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Defect Detection in Fabrics Using Back Propagation Neural Networks

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Abstract: Defect detection in Fabrics plays an significant role in automatic defect detection system in textile industries. Identification of fabric fault mainly include three parts: The first, preprocessing with Frequency domain Butterworth Low pass Filter and Histogram Equalization. The second, texture features extraction of fabric with Gray Level Co-occurrence Matrix (GLCM).The GLCM characterizes the distribution of co-occurring pixel values in an image to be at a given offset, and then the statistical texture features are obtained from this GLCM. Third, the fault is identified using Back Propagation Neural Network with different combinations of GLCM features as an input

Index Terms; Back Propagation Neural Network, Butterworth Low Pass Filter, Gray Level Co-Occurrence Matrix, Histogram Equalization.

I. INTRODUCTION

Over the decades, the automation process has been of increasing interest in textile and clothing manufacturing industries. Due to the changeability in the textile fabric property, automation is still a demanding task. Therefore the progress of efficient computer vision techniques for the computerized control of the textile manufacturing process is necessary.

Yarns are interlaced to form woven fabrics. Basically two yarns: "warp" and "weft". The lengthy upright yarn wrapped around the loom is known as Warp. The flat yarn woven throughout the warp yarn is known as Weft.

In [1], a novel scheme is proposed based on morphological filters to solve the difficulty of automatic fabric defect detection. Important texture features of the fabrics are extracted using a trained Gabor wavelet.

In [2], an approach for modelling features scale of fabric deformations and defects is proposed. A high fidelity digital element method is used for predicting the as-woven geometry of a single unit cell. By geometric reduction, a macro-scale fabric model is obtained from the unit cell geometry. Two and three dimensional approaches with an accompanying yarn mechanical model for yarn geometry representation are proposed.

In [3], a new improved approach is proposed for fabric defect classification with Gaussian mixture model (GMM) and radial basis function (RBF).

In [4], a plain white fabric has taken as the sample and the pre processing is done with filtering and thresholding. The filtered and threshold image data are then given to the neural network input.

In [5], Lucia Bissi et al. propose a method in two phases namely feature extraction phase and defect identification phase. A complex symmetric Gabor filters bank and Principal Component Analysis (PCA) is employed in a feature extraction phase and the Euclidean norm of features is employed for defect identification phase.

In [6], Soft computing techniques such as fuzzy logic, Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) approaches are used.

In [7], a new scheme for automated Fabric Defect Detection System implementation using GLCM and also it is compared with Gabor filter approach.

In [8], various image processing techniques are used for evaluating the yarn defects. The yarn defects were identified based on their geometric shape and surface area.

In [9], an optimized elliptical Gabor filter (EGF) is proposed to detect defects in textured surface. A genetic algorithm (GA) is used to tune the proposed EGF.

In [10], a new cluster-based approach to extract features from the coefficients of a two-dimensional discrete wavelet transform method is proposed.

In [11], the application of harmony search algorithms for the supervised learning of feed-forward (FF) type neural networks used for classification problems. Studies on five different variants of harmony search algorithms are performed by giving special consideration to Self-adaptive Global Best Harmony Search (SGHS) algorithm.

In [12], Adaptive Neuro Fuzzy Inference System (ANFIS) based software fault prediction problem is proposed.

In [13], gray level co-occurrence matrix is used to extract automatic woven fabric image with 2-D wavelet transform and neural network with learning vector quantization is used for classification.

In [14], Gabor filters of two scales and six orientations is proposed.

In [15], a machine vision system for detecting surface defects using basic patch statistics from raw image data combined with a two layer neural network is presented.

In [16], gray level co-occurrence matrix (GLCM) is used to extract the textural features of fabric images. From the GLCM of the fabric image, a textural energy is computed by a sliding window technique for defect detection.

In [17], a view of automated fabric defect detection methods developed in recent years are projected.

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In [18], a study of motif-based patterned fabric defect detection using ellipsoidal decision regions which improves the original detection success using max–min decision region of the energy-variance values are provided.

In [19], Grey Level Co-occurrence Matrices as well as Binary Level Co-occurrence Matrices are used for fabric texture features extraction. The extracted GLCM and BLCM features are used to classify the texture by Bayesian classifier to compare their effectiveness.

In [20], the classification of textile fabrics with multiclass SVM classifier with co-occurrence matrix based pattern recognition system is proposed.

In [21] and [22], GLCM features are given as the input to the BPNN with single input neurons..

The proposed methodology of defect detection in fabric includes two phases:1) The Grey level Co-occurrence matrix for feature extraction and 2) back propagation neural network classifier for detection defects.

II. FABRIC DEFECT IDENTIFICATION

The fabric defect identification technique is proposed below.

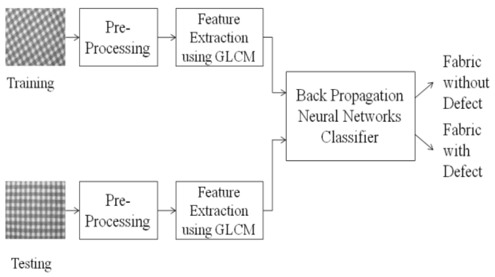

Fig. 1.Defect identification of Woven Fabrics

A. Preprocessing

A Preprocessing of an image is performed to enhance the image quality and remove unnecessary distortion. All the images are resized into a standard size of 256 X 256 pixels in order to increase the processing speed.

Butterworth low-pass filters in frequency-domain and histogram equalization techniques are used for noise reduction and image enhancement respectively.

B. GLCM feature extraction

Gray level co occurrence matrix is the standard second order statistical feature extractor for texture investigation. The Grey Level Co occurrence Matrix signifies that, how often various combinations of gray levels co occurs in an image at a given offset. GLCM based texture features are obtained by image pixel properties. In this method, the characteristics of texture images analyzed by extracting GLCM statistical features.

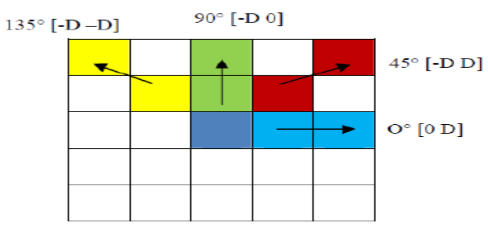

Fig. 2 Grey Level Co occurrence Matrix direction analysis

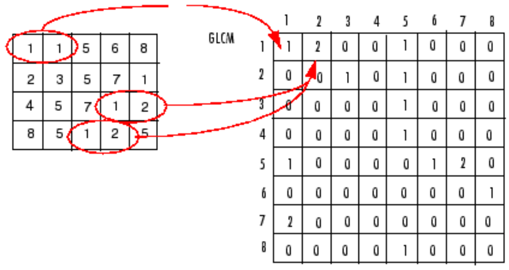

Fig. 3 Creation of GLCM

GLCM of an image is computed using a displacement vector D and orientation θ. The co-occurrence matrix calculation is depends on two parameters. These are D, the space connecting the pair of pixels,θ is the location direction connecting the pair of pixels (*i,j*) and (*k,l*).The four possible location angle is exposed in Fig. 2.The location angle for the horizontally directed pixel is 0 degree , position angle for the right diagonal direction is 45 degree, the position angle for the vertical direction is 90 degree and the position angle for the left diagonal direction is 135 degree. The grey level co-occurrence matrix with normalized value can be represented as:

$$P_{ij} = \frac{P_{ij}}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{ij}} \qquad (1)$$

Haralick defined the statistical features which is extracted from grey level co-occurrence matrices (reference) to explore textural characteristics. The mathematical representation of extracted statistical features are described below.

Contrast: Determines the confined variation in Grey level Co-occurrence matrix

$$CON = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 P_{ij} \qquad (2)$$

Correlation: Determines the joint probability occurrences of the specified pixel pair

$$COR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{ij}\frac{(1-\mu_i)(1-\mu_j)}{\sigma_i\sigma_j} \qquad (3)$$

Entropy: Determines the random distribution of the picture elements of an image.

$$ENT = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{ij}\log_2(P_{ij}) \qquad (4)$$

Homogeneity: Determines the picture element closeness distribution of the Co occurrence matrix to the GLCM diagonal.

$$HOM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P_{ij}}{1+(i-j)^2} \qquad (5)$$

Angular Second Moment: Determines homogeneity of an image. A homogeneous scene will contain only a few gray levels, giving a GLCM with only a few but relatively high values of P(i, j).

$$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\{P(i,j)\}^2 \qquad (6)$$

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Inverse Difference Moment: Determines local homogeneity

$$IDM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2} \quad (7)$$

Variance: Determines the gray level variability of the pixel pairs and is a measurement of heterogeneity.

$$VAR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-\mu)^2 P(i,j) \quad (8)$$

Cluster shade: Determines the skewness of the matrix and is believed to gauge the perceptual concepts of uniformity.

$$Shade = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i+j-\mu_x-\mu_y)^3 \times P(i,j) \quad (9)$$

Cluster prominence: Determines asymmetry

$$Prom = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i+j-\mu_x-\mu_y)^4 \times P(i,j) \quad (10)$$

Sum Average:

$$AVG = \sum_{i=0}^{2N-1} iP_{x+y}(i) \quad (11)$$

Sum Entropy:

$$SENT = -\sum_{i=0}^{2N-1} P_{x+y}(i)\log_2\left(P_{x+y}(i)\right) \quad (12)$$

Difference Entropy:

$$DENT = -\sum_{i=0}^{N-1} P_{x-y}(i)\log_2\left(P_{x-y}(i)\right) \quad (13)$$

Sum Variance:

$$SVAR = \sum_{i=0}^{N-1}\left\{i - \sum_{i=0}^{2N-2} P_{x+y}(i)\log_2\left(P_{x+y}(i)\right)\right\}^2 * P_{x+y}(i) \quad (14)$$

Difference variance:

$$DVAR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i^2) * P_{x-y}(i) \quad (15)$$

Dissimilarity:

$$Dissim = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)P(i,j) \quad (16)$$

Homogeneity(M):

$$Homogenity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P(i,j)}{1+|i-j|} \quad (17)$$

Correlation:

$$Corr = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i\times j)\times P(i,j)-\{\mu_x\times\mu_y\}}{\sigma_x\times\sigma_y} \quad (18)$$

Maximum Probability:

$$MaxProb = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \max\left(\max\left(P(i,j)\right)\right) \quad (19)$$

Autocorrelation:

$$ACorr = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\{i\times j\}\times P(i,j) \quad (20)$$

C. Artificial Neural Network

Artificial neural network is one amongst the computationally effective and most adaptive classifier for defect identification in woven fabric because of its non-parametric nature and complex decision regions description ability.Artificial neural network is the interconnection of the computational units namely nodes and it is anticipated to mimic some of the functions of the human intelligence. The attribute to the computational unit is the sum of the product of the preceding computational unit outputs and its weight to the node is joined. The outcome of the computational unit is an activation function of its input. In ANN the weight function w_{ij} is involving the input attribute of the jth computational unit and the outcome of the ith computational unit.

In this paper back-propagation neural network architecture consist of one input layer, hidden layer with twenty neurons and a single output layer. In the designed neural network, the obtained GLCM attributes are continuously provided to the input of the network and then it is processed through a non linear activation function and output is generated. At the end of each forward processing the mean square error is calculated by comparing desired output value and targeted output values. The calculated mean square error is given back to the preceding layers of the network and then the weight associated with each neuron is adjusted so that the mean square error is reduced with every pass and the network model is trained to achieve a desired performance. The complete forward and backward process is identified as training phase.

During training phase of the network, a series of inputs are mapped with a series of outputs to get desired output. The weight w_{ij} is adjusted to get the mapping result so skilful with a help of learning rule of back propagation neural network and the generally accepted learning rule is generalized delta rule. Once the weight adjustment has been done on the training set of data, the updated weights are fixed and the same network is used for testing a new set of data.

Back Propagation Training Algorithm

In each iteration of the training phase, jth layer weight W^j and bias B^j updates are calculated as follows

$$W^j(n) = W^j(n-1) + \Delta W^j \quad (21)$$

$$B^j(n) = B^j(n-1) + \Delta B^j \quad (22)$$

i. Gradient descent algorithm

$$\Delta W^j = \eta_{W^j}\frac{\partial E}{\partial W^j} \quad (23)$$

$$\Delta B^j = \eta_{W^j}\frac{\partial E}{\partial B^j} \quad (24)$$

ii. Gradient descent with adaptive learning rate algorithm

$$\Delta W^j = \eta_{W^j}\frac{\partial E}{\partial W^j} \quad (25)$$

$$\Delta B^j = \eta_{W^j}\frac{\partial E}{\partial B^j} \quad (26)$$

iii. Gradient descent with momentum algorithm

$$\Delta W^j = M * \Delta W^{j-1} + \eta * (1-M) * \frac{\partial E}{\partial W^j} \quad (27)$$

$$\Delta B^j = M * \Delta B^{j-1} + \eta * (1-M) * \frac{\partial E}{\partial B^j} \quad (28)$$

iv. Gradient descent with momentum and adaptive learning rate algorithm

$$\Delta W^j = M * \Delta W^{j-1} + \eta * M * \frac{\partial E}{\partial W^j} \quad (29)$$

$$\Delta B^{j} = M * \Delta B^{j-1} + \eta * M * \frac{\partial E}{\partial B^{j}} \quad (30)$$

v. Resilient Backpropagation

Weight Updation

$$\Delta W^{j} = \begin{cases} +\Delta^{j}, if \frac{\partial E}{\partial w^{j}} > 0 \\ -\Delta^{j}, if \frac{\partial E}{\partial w^{j}} < 0 \\ 0 \quad , \ otherwise \end{cases} \quad (31)$$

Exception:

$$\Delta W^{j} = -\Delta W^{j-1}, if \frac{\partial E}{\partial w^{j-1}} \cdot \frac{\partial E}{\partial w^{j}} < 0 \quad (32)$$

Learning Rule:

$$\Delta^{j} = \begin{cases} \eta^{+} . \Delta^{j-1}, if S > 0 \\ \eta^{-} . \Delta^{j-1}, if S < 0 \\ \Delta^{j-1}, otherwise \end{cases} \quad (33)$$

$$Where,\ S = \frac{\partial E}{\partial w^{j-1}} \frac{\partial E}{\partial w^{j}}$$

vi. Scaled Conjugate Gradient algorithm

a. *Steepest descent direction on the first iteration*

$$p_0 = g_0 \quad (34)$$

b. *Optimal distance along the current search direction*

$$x_{k+1} = x_k + \alpha_k g_k \quad (35)$$

c. *Next Search direction*

$$p_k = -g_k + \beta_k \quad (36)$$

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \quad (37)$$

vii. Levenberg Marquardt algorithm

$$\text{Gradient}, \quad g = J^T \quad (38)$$

Where J is the Jacobian Matrix

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (39)$$

The performance of generalized delta learning rule is evaluated by minimal error function

$$E_p = \frac{1}{2} \sum_j \left(t_{pj} - o_{pj}\right)^2 \quad (40)$$

In this paper back propagation neural network architecture is made up of one input layer of twenty two neurons, a hidden layer of twenty neurons, and an output layer of one neuron. In this network architecture hyperbolic tangent function with a rate of learning should be 0.07 and moment factor value with 0.7. The defect detection technique is divided into two phases such as training and testing phases. In training phase 210 data sets are used and in testing phase 100 data sets are used. Extracted statistical features are the input attributes for the designed neural network.

III. RESULTS AND DISCUSSION

In this paper nearly 310 different textured fabric images with and without defects are used for the analysis of the performance of the network. Among 310 fabric samples, 210 fabric samples are used in training phase and 100 fabric samples are used in testing phase to analyze the performance of the network for defect detection in fabric. Implementation of an algorithm has been done in MATLAB R2013a..

Fig. 4 shows a few of the sample fabric images used in training and testing phases

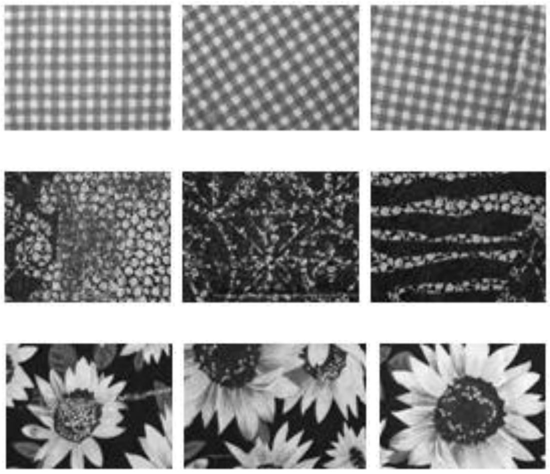

Fig.4 Training and testing Samples

Accuracy: Accuracy is a statistical measure of how well a classifier correctly identifies or excludes a condition. The accuracy is the proportion of true results (both true positive and true negative) in the population.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (41)$$

Table I shows the Comparison of Minimum and Maximum value of GLCM features for the defected and non defected fabrics

TABLE I Comparison of GLCM Features

Sl. No.	GLCM Features	Non Defected Fabric		Defected Fabric	
		Max value	*Min value*	*Max value*	*Min value*
1	Contrast(M)	1.3039	0.3367	1.3479	0.3264
2	Correlation(M)	0.9676	0.8760	0.9690	0.8723
3	Correlation	0.9676	0.8760	0.9690	0.8723
4	Cluster prominence	762.65	683.49	759.52	691.40
5	Cluster Shade	4.7376	-3.770	3.3116	-3.2354
6	Dissimilarity	0.8164	0.3124	0.8404	0.2926
7	Energy(M)	0.0696	0.0395	0.0717	0.0378
8	Entropy	3.4409	2.8919	3.4705	2.8681
9	Homogeneity(M)	0.8506	0.6462	0.8592	0.6567
10	Homogeneity	0.8472	0.6253	0.8570	0.6303
11	Max Probability	0.1229	0.0864	0.1173	0.0867
12	Sum of Squares: Variance	25.574	25.175	25.611	25.082

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13	Sum average	9.0490	8.9579	9.0752	8.9428
14	Sum variance	61.705	59.221	62.104	59.073
15	Sum Entropy	2.7002	2.6080	2.7018	2.6069
16	Difference Variance	1.3039	0.3367	1.3479	0.3264
17	Difference Entropy	1.1361	0.6620	1.1348	0.6525
18	Infn. Measure of Correlation 1	-0.3450	-0.6085	-0.3301	-0.6206
19	Infn. Measure of Correlation 2	0.9593	0.8728	0.9614	0.8640
20	Inverse Difference normalized	0.9655	0.9130	0.9678	0.9120
21	Inverse Difference Moment normalized	0.9948	0.9809	0.9950	0.9801
22	Autocorrelation	25.44	24.744	25.523	24.7400

TABLE II. Comparison of Accuracy % of different BPNN Learning Algorithm

Sl. No.	GLCM Features	Back Propagation Learning Rule						
		gd	gda	gdm	gdx	lm	rp	scg
1	Contrast(M)	65.7	68.5	64.7	64.7	70.4	70.4	61.9
2	Correlation(M)	59.0	60.9	59.0	58.0	60	60	56.1
3	Correlation	59.0	60.9	59.0	58.0	60	60	56.1
4	Cluster prominence	51.4	47.6	60	50.4	47.6	47.6	52.3
5	Cluster Shade	49.5	49.5	48.5	48.5	46.6	45.7	47.6
6	Dissimilarity	53.3	60	53.3	53.3	61.9	55.2	53.3
7	Energy(M)	49.5	48.5	49.5	46.6	44.7	47.6	43.8
8	Entropy	62.8	71.4	60	61.9	67.6	68.5	61.9
9	Homogeneity(M)	40.9	40.9	40	39.0	42.8	40	39.0
10	Homogeneity	44.7	40.6	49.5	45.7	43.8	40	45.7
11	Max Probability	45.7	45.7	44.7	45.7	45.7	40	44.7
12	Sum of Squares: Variance	54.2	48.5	54.2	43.8	49.5	50.4	48.5
13	Sum average	50.4	47.6	50.4	49.5	45.7	46.6	49.5
14	Sum variance	42.8	38.0	40.9	40.9	36.1	34.2	42.8
15	Sum Entropy	48.5	47.6	40.9	39.0	44.7	40.9	38.0
16	Difference Variance	65.7	70.4	64.7	64.7	70.4	70.4	61.9
17	Difference Entropy	61.9	67.6	61.9	60.9	63.8	68.5	63.8
18	Infn. Measure of Correlation 1	62.8	73.3	62.8	65.7	68.5	72.3	65.7
19	Infn. Measure of Correlation 2	60.9	57.1	60.9	57.1	57.1	43.8	60.9
20	Inverse Difference normalized	48.5	44.7	48.5	48.5	47.6	46.6	51.4
21	Inverse Difference Moment normalized	62.8	60	62.8	59.0	55.2	56.1	58.0
22	Autocorrelation	60.9	56.1	54.2	51.4	57.1	44.7	52.3

TABLE III. Comaprison of Accuracy % of BPNN Learning Algorithms for different combinations of GLCM Features

Sl. No.	BPNN Learning Algorithm	GLCM Feature Combination	Accuracy %
1	Gradient Descent	Contrast(M),Correlation(M),Correlation and Cluster prominence	79.04
2	Gradient descent with adaptive learning rate	Cluster Shade, Energy(M),Dissimilarity, Entropy,Homogeneity(M),Homogeneity, Sum Entropy, Difference Variance and Difference Entropy,Max Probability,Sum of Squares:Variance,Sum average and Sum variance.	80.95
3	Gradient descent with momentum	Correlation,Cluster prominence,Cluster Shade, Dissimilarity, Energy(M),Entropy,Homogeneity(M), Homogeneity,Max Probability, Sum of Squares:Variance,Sum average,Sum variance,Sum Entropy,Difference Variance,Difference Entropy,Infinite Measure of Correlation 1 and Infinite Measure of Correlation 2	75.23

4	Gradient descent with momentum and adaptive learning rate	Correlation,Cluster prominence,Cluster Shade, Dissimilarity,Energy(M),Entropy,Homogeneity(M), Homogeneity,Max Probability,Sum of Squares:Variance,Sum average,Sum variance,Sum Entropy,Difference Variance,Difference Entropy,Infinite Measure of Correlation 1,Infinite Measure of Correlation 2	76.19
5	Resilient Backpropagation	Cluster Shade, Energy(M),Dissimilarity, Entropy, Homogeneity, Homogeneity(M), Max Probability, Sum of Squares: Variance, Sum variance, Sum average, Sum Entropy, Difference Entropy, Difference Variance, Infinite Measure of Correlation 1 and Infinite Measure of Correlation 2	76.19
6	Scaled Conjugate Gradient	Contrast(M),Correlation(M),Correlation,Cluster prominence,Cluster Shade,Dissimilarity,Energy(M), Entropy,Homogeneity(M),Homogeneity,Max Probability,Sum of Squares:Variance,Sum average, Sum variance,Sum Entropy,Difference Variance and Difference Entropy	73.33
7	Levenberg Marquardt	Cluster Shade, Energy(M),Dissimilarity, Entropy, Homogeneity, Homogeneity(M), Max Probability, Sum of Squares: Variance, Sum variance, Sum average, Sum Entropy, Difference Entropy, Difference Variance and Infinite Measure of Correlation 1	72.38

The performance evaluation of the back propagation neural networks of different learning rule for defect detection in fabrics with extracted GLCM features are shown in Table II in terms of accuracy as a performance metric. The *GLCM* statistical feature Contrast *produces* improved performance in back propagation neural networks with *Gradient descent learning algorithm*. *Gradient descent with adaptive learning rate algorithm* of back propagation neural networks *produces* improved performance with the *GLCM* statistical feature Infn. Measure of Correlation 1. The *GLCM* statistical feature Contrast *produces* improved performance in back propagation neural networks with *Gradient descent with momentum algorithm*. The *GLCM* statistical feature Contrast *produces* improved performance in back propagation neural networks with *Gradient descent with momentum algorithm*. The *GLCM* statistical feature Infn. Measure of Correlation 1 *produces* improved performance in back propagation neural networks with *Gradient descent with momentum and adaptive learning rate algorithm*.

The *GLCM* statistical feature Contrast *produces* improved performance in back propagation neural networks with *Levenberg Marquardt algorithm*. The *GLCM* statistical feature Contrast *produces* improved performance in back propagation neural networks with *Resilient Back propagation algorithm*. The *GLCM* statistical feature Infn. Measure of Correlation 1 *produces* improved performance in back propagation neural networks with *Scaled Conjugate Gradient algorithm*.

From the Table II it shows that the designed back propagation neural network architecture gives average performance for the single feature input. The performance of the network architecture is improved with various combinations of GLCM statistical features as the input of the network instead of single feature input.

The performance evaluation of back propagation neural networks with various combinations of GLCM statistical features are shown in Table III. Amongst extracted 22 GLCM statistical features, combinations of the GLCM statistical features Dissimilarity, Homogeneity, Entropy, Sum Entropy and Difference Entropy plays a significant meaning in producing better performance of the network. Amongst seven learning algorithm used in back propagation neural network architecture Gradient Descent with Adaptive Learning rate produces improved result than other learning rules.

IV. CONCLUSION

The back-propagation neural network architecture developed in this paper is used to detect fabric defects. The characteristics of textured fabric images are analyzed with the help of grey level co-occurrence matrix. Statistical features which are extracted from GLCM are used to analyze their performance of the designed network architecture. Extracted GLCM statistical are used as the input attributes of the designed neural network architecture with various learning rule to process the given input. The significant role of extracted GLCM statistical features evaluated with various back propagation training algorithms. By evaluating the role of individual GLCM features, Contrast and Infn. Measure of Correlation 1 gives better result than other GLCM features with various learning rule of back propagation neural network. By evaluating the role of various combinations of GLCM features such as Dissimilarity, Energy, Entropy, Homogeneity, Cluster Shade, Max Probability, Sum of Squares: Variance, Sum average & variance, Sum Entropy, Difference Variance & Entropy produces improved performance with Gradient Descent with Adaptive Learning rate learning algorithm amongst other learning rules.

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