = np.sum(X[6:11,:5,:] * W0) + b0

V represents the output volume. The operation * above denotes element wise multiplication between the arrays, WO is the weight vector of the neuron and *bo* is the bias.

To construct a second activation map in the output volume.

V[0,0,1] = np.sum(X[:5,:5,:] * W1) + b1

V[1,0,1] = np.sum(X[2:7,:5,:] * W1) + b1

V[2,0,1] = np.sum(X[4:9,:5,:] * W1) + b1

V[3,0,1] = np.sum(X[6:11,:5,:] * W1) +b1

V[0,1,1] = np.sum(X[:5,2:7,:] * W1) + b1

V[2,3,1] = np.sum(X[4:9,6:11,:] * W1) + b1

The second depth dimension in v denotes output, w1 is the weight vector of the neuron and *b1* is the bias.

2.2.4 Testing neural network

The trained neural network was used to test the given images. After training the neural network, 40 images were used for testing. The images were uploaded one by one to test the trained model. From these 40 images, it was divided into 4 parts, penalty point1, penalty point 2, penalty point 3, and penalty point 4. For each penalty points 10 images were taken. This entire image gives a percentage value for each image. These percentages were used to calculate the efficiency percentage of the training machine and the neural network.

2.2.5 Experimental result for CNN:

1. Confusion matrix

A confusion matrix is a table that's typically describes the performance of a classification model (or "classifier"). It summarizes the accuracy of models predictions. The y axis (Class) represents the category of samples. The x axis (Prediction) represents the category of model. The confusion matrix is shown in the figure 9.

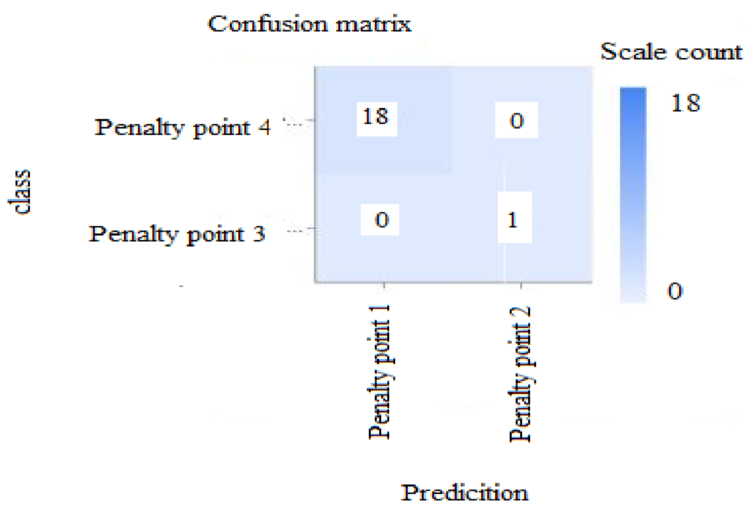

Figure 9: Confusion matrix

2. Accuracy per epoch

Accuracy is the proportion of classifications that a model gets right during training. If the model's prediction is perfect, the accuracy is one; otherwise, the accuracy is lower than one. The accuracy per epoch is shown in the figure 10.

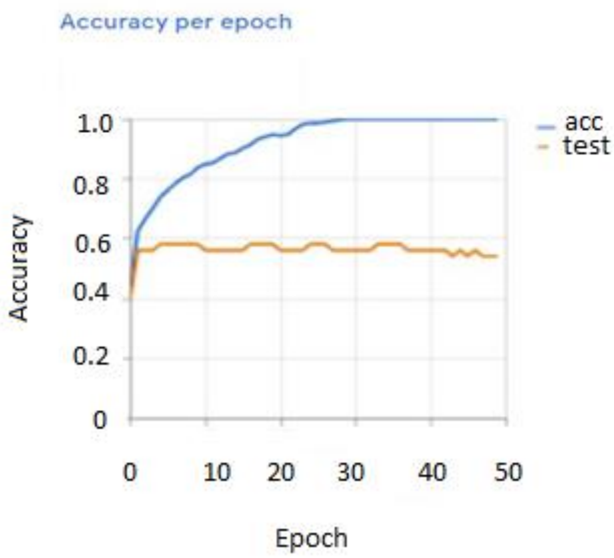

Figure 10: Accuracy per epoch

3. Loss per epoch:

Loss is a measure for evaluating how well a model has learned to predict the right classifications for a given set of samples. If the model's predictions are perfect, the loss is zero; otherwise, the loss is greater than zero. The loss per epoch is shown in the figure 11.

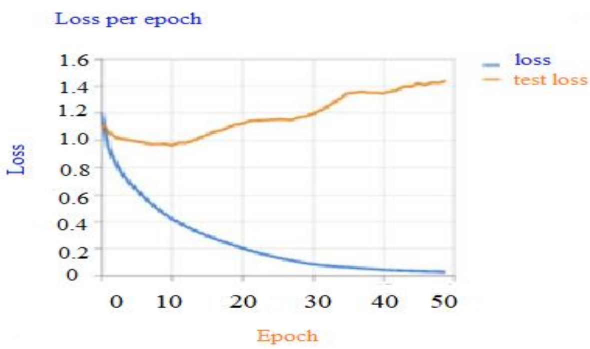

Figure 11: Loss per epoch

2.2.6 Efficiency percentage for CNN:

The images were tested in the trained neural network. The efficiency for four different penalty points in woven fabric was tested and calculated. A total of 40 random samples were taken from the data set and efficiency was derived and average was calculated. All the images were 128x128 in size for the experiments. The experimental results after training and testing for CNN are given in the Table 3.

Table 3: Efficiency percentage for CNN

PENALTY POINTS	EFFICIENCY PERCENTAGE FOR CNN
1	91.5%
2	86.5%
3	89.5%
4	90%

2.3 Multilayer perceptron network:

A multilayer perceptron (MLP) is a category of feed forward artificial neural network (ANN). An MLP consists of at three layers of nodes an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. Information is fed to the input layer, there may be one or more hidden layers providing predictions that are made on the output layer, also called the visible layer. MLPs are used for tabular dataset, classification prediction issues and regression prediction problem. Disadvantage of MLP is total number of parameters can go very high. Number of perceptron in layer 1 is multiplied by perceptron in layer 2 and is multiplied by perceptron in layer 3. Another disadvantage is that it disregards spatial information. Multi-layer perceptron is the classical type of neural network. The structure of MLP is shown in figure 12.

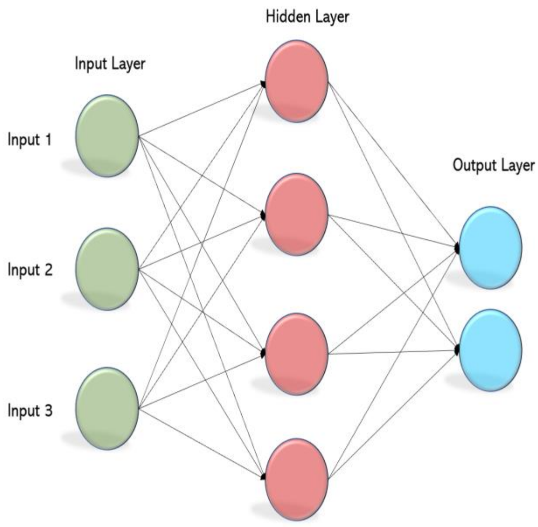

Figure 12: Structure of MLP

2.3.1 Methodology for MLP:

For MLP Anaconda Python was used. Anaconda software was downloaded from web. A folder was created using the images collected with classifies folders of penalty points and it was assigned with the code that is to be installed and used in Anaconda. Initially, a class called project was created.

Spyder software is launched in Anaconda and the file with algorithm is opened in Spyder .When the program is run, then some other modules like tensor flow. os, sklearn were installed and launched using Anaconda. The images to be trained are kept in a folder named Dataset and images to be tested are kept in the folder named Testing. This was assigned in the program installed. Then epoch value is to be set. This determines the iterations to be made. Finally the image number to be tested in given inside the assigned quotation.

First the program is run, and then number of images in each folder of penalty point is notified now the neural network is trained. For testing the run from current selection is given from keras were the images is tested. Now four different values were showing the accuracy rate of image that notifies to which type of penalty points the image belongs. The most nearest value to 1 is considered to be the correct type to which the image belongs.

2.3.2 Training of MLP:

For training the neural network a total of 400 defective images were used. The MLP consists of input layer and hidden layers and output layer. The number of neurons in the input layers depends on the size of the input image. For training the neural network, the epochs and learning rate values had been adjusted to increase the efficiency of the process. The value of epoch used here is 100 and the learning rate is fixed as 0.001 for getting a good result.

Mathematical calculation of MLP is shown below:

$$F(x) = \left(\sum_{i=1}^{m} w_i * x_i\right) + b$$

Where

- m is the number of neurons in the previous layer,
- w is a random weight,
- x is the input value
- b is a random bias

2.3.3 Testing of MLP:

The trained neural network was used to test the given images. After training the neural network, 40 images were used for testing. The images were uploaded one by one to test the trained model. From these 40 images, it was divided into 4 parts, penalty point1, penalty point 2, penalty point 3, and penalty point 4. For each penalty points 10 images were taken. Now four different values were showing the accuracy rate of image that notifies to which type of penalty points the image belongs. The most nearest value to 1 is considered to be the correct type to which the image belongs.

2.3.4 Experimental results:

1. Accuracy per epoch:

Accuracy is the proportion of classifications that a model gets right during training. If the model's prediction is perfect, the accuracy is one; otherwise, the accuracy is lower than one. The accuracy per epoch is shown in the figure 13.

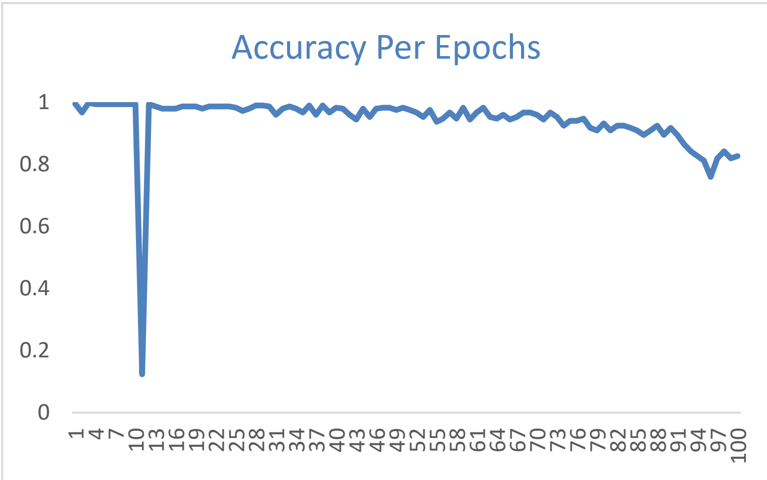

Figure 13: Accuracy per epoch

2. Loss per epoch:

Loss is a measure for evaluating how well a model has learned to predict the right classifications for a given set of samples. If the model's predictions are perfect, the loss is zero; otherwise, the loss is greater than zero. The loss per epoch is shown in the figure 14.

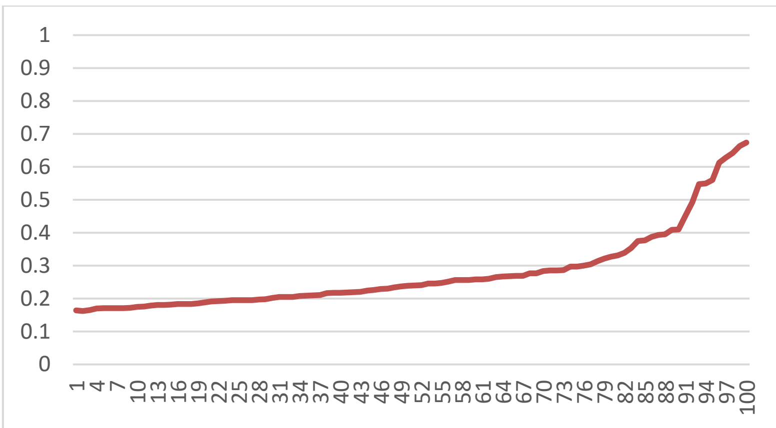

Figure 14: Loss per epoch

2.3.5 Efficiency percentage for MLP:

The images were tested in the trained neural network. The efficiency for four different penalty points in woven fabric was tested and calculated. A total of 40 random samples were taken from the data set and efficiency was derived and average was calculated.The classification accuracy of the test samples were calculated in test phase and same has been represented below

$$\text{Performance index} = \frac{\text{No. of correct classification}}{\text{Total no of defected images presented}} * 100$$

All the images were 128x128 in size for the experiments. The experimental results after training and testing for MLP are given in the Table 4.

Table 4: Efficiency percentage for MLP

PENALTY POINTS	EFFICIENCY PERCENTAGE FOR MLP
1	90%
2	80%
3	80%
4	70%

2.4 Results and discussions:

The table 3 and 4 shows that experimental results of the CNN and MLP based classification were applied on the input data set for each class of the defects. The application of Yarn dyed fabric defects were classified and reported by using CNN [12]. The efficiency in colored fabric defects were detected as 99.75% through CNN algorithm in deep learning [5]. The application of fibers, yarn, fabrics, colors and non-woven were investigated through ANN [25]. The efficiency of fabric defect classification using modular neural network was predicted as 92.65% [3].The visual-based defect detection and classification for industrial applications had been performed through survey [21].The applications of Neural Networks (NNs) for Fabric Defect Classification were classified with an accuracy rate of 96.3% [6].Fabric Defect

Detection Using Local Homogeneity Analysis and Neural Network were proposed with an accuracy of 97.35% .Fabric Defect Detection Using Activation Layer Embedded Convolutional Neural Network was predicted as 98% [19]. The application in classification of woven fabric defects in 4 point inspection system using CNN and MLP was not investigated and reported in any technical literature. In the present study, efficiency was predicted for the Penalty point 1, 2, 3, and 4 was based on the data set prepared under industrial condition by using convolutional neural network and Multilayer perceptron neural network. This provides an efficiency rate for the defects CNN such as penalty point 1 is 91.5%, penalty point 2 is 86.5%, penalty point 3 is 89.5% and penalty point 4 is 90% and for MLP such as penalty point 1 is 90%, penalty point 2 is 80%, penalty point 3 is 80% and penalty point 4 is 70%.

2.5 Conclusion:

Artificial neural network for classification of woven cotton fabric defects in 4 point inspection system was proposed based on the convolutional neural network and multilayer perceptron network. The experiments were carried out for several times to yield better result. The performances of the neural network were evolved on real samples. The automatic identification of fabric defects classification based on CNN and MLP in deep learning was achieved and the tested image exhibited the percentage efficiency for CNN is 91.5% (penalty point 1), 86.5% (penalty point 2), 89.5% (penalty point 3) and % 90.5(penalty point 4) and MLP is 90% (penalty point 1), 80% (penalty point 2), 80% (penalty point 3) and % 70% (penalty point 4). Comparing these two neural networks CNN gives the good results because the number of networks in CNN is high. However, the efficiency can be increased by enhancing the sample size and subsequent training of the neural network to improve the accuracy. The productivity and quality of the apparels would be increased to a greater extent on the application of this kind of automatic defect classification system in the apparel industry.

Reference

[1] Abid, Sabeur.2019. “Texture defect detection by using polynomial interpolation and multilayer perceptron.” *Journal of Engineered fiber and fabric*s 14(1): 1-12.

[2] Ali, Rebhi. Issam Benmhammed, Sabeur Abid and Farhat Fnaiech. 2015. “Fabric defect detection using local homogeneity analysis and neural network.” *Journal of Photonics* 6(1):1-9.

[3] Agrawal, V.L., Y.P Sushir, and Rupali, N.Tirale. 2019. “Fabric defect classification

using modular neural network." *International Research Journal of Engineering and Technology (IRJET)* 6(4):3353-58.

[4] Banumathi, P., and G. M. Nasira. 2012. "Fabric Inspection System using Artificial Neural Networks." *International Journal of Computer Engineering Science (IJCES)* 2(5):20-27.

[5] Barua, Srikant., Hemprasad Patil, Parth Dharmeshkumar Desai and Manoharan Arun. 2020. "Deep learning - based smart colored fabric defect detection system." *Applied computer vision and image processing* 11(55): 212-19.

[6] Celik, Hayati., Lale Canan Dulger and M. Land Topalbekiroglu. 2013. "Development of a machine vision system: Real-time fabric defect detection and classification with neural networks." *The Journal of the Textile Institute* 105(6):37-41.

[7] Chan, Chi-ho., and Grantham K. H. Pang. 2000. "Fabric defect detection by Fourier analysis & quot." *IEEE Trans. on Ind. Apparel* 4 (2):267-76.

[8] Chauhan, Neha., Nirmal Yadav and Nisha Arya. 2013. "Applications of Artificial Neural Network in Textiles." *International Journal of Current Microbiology and Applied Sciences (IJCMAS)* 7(4):3134-43.

[9] Habib, Tarek., Rahat Hossain Faisal, M. Rokonuzzaman and Farruk Ahmed 2014. "Automated fabric defect inspection: a survey of classifiers." *International journal in foundations of computer science & amp; technology (IJFCST)* 4(1):17-25.

[10] Huanhuan, *Zhang*., Jinxiu *Ma*, Junfeng *Jing* and *Pengfei* Li .2019. "Fabric defect detection using LO gradient minimization and fuzzy C-means." *Applied Sciences* 9(1):3506-10.

[11] Jianli, Liu., and Zuo Baoji 2007. "Identification of fabric defects based on discrete wavelet transform and back-propagation neural network." *Journal of the Textile Institute* 98(4): 355-62.

[12] Junfeng, *Jing*., Zanzan *Zhang* and JianYuan *Jia*. 2012. "Objective evaluation of fabric pilling based on wavelet transform and the local binary pattern." *Text. Res. J.* 82(2):1880-87.

[13] Jing, Junfeng., Amei Dong, Peng fei and Kaibing Zhang. 2017. "Yarn dyed fabric defect classification based on convolutional neural network." *Optical Engineering* 56(09): 56-61.

[14]Jingjing, *Liu*., Shaoting *Zhang*, Shu *Wang* and Dimitris *Metaxas*. 2016. "Multispectral deep neural networks for pedestrian detection." *The British Machine*

Vision Conference 6 (4):155–59.

[15] Kang, Zhiqiang., Chaohui Yuan, and Qian Yang.2013. “The fabric defect detection technology based wavelet transform and neural network convergence.” *International conference on information and automation.* 3(1)597-601.

[16] Kazim, Hanbay., Muhammed Fatih *Talu*b and Omer Faruk Ozguvenc. 2016. “Fabric defect detection systems and methods.” *A systematic literature review. Optik* 127(1):11960-73.

[17] Kumar, A. 2008. “Computer-vision-based fabric defect detection*.” A survey. IEEE Trans. Ind. Electron.* 55(1) 348–63

[18] Kwak, Choonjong., Jose Aventura and kari fang-sazi. 2000. “A neural network approach for defect identification and classification on leather fabric.” *Journal of Intelligent Manufacturing* 11(1) 485- 99.

[19] Ouyang, wenbin., Bugao Xu , Jue Hou, and Xiaohui Yuan.2019. “Fabric Defect Detection Using Activation Layer Embedded Convolutional Neural Network.” *IEEE Access* 4 (2): 70130- 140.

[20] Priya, S., and V. Paul. 2011. “A novel approach to fabric defect detection using digital image processing.” I*nternational Conference on Signal Processing, Communication, Computing and Networking Technologies 2(1)*: 228-32.

[21] Roccella, Stefano., Tamás Czimmermann, Gastone Ciuti, Mario Milazzo, Marcello Chiurazzi, , Calogero Maria Oddo and Paolo Dario. 2020. “Visual-Based Defect Detection and Classification Approaches for Industrial Applications—*A SURVEY.” Sensors* 20(5):1-25.

[22] Sabeenian, Royappan Savarimuthu., Paramasivam Muthan and P. Dinesh. 2011. “Detection and Location of Defects in Handloom Cottage Silk Fabrics using MRMRFM & MRCSF.” *International Jornal of Technology and Engineering System (IJTES)* 2(2):133-38.

[23] Sekar, Abdulkadir. Ahmet Gürkan, and Yuksek. 2017. “Stacked Autoencoder Method for Fabric Defect Detection.” *Cumhuriyet University Faculty of Science Science Journal (CSJ)* 38(2):342-54.

[24] Takada, Y., T. Shiina, H. Usami .2017. “Defect detection and classification of electronic circuit boards using key point extraction and CNN features.” *The ninth international conferences on pervasive patterns and applications (PATTERNS),*

*Athens.*1(2)19–23.

[25] Vassiliadis, Savvas., Maria Rangoussi, Ahmet Cay and Christopher Provatidis. 2010. “Artificial Neural Networks and Their Applications in the Engineering of Fabrics.” *Textile Research Journal* 2(1):111-35.

[26] Wang, Tian., Yang Chen, Meina Qiao and Himchen Snoussi. 2018. “A fast and robust convolutional neural network-based defect detection model in product quality control.” *The International Journal Advanced Manufacturing Technology* 94(1):3465–71.

[27] Xiang, Jun., Jingan Wang, and Jian Zhou. 2020. “Fabric defect detection based on a deep convolutional neural network using a two-stage strategy.” *Textile Research Journal* 91:1-2.

[28] Yang, Chin- Shan., Cheng-Jian Lin and Wen-Jong Chen. 2019. “Using Deep Principal Components Analysis-Based Neural Networks for Fabric Pilling Classification.” *Journal of electronics* 8(5): 1-10

[29] Zhang, Y.2010. “Fabric defect classification using radial basis function network.” *Pattern Recognition* 31(13): 2033–42.