Varieties Classification into Plain, Patterned and Un-patterned from Fabric Images

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Abstract

The presented work gives a methodology to classify fabric images as plain, patterned and un-patterned. Discrete Wavelet Transform is applied and wavelet features are extracted. Feed Backward Selection Technique is used in the feature selection phase. Two prediction models, namely, Support Vector Machine and Artificial Neural Network are used. The overall classification rates of 81% and 86.5% are obtained for fabric types using Support Vector Machine and Artificial Neural Network classifiers. The classification rates for varieties of non-plain fabric images are found to be 84% and 88% respectively.

Keywords: *Plain, Pattern, Un-pattern, Wavelets, Feature extraction, Fabric type*

INTRODUCTION

Image processing is an interdisciplinary field, concerned with the extraction, analysis and understanding of useful information from the input images. It is used in many fields, such as, agriculture, industry, biological field, medical field and the like. The textile industry play important role to Indian economy and also in the international economy, contributing through its export earnings. India is the world's second largest producer of textiles which is next to China. The various forms of textiles are fabrics, medical textiles, geo-textiles, agro-textiles, etc. India is one of the largest producers of cotton in the world. We find good resources of fibres like wool, polyester, silk, jute, denim, etc. The different fabric materials have different natural colors and textures. The type and quality of the fabric materials play an important role in textile, apparel industry, fashion designing, etc.

The fabric materials are available as plain and non-plain types. In non-plain fabric materials, we have patterned and un-patterned fabric varieties. Sample images of plain, patterned and un-patterned varieties are shown in Figure1.

(a)

(b)

(c)

Figure 1:*Varieties of Fabric Images, (a) Sample Images of Plain Fabric, (b) Sample Images of Patterned Fabric, (c) Sample Images of Un-Patterned Fabric.*

The work is carried out to classify the fabric images into two types as plain and non-plain. The non-plain fabric images are further classified into two varieties, namely, patterned and un-patterned.

The remaining part of the paper is organized into four sections. Section two contains the literature survey carried out related to the proposed work. Section three contains proposed methodology, Feature extraction using DWT, Feature selection using BFST and two different approaches to classify the fabric images and results. Section four contains discussion of results obtained using two approaches. Section five contains the conclusion of the work.

Literature Survey

We have carried out a literature survey and the gist of papers cited during the survey is given as under.

[Zhong, Xiang, *et al.*, 2018] have proposed a paper on vision based portable yarn density measure method for a single colored woven fabric.A portable yarn density measurement system is developed. A DFT is used to compute the density of the woven fabric images. The fabric images are collected using a high resolution smart-phone. The results obtained state that, the system is robust to meet fabric industry requirements [1].

[*Khan, Babar, et al.*, 2017] presented a paper on fabric weave pattern and yarn color recognition where, a deep ELM network is applied.A model for fabric weave pattern descriptor is used for computer vision. The proposed methodology is biologically plausible. The performance of the proposed method shows that, models provide fast, reliable, accurate and cost-effective solution for industrial automation [2].

[*Gupta, Dipalee and Siddhartha Choubey*, 2015] presented a paper on DWT for image processing, where, the comparison of the performance of DWT like Haar Wavelet is proposed. It presents a wavelet to implement in a still image compression system. The main objective of the work is the investigation of still image compression of a gray scale image using the wavelet theory. The proposed methodology gives good reference for

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developers to select a proper wavelet compression system for their applications [3].

[*Doost, et al.*, 2013] have presented a paper on texture classification with local binary patterns using continuous wavelet transformation. A new algorithm based on the continuous wavelet transformation and local binary patterns is proposed. Two experiments are carried out to prove the worth of the developed algorithm. The database considered to carry out experiments are Brodatz database. It is stated that, the proposed method is very good and efficient to classify texture image [4].

[*Ananthavaram, RK Rao, et al.*, 2012] presented a work on "An automatic defect detection of Patterned Fabric", in which, the RB method and independent component analysis are used.The main objective of presented work is to find independent components of regular bands method of patterned fabric to defect defects. ICA that solves the problem of defect detection is proposed. The proposed method along with RB method is used to enhance the quality and efficiency of the fabric material [5].

[*Ren et al.*, 2012] presented a paper on "Comparative analysis of ANN and SVM"where, a new method, namely balanced learning with optimized decision making is used to enable effective learning. It is observed that, even though the ANN classifier outperforms SVM, the performance of two classifiers give different results when balanced learning and optimized decision making methods are used. The work gives the effectiveness of proposed method in classifying the clustered micro calcification [6].

[*Kumar, et al.*, 2012] have presented a paper on importance of statistical measures in image processing. The comprehensive study of many statistical measures and their applications are discussed. Majority of statistical measures are simulates and reviewed the existing applications. Comparative analysis is carried out to simplify the selection of statistical parameters for various image processing techniques, namely, image enhancement, restoration, de-noising,edge detection etc.

[*Hu, Haifeng*, 2011] have presented a DWT- based illumination normalization approach for face recognition with varying light intensity conditions. It uses three methods, namely, DWT-based denoising technique, smooth version of the input image obtained by applying the inverse DWT, a multi-scale reflectance model presented for the extraction of illumination invariant features. It is shown that, the advantages of the proposed method preserve the illumination discontinuities during smoothing of an image.

[*Zhongwei He, et al.*, 2011] proposed a paper on "Digital image splicing detection based on Markov features in DCT and DWT". In this work, a Markov based method is presented for the detection of specific artifact. The features are extracted using DWT to characterize the three types of dependencies among wavelet coefficients. A feature selection technique SVM-RFE is used during feature reduction phase. SVM classifier is used to classify the images. The experimental results show that, the proposed method gives better results than some state-of-the-art methods.

[*Rohini S., et al.*, 2010] have presented a paper on interpolation of images using DWT.A novel way of applying DWT and IDWT by non-uniform down-sampling or up-sampling of the images to achieve partially sampled versions is proposed. The partially sampled versions are then aggregated to achieve the final variable scale interpolated images. The non-uniform down- or up-sampling is a function of the required interpolation scale. The interpolated images are reconstructed using the visual comparison and statistical parameters. The approach performs better when compared with bi-linear and bi-cubic interpolation techniques.

[*Asamwar, Rohini S, et al.*, 2008] proposed a paper on computation of variable size interpolated versions of an image. It uses DWT with Haar wavelets. In the proposed method, a new method of applying DWT and IDWT in a piece-wise manner is presented to achieve partially sampled versions. The work focuses on the computation of variable-size images at less computational load. This is achieved without compromising with the quality of image. The proposed method is found to perform better when compared with bi-linear and bi-cubic interpolation methods.

From the literature survey, it is observed that, the work related to fabric defect detection, fabric texture analysis, yarn hairiness determination of foreign fibers in fabric images is carried out. Also, the work on yarn density measurement, applications of image analysis techniques for textile identification and the like is carried out. The morphological features, texture features, color and pixel intensities, etc. are used.In fabric materials, identifying the pattern of fabric is also important as people prefer varieties of designs with different patterns. Knowing the fabric types as plain, patterned and un-patterned fabric, finds many applications, namely, online purchase of fabric, cost estimation and the like. Thus, the motivation for the proposed methodology.

Proposed Methodology

The proposed work comprises of four phases, namely, Pre-processing, Feature extraction, Feature selection and SVM/ANN based classification. Different phases used in the work are shown in Figure2.

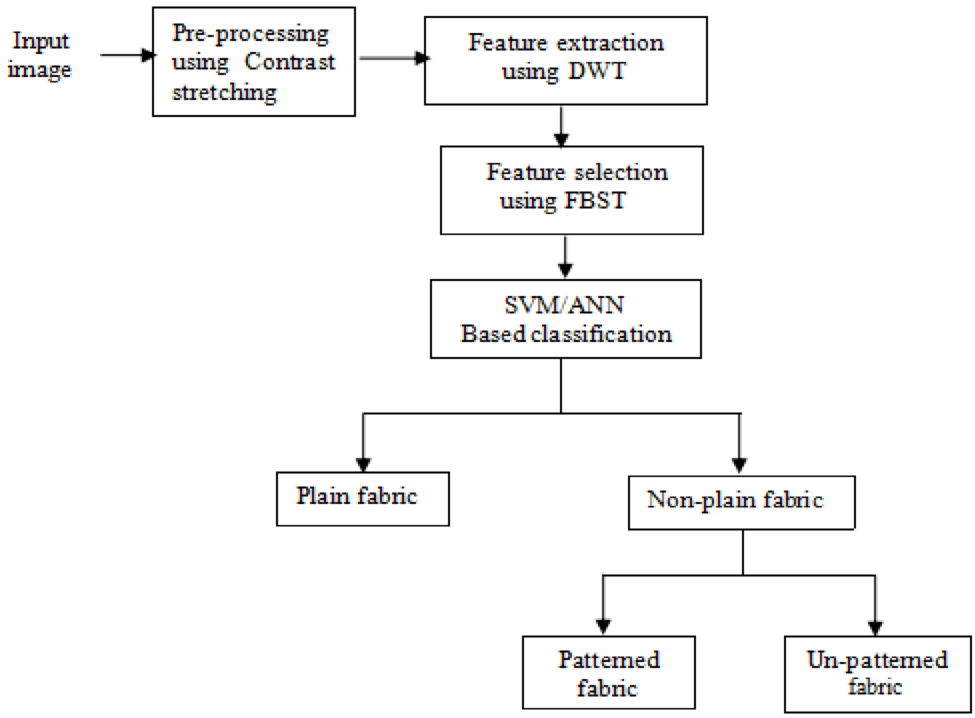


Figure2:*Phases in the Proposed Methodology.*

Varieties of plain, patterned and un-patterned fabric images are captured using a high resolution digital camera of 32 Mega pixels under a constant natural light intensity of 1000 Lux. A fixed distance of 0.5 metre is maintained while capturing the images. The images are collected by visiting textile industries and garment shops. The total number of images of plain and non-plain fabric images collected are given in Table 1.

Table 1:*Varieties of Fabric Images*

Fabric Type	Count	Total Count
Plain	100	300
Patterned	100	
Un-patterned	100	

Pre-processing:

The images are scaled to 100*100 from their original size. The contrast stretching is applied to the input image to enhance the quality of fabric images. This gives better feature values and helps in the process of feature extraction. The images before and after contrast stretching are shown in Figure 3.

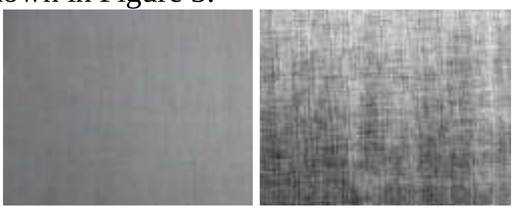


Figure 3:*Image Before and After Contrast Stretching.*

Feature extraction using DWT:

The plain fabric images contain single color and do not have pattern. But, the non-plain fabric images contain two or more colors. The patterned fabric image is an arrangement of repeated decorative designs where in, the un-patterned fabric images contain random arrangement of objects. In un-patterned fabric images, there is no regular appearance of design. Thus, the patterned and un-patterned fabric images have different visual characteristics. Wavelets are used to represent inputs such as curves, images etc. Hence, the Discrete Wavelet Transform (DWT) is applied to identify the variations in the fabric design. Discrete wavelet transform function with scale parameter j and shift parameter k used is given in expression (1)[12].

$$f(t) = \sum_{j\,k} f(t) 2^{j/2} \Psi(2^j t - k) \qquad (1)$$

The approximation and detail coefficients (cA, cD) are extracted from the images. The features, namely, variance_w1(F_1), variance_w2 (F_2), mean_w1 (F_3), mean_w2 (F_4), median_w1(F_5) and median_w2 (F_6) are computed for both approximation and detail coefficients. The feature values of 10 sample images for plain and non-plain fabric images are given in Table 2 and Table 3 respectively[7].

Table 2:*Feature Values of Plain Fabric Images.*

Sample images	variance_w1 F_1	variance_w2 F_2	mean_w1 F_3	mean_w2 F_4	median_w1 F_5	median_w2 F_6
1	809.95630	0.807380	209.02126	-0.17233	211.4249	0
2	372.16530	188.8792	87.158688	0.261205	84.14570	0
3	0.095008	0.005433	53.802340	0.002602	53.74011	0
4	95.65880	0.061303	240.03972	-0.05969	241.8305	0
5	142.2681	0.612493	192.23977	-0.05105	195.1614	0
6	202.4942	0.700217	101.39101	0.011583	95.45941	0
7	176.5833	128.1125	126.52714	0.037335	126.5721	0
8	935.4563	7.608413	208.56298	-0.10592	208.5965	0
9	528.3650	1.987356	173.51151	-0.01664	174.6553	0
10	97.18553	0.117135	237.70777	-0.06195	140.4163	0

Table 3:*Feature Values of Non-plain Fabric Images.*

Sample images	variance_w1 F_1	variance_w2 F_2	mean_w1 F_3	mean_w2 F_4	median_w1 F_5	median_w2 F_6
1	4327.8373	140.799835	201.479	-0.02380	205.7680	0.70
2	2276.2800	49.7767489	300.071	0.02909	322.4406	0
3	4903.3798	425.087622	172.249	-0.15344	162.6345	0.70
4	2622.6494	79.5652881	298.804	0.14935	316.0767	0
5	2393.4686	44.8919255	208.239	0.06576	229.1025	0
6	2852.98118	15.2336977	162.860	0.02385	157.6848	0
7	1313.35351	28.1118959	180.453	-0.01428	175.3624	0
8	1296.17343	27.4767024	212.488	0.01937	214.9604	0.70
9	771.014683	4.14586719	213.481	0.02159	223.4457	0
10	1118.70059	115.182135	173.783	-0.13024	165.4629	0

From Table 2 and Table 3, it is observed that, the feature values of F_1 in plain fabric images are smaller, than that of non-plain fabric images. Also, most of the feature values of F_2, F_3, F_4 and F_5 in plain fabric images are smaller, when compared with the non-plain fabric images. Further, it is observed that, the feature values of F_6 in plain fabric images contain only zero elements; where in, the F_6 feature values in non-plain fabric images have few non-zero elements. Hence, these unique features are used to classify the type and variety of fabric images.

Table 4:*Feature Values of Patterned Fabric Images.*

Sample images	variance_w1 F_1	variance_w2 F_2	mean_w1 F_3	mean_w2 F_4	median_w1 F_5	median_w2 F_6
1	4903.37980	425.08762	172.2492	-0.15344	162.6345	0.70
2	2622.64948	79.565288	298.8044	0.14935	316.0767	0
3	2393.46864	44.891925	208.2398	0.06576	229.1025	0
4	9235.30671	119.84313	194.0860	0.19209	184.5548	0
5	310.794603	94.333082	82.08309	-0.03508	80.61017	0
6	4327.83730	140.79983	201.4794	-0.02380	205.7680	0.70
7	2289.32253	287.98125	180.2451	0.27346	176.0695	0
8	2125.54652	68.433446	166.0404	0.05053	161.2203	0
9	638.475127	6.3987569	138.3963	-0.01191	137.8858	0
10	4222.76765	121.79247	168.2848	-0.17135	161.2203	0.70

Table 5:*Feature Values of Patterned and Un-patterned Fabric Images.*

Sample images	variance_w1 F_1	variance_w2 F_2	mean_w1 F_3	mean_w2 F_4	median_w1 F_5	median_w2 F_6
1	1114.35078	109.4018	172.6415	-0.09626	162.6345	0
2	1514.17404	10.34296	189.3726	0.02234	193.7472	0.70
3	3168.00182	61.64025	176.1253	0.00273	182.4335	0
4	2852.98118	15.23369	162.8602	-0.02385	157.6848	0
5	1313.35351	28.11189	180.4536	-0.01428	175.3624	0
6	1296.17343	27.47670	212.4886	-0.01937	214.9604	0
7	771.014683	4.145867	213.4815	0.02159	223.4457	0
8	1118.70059	115.1821	173.7834	-0.13024	165.4629	0
9	3049.61496	34.67605	156.5323	-0.04846	144.9568	0
10	419.970179	7.079545	72.54324	0.08637	65.76093	0.70

From Table 4 and table 5, it is observed that, most of the feature values of F_2, F_3, F_4 and F_5 in patterned fabric images are larger than feature values of un-patterned fabric images. Also, the feature values of F_6 in patterned fabric images have more number of non-zeroes, when compared with, the un-patterned fabric images.

Hence, these features help us to classify the patterned and un-patterned varieties of fabric images.

Feature Selection Using FBS Technique

The feature selection is carried out using Feed Backward Selection Technique (FBST). The classification rates computed using SVM and ANN classifiers are given in table 6. In this technique, initially, the classification rate is computed using the feature set {F_1, F_2, F_3, F_4, F_5, F_6}. In the next step, the accuracy is computed by eliminating one feature each time. Further, the feature set {F_1, F_2, F_3, F_4, F_5}, containing five features, that gives highest classification rate is selected. This process is repeated till the feature set {F_4, F_3} is reduced to feature set {F_3} containing single feature.

Table 6:*Classification Rates with Combination of Features.*

Features	**Classification rate**	
	SVM	**Neural network**
F_1+ F_2+F_3+F_4+F_5+F_6	81	84
F_1+ F_2+F_3+F_4+F_5	**81**	**84**
F_1+ F_2+F_3+F_4	78	82
F_2+ F4+F_3	72	76
F4+ F_3	40	52
F_3	30	46

From the Table 6, it is observed that, the feature sets {F_1, F_2, F_3, F_4, F_5} and {F_1, F_2, F_3, F_4, F_5, F_6} are found to give same and maximum accuracy. But, elimination of features in the further steps decreases the classification accuracy. Hence, it is identified that, the elimination of feature F6 does not affect the rate of classification. But, the removal of any feature other than F6, decreases the classification rate. Hence, the feature set {F_1, F_2, F_3, F_4, F_5} is selected in the classification process.

CLASSIFICATION

The prediction models namely, support vector machine (SVM) and artificial neural network (ANN), are used to classify the type and variety of fabric images. The parameters, namely, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are used to compute metric values. The metric values, namely, precision, recall, F1 Score and accuracy are calculated using the equations (2), (3), (4) and (5).

$$\mathrm{Precision} = TP/(TP+FP) \tag{2}$$

$$\mathrm{Recall} = TP/(TP+FN) \tag{3}$$

$$F_1\ Score = 2*(\mathrm{Recall}*\mathrm{Precision})/(\mathrm{Recall}+\mathrm{Precision}) \tag{4}$$

$$\mathrm{Accuracy} = \mathrm{TP}+\mathrm{TN}/\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN} \tag{5}$$

The performances of classifiers are measured by computing the metric values. The metrics values of plain and non-plain fabric images using SVM and ANN classifiers are given in Table 7.

Table 7:*MetricsValues of Plainand Non-plainFabric Images.*

Classifier	**Precision**		**Recall**		**F_1 Score**		**Accuracy**	
	Plain	**Non-plain**	**Plain**	**Non-plain**	**Plain**	**Non-plain**	**Plain**	**Non-plain**
SVM	82	90	80	82	76	76	74	88
ANN	92	92	80	90	80	84	83	86

Support vector machine

We have used support vector machine to separate the feature values of two classes. Given training data (x_i, y_i) for i = 1 . . . N, with $x_i \in R^d$ and $y_i \in \{-1, 1\}$, the classifier f(x) that classifies input pattern into suitable class is given by expression (6).

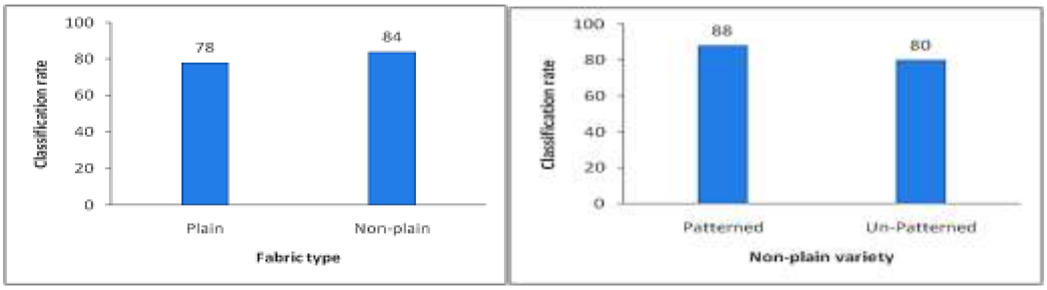
$$f(x_i) = \begin{Bmatrix} \geq 0 & y_i = +1 \\ < 0 & y_i = -1 \end{Bmatrix} \quad (6)$$

In general, a SVM classifier can be represented with expression (7).

$$f_{svm}(X) = W^T \phi(X) + b \quad (7)$$

RESULTS

Experiments are conducted using SVM classifier and the results are given in this section. A plot of classification rates of plain and non-plain fabric images shown in Figure 4(a). The classification rates of 78% and 84% are obtained for plain and non-plain fabric images. The overall classification rate of 81% is obtained. The classification rates for varieties of non plain fabric images are shown in Figure 4(b). The classification rates of 88% and 80% are obtained for the same.



(a) (b)

***Figure 4:**Classification Rates (a) Types of Fabric Images, (b) Varieties of Non-plain Fabric Images.*

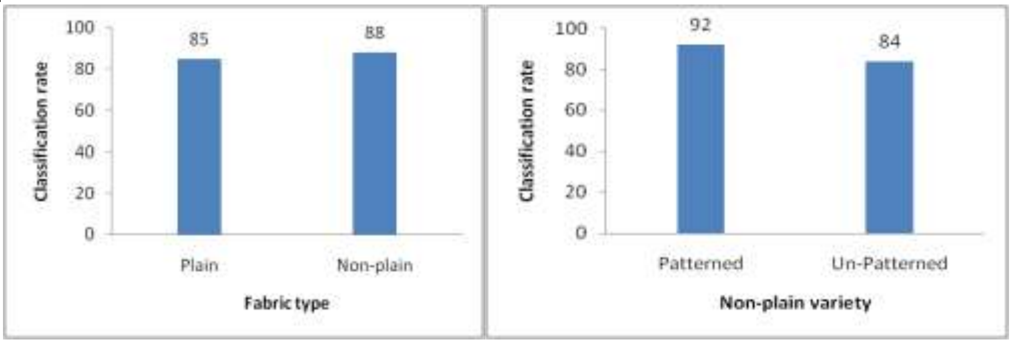
ANN Based Classifier

ANN classifier with back propagation learning algorithm is used. Feature vector X_i contains six parameters which are given as input to the ANN. It is applied in two levels. Initially, ANN classifies fabric images into two types as plain and non-plain. In the next level, the non-plain fabric images are categorized into their respective varieties producing two outputs as shown in Fig.2. Three hidden layers containing ten nodes in each layer are used to predict two output targets.The output of a neuron z is determined using expression (8).[10]

$$z = g(W^T X - b) = g\left(\sum_{i=1}^{d} W_i X_i - b\right) \quad (8)$$

RESULTS

The classification rates of plain and non-plain fabric images Using ANN classifier are shown in Figure 5(a). The classification rates of 85% and 88% are obtained for plain and non-plain fabric images. The overall classification rate of 86.5% is obtained. The classification rates of non-plain fabric varieties are found to be 92% and 84% and are shown in Figure 5(b).



(a) (b)

***Figure 5:**Classification Rates (a) Types of Fabric Images, (b) Varieties of Non-Plain Fabric Images.*

DISCUSSION

It is observed that, the classification rate of non-plain fabric images is more than the plain fabric images. But, in case of non-plain fabric images, the accuracy of patterned fabric images is found to be greater, when compared with un-patterned fabric images. Further, it is observed that, the ANN model gives better classification rate than the SVM model to classify the fabric type and variety. Hence, ANN prediction model is found to be better classifier than SVM model.

CONCLUSION

The proposed methodology is used to classify plain, patterned and un-patterned fabric varieties. The ANN classifier is found to give better results. The classification rates for plain and non-plain fabric images are found to be 81% and 84% using SVM classifier. The classification rates for varieties of non-plain fabric images are 88% and 80%. The classification rates for plain and non-plain fabric images are found to be 85% and 88% using ANN classifier. The classification rates for varieties of non-plain fabric images are found to be 92% and 84%. The work finds applications in online purchase of fabric, quality analysis, cost estimation and the like.

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