Texture based Classification of Fabric Material

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Fabric recognition faces several challenges due to its reliance on manual visual inspection. Early machine learning systems also rely on handcrafted features, which are time-consuming and error-prone operations.As a result, an automated fabric classification system is required to boost productivity. This study provides a system based on data gathering and transfers learning for fabric categorization and recognition. Fabric texture features are extracted using color, brightness, GLCM, and Gabor texture features, which are then classified using the K-Nearest Neighbors Classifier.

Keywords: Fabric Identification, Texture, Feature Extraction, GLCM , Gabor filter, Distance measure, K-Nearest Neighbors Classifier, Accuracy

1 Introduction

The styles based on the fabrics are a mix of different ones. There appears to be no shape in location for handling a huge quantity of fabrics to avoid growing or creating objects which can be comparable to people who have formerly been developed fabric weave sample identification on the thread stage is traditionally done manually within the fabric laboratory with human eyes, at the same time as it's far an critical step earlier than material manufacturing [25]. This technique is an inefficient time-ingesting effect on inspectors' know-how and experience. The structural houses of a cloth, inclusive of weave pat-terns, material counts, and thread twist characteristics, together with twist orientations and angles, are

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used to pick out it. In this text, the texture is the most vital issue. The writer hired GLCM and Gabor clear out techniques to extract texture features, which then mixed with shade and luminance feature extraction approaches to improve. Cotton, crepe, rayon, georgette, synthetic, wool, linen, and silk had been many of the eight exceptional cloth instructions used on this have a look at.
The following sections comprise this paper: The second section provides a quick overview of the relevant studies. In sections 3 and 4, dataset and feature extraction approaches are discussed. The K-Nearest Neighbors Classifier is explained in section 5 utilizing various distance algorithms. Section 6 contains results and discussions. Section 7 contains conclusions.

2 Literature Review

Various algorithms for encoding fabric images to feature vectors have been proposed. Ravandi and Toriumi [4]. hired Fourier rework to assess cloth appearance traits Consisting of directionality, sticking out thread mass, and thread locating in a plain weave. Nishimatsu T. [3] evolved computerized recognition of weave kinds with the aid of part enhancement, Thresholding, improvement, patchwork aligning, interlocking and flattening. Xu B [5] defined strategies for the usage of FFT to pick out weave styles, material count numbers, and cloth skewness.To represent fabrics, Suciati N [18] used fractal-based texture feature, HSV features. Cao Y [23] suggested a fabric image matching technique based on the KMeans algorithm for creating a bag of visual words. However, a common issue with these approaches that tested on a small dataset their retrieval performance needs to be improved. To categorize 700 textiles images, Jing J [19] devised an approach that included color moments and gist characteristics.

3 Dataset of Fabric Pattern

4000 cloth photos were prepared for the dataset from the online shopping website. The images are 1800 x 1800 pixels. Images are twisted, clipped, reverse and resized into patches before being used for classification. The very last entered image is 224 x 224 pixels. Fig 1 shows Samples images of fabric material.

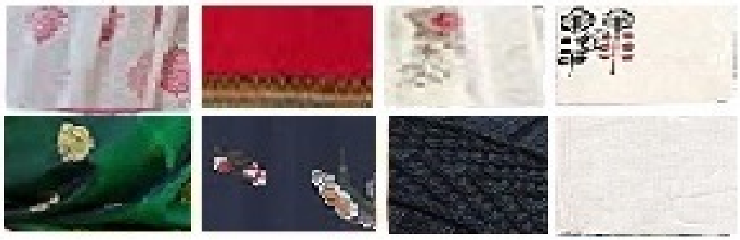

Figure 1: Samples images of fabric material

4 Feature Extraction Technique

4.1 Color and Luminance Extraction techniques

Every color is made from three primary hues: red, green, and blue [20]. Primary 3 colour additives are used in this experiment to assemble histogram-based totally characteristics for every coloration channel. These statistical values were used to find the picture magnificence.Whereas, Luminance gives brightness statistics of an picture with out coloration. [21] Increasing or reducing Luminance values make hues lighter or darker, respectively. [21] Luminance, that's defined through,

$$L_{uminance} \leftarrow 0.3R_{edness} + 0.59G_{reeness} + 0.11B_{lueness} \tag{58.1}$$

4.2 Feature Extraction using GLCM and Gabor

Gray Level Co-Occurrence Matrix (GLCM) is a statistical technique that takes texture features from images. Haralik defines fourteen texture features that are extracted from remote sensing picture probability matrices. [1] The author provides six GLCM features. Fig. 2. shows GLCM features of Silk and wool fabric image. Two-dimensional Gabor filter attuned to drawing out texture attributes. The Two-dimensional Gabor is determined as [2]

$$Gabor(A, B; lambda, psi, theta, gamma, sigma) = exp(-\frac{A'^2 + gamma^2 B'^2}{2sigma^2})cos(2\Pi\frac{A'}{lambda} + psi) \tag{58.2}$$

While Gabor is enforced, the topmost retort receives at edges and the component wherein the texture alterations of the image [14] The following Fig. shows Gabor filter applied silk and wool fabric images.

Energy = 0.3684	Energy = 0.2693
Entropy = 6.2641	Entropy = 3.5088
Contrast = 670.1362	Contrast = 235.7435
Homogeneity = 0.0027	Homogeneity = 1.1214e-04
Correlation = 1.1083e-04	Correlation =1.4361e-04
Dissimilarity = 11.8049	Dissimilarity = 4.1909

Figure 2: GLCM features of Silk and wool fabric image.

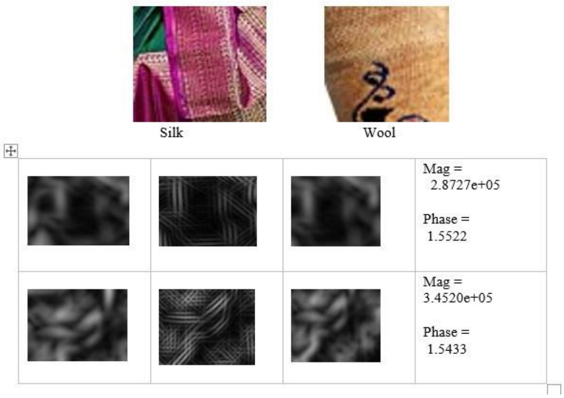

Figure 3: Gabor filter applied on images.

5 K-Nearest Neighbors Classifier

K-Nearest Neighbors examined adjacent and calculated the distance between them using four distinct distance metrics. All distance measures are composited with the classifier to see which distance measure directly finds the image's class and can calculate combining the differences between two objects using the distance function.$Distance(a; t)$, where a and t are objects with M features and $a = a_1, ...a_M, t = t_1, ..., t_M$.

5.1 Euclidean distance

$$distance(a, t) = \sqrt{\sum_{i=0}^{M} a_i^2 - t_i^2} \tag{58.3}$$

5.2 Manhattan distance

$$distance(a,t) = \sum_{i=0}^{M} |a_i - t_i| \tag{58.4}$$

5.3 Chebyshev distance

$$distance(a,t) = max_i(|a_i - t_i|) \tag{58.5}$$

5.4 Minkowski distance

$$distance(a,t) = (\sum_{i=0}^{M} |a_i - t_i|^F)^{\frac{1}{F}} \tag{58.6}$$

Procedure: Look for a class label
Input: k, total number of Nearest Neighbors; The term Test_sample refers to a collection of test samples.Set of training samples,Train_sample
Output: *Class_Label*, class label set of test sample
1. Read DataFile (DataSet_Train)
2. Red DataFile (DataSet_Test)
3. *Class_Label*= {}
4. For each *distance* in *Test_sample* and each *train_sample* in Train_sample do
5.Nearest_Neighbors(*distance*)= {}
6. If (Nearest_Neighbors(*distance*)) < k then
7.Nearest_Neighbors(*distance*)=Distance(*distance*,*train_sample*) ∪Nearest_Neighbors(*distance*)
8. End if
9. If Nearest_Neighbors(*distance*))= k then
10. Break
11. *Class_Label*=TestClass (Nearest_Neighbors(*distance*)) ∪ *Class_Label*
12. End For [24]
Notes :
Nearest adjacent distance k gets from Nearest_Neighbors(*distance*).
Distance(distance,Train_sample) gives forthcomming elements of train_sample.
Label of SampleClass retrive from TestClass (SampleClass)

6 Result and Discussions

More than 4000 images were utilized in an experiment that involved eight fabric classes. Each class has 500 images, all of which are used during the learning and testing process. Three, one, six, and sixteen feature vectors were retrieved using the Color, Luminance, GLCM, and Gabor feature extraction approach. The author compares GLCM and Gabor filter with Color and Luminance characteristics and KNearest Neighbors Classifier in all of the trials and varied the distances of the features. The table describes the outcomes of the experiments. The table below shows how various distance metrics affect recognition accuracy. The classification accuracy was calculated using the confusion-matrix approach. Kazim Yildiz's [22] work executed on fleece fabric images taken via the thermal camera. The KNN implemented distance metrics for categories (Euclidean and correlation). Euclidean and correlation metrics at the category manner compared. Features acquired from texture images aren't variables. So correlation distance metric powerful than Euclidean withinside the manner. In this work, KNN is used to classify Cotton, crepe, rayon, georgette, synthetic, wool, linen, and silk fabric material images. four different distance-vector were used. From that Minkowski, distance vector gives better performance than another distance vector.

classnm	Cotton	Crepe	Rayon	Georgette	Linen	Synthetic	Wool	Silk
Cotton	1200	513	405	413	436	275	647	111
Crepe	263	2020	247	264	239	207	406	354
Rayon	159	443	1680	363	423	227	471	234
Georgette	111	139	362	2106	242	535	192	313
Linen	591	219	430	343	1680	104	511	122
Synthetic	312	234	231	240	224	2320	258	181
Wool	942	310	415	228	570	210	1200	125
Silk	422	122	230	43	186	122	315	2560

Figure 4: Confusion matrix of RGBL+GLCM.

classnm	Cotton	Crepe	Rayon	Georgette	Linen	Synthetic	Wool	Silk
Cotton	2400	123	371	208	126	201	320	251
Crepe	172	2320	222	222	240	356	107	361
Rayon	214	260	1920	330	271	352	205	448
Georgette	221	248	402	1840	354	432	143	360
Linen	228	221	261	317	2080	311	141	441
Synthetic	321	317	478	325	448	1578	171	362
Wool	342	120	153	168	146	154	2720	197
Silk	102	391	193	590	335	616	193	1580

Figure 5: Confusion matrix of RGBL+Gabor.

7 Conclusion

A GLCM-based system can swiftly extract and assess the textures of plain, twill, silky weaves. GLCM is good for analyzing regular texture units, but it's difficult to evaluate textiles with irregular textures with it. It's appropriate for locating the thread in the repeated unit. GLCM describes texture information and characterizes pixel relationships. In this experiment, the GLCM with color and luminance shows higher precision than Gabor for the silk and synthetic fabric.Silk and synthetic have the finner finish, refractive, and brightness in color has a closed view. Gabor channel can productively disengage pictures having districts changing in one of the accompanying properties: Spatial recurrence, the thickness of components, direction, stage, and energy. Gabor channel joined with color and luminance highlights gives higher precision than GLCM executions for the cotton and wool texture. Cotton and wool are faint in shading with a coarse completion.

Table 1: Distance measure of Fabric using different features.

2*Fabric_Class	2*Feature_Vector	Distance_Measures			
		Euclidean	Manhattan	Chebyshev	Minkowski
5*Cotton	RGBL	30	32	36	32
	GLCM	16	18	18	22
	Gabor	58	58	58	56
	RGBL+GLCM	34	44	38	32
	RGBL+Gabor	58	58	58	58
5*Crepee	RGBL	32	32	26	32
	GLCM	42	32	36	36
	Gabor	50	48	50	50
	RGBL+ GLCM	44	34	40	46
	RGBL+ Gabor	48	48	36	52
5*Rayon	RGBL	48	48	48	44
	GLCM	44	44	44	42
	Gabor	56	56	58	58
	RGBL+ GLCM	48	48	48	44
	RGBL+ Gabor	60	58	58	58
5*Georgette	RGBL	42	42	42	42
	GLCM	40	34	34	34
	Gabor	46	50	46	48
	RGBL+ GLCM	42	42	42	42
	RGBL+ Gabor	46	50	46	48
5*Linen	RGBL	32	30	28	28
	GLCM	28	44	40	42
	Gabor	42	42	38	46
	RGBL+ GLCM	30	46	42	44
	RGBL+ Gabor	52	48	40	52
5*Syntheticr	RGBL	44	48	42	42
	GLCM	52	48	54	54
	Gabor	34	54	32	34
	RGBL+ GLCM	60	60	58	50
	RGBL+ Gabor	40	46	38	40
5*Wool	RGBL	16	16	14	16
	GLCM	40	38	38	40
	Gabor	44	40	48	44
	RGBL+ GLCM	64	60	58	54
	RGBL+ Gabor	68	68	68	62
5*Silk	RGBL	48	40	48	40
	GLCM	38	48	44	44
	Gabor	16	18	22	16
	RGBL+ GLCM	58	62	56	56
	RGBL+ Gabor	32	20	40	36

Figure 6: Category wise classification accuracy.

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