Comparative Analysis of Rule Based and K-Nearest Neighbour Approaches for Classification of Different Shades of Basic Colours in Fabric Images

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Abstract
Proposed work presents comparative analysis of rule based and K-nearest neighbour approaches to classify the different shades of basic colours in fabric images. The mean and standard deviation of CIE Lab features of shades of red, green and blue colours are computed. A rule base is designed. An overall recognition rate of 97% is obtained in case of rule based approach. K-nearest neighbour classifier is designed taking into account, the average Lab values. The overall recognition rate of 94% is obtained in case of K- nearest neighbour approach.

Keywords: *Rule based, K-nearest neighbour, lab features, fabric images, feature extraction*

INTRODUCTION
Today, Computer vision and image process (CVIP) techniques are wide employed in business, biology, material science, bioscience. Computer vision applications within the field of textile are taking momentum. The textile business occupies an important place within the Indian economy further as within the international textile economy and contributes well through its exports earnings. Textile exports represent nearly 30% of India’s total exports. India is the Asian country which is world’s second largest producer of textiles after China.

The various varieties of textiles are agro-textiles, geo-textiles, inexperienced chemistry, medical textile etc. Asian country is one in every of the most important producers of cotton yarn round the globe, and conjointly there are sensible resources of fibre like polyester, silk, jute, denim, wool etc.

Connected with material, there are measure several applications attainable, such as, material characterization, internal control, quality assurance, pattern identification, count estimation, material content identification, price estimation, defect detection etc. The color of the material material plays a very important role in fashion industry, fashion coming up with, etc.

Texture is one in all the foremost necessary options employed in characteristic objects or regions of interest in a picture. Once objects have similar texture and color, the identification becomes complicated. The material materials are on the market in several reminder colors and named for convenience of a typical man, like navy blue, light blue, medium blue, turquoise, blue etc. We have got thought of the fundamental colors, namely, red, blue and inexperienced. The reminder these colors have varied hue and saturation. These color options become necessary in recognition. Some shades of basic coloured fabric images and their names are shown in Figure 1 [1–4].

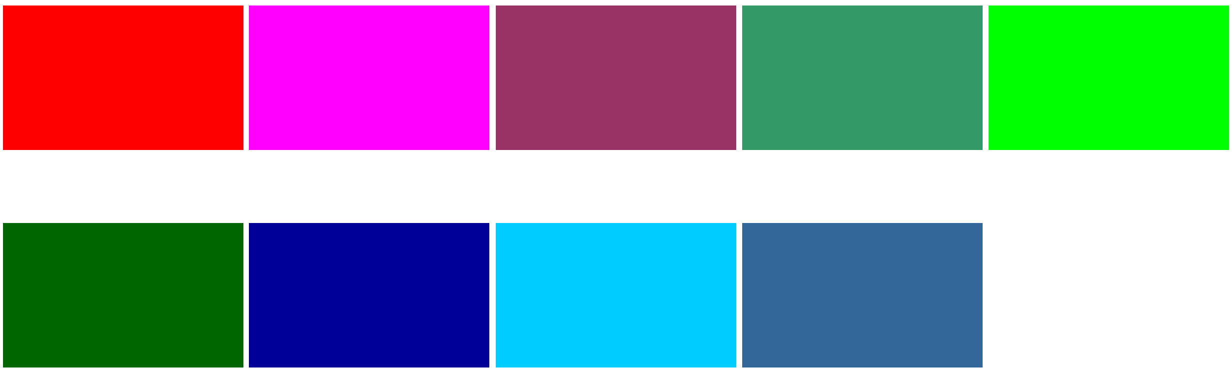

Fig. 1: *Shades of Basic Colour Fabric Images.*

The work is carried out to classify the different shades of basic colours of fabric images. The Lab mean and standard deviation features are deployed. The clue of dominant colour is used, in devising the rules. A rule based approach is developed to classify the given image colour into appropriate shades [5–8].

LITERATURE SURVEY

To know the state-of-the-art of computer applications, we have carried a literature survey. Following is the gist of papers cited during the survey of the literature.

Michael Harville, *et al.*, 2005 have proposed a method on Consistent Image-based measurement and classification of skin color. The paper presents new methods for fast, easy-to-use image colour correction, with specialization toward skin tones, and fully automated estimation of facial skin colour, with robustness to shadows, specularities and blemishes. Each of these is validated independently against ground truth, and then combined with a classification method that successfully discriminates skin colour across a population of people imaged with several different cameras. Evaluation of effects of image quality and various algorithmic choices on classification performance is described [9, 10].

S. Arivazhagan, *et al.*, 2006 have given a paper on fault segmentation in material pictures mistreatment Dennis Gabor riffle remodel. Dennis Gabor riffle remodel is applied to discover the defects in materials. Defects may be mechanically metameric from the regular texture by applying the planned methodology. It is shown that it also can be applied to discover defects on surfaces and materials that have regular periodic texture.

A. M. O. Obiazi, 2009 bestowed a completely unique approach for determination of the insulation classification of Nigerian fabric materials. During this approach, the temperature rise, that electrical machines safely face up to, is set by the limiting temperatures of the insulating materials utilized in them.

Dariush Semnani, *et al.*, 2009 have proposed a method for detecting and measuring fabric pills using digital image processing techniques. This work provides a technique for detecting pills and also measuring their heights, surfaces and volume. An algorithm is developed, which finds pills and then measures their average intensities by three criteria, namely height, surface and volume.

Junmin zhang, *et al.*, 2010 have conferred an approach for identification of animal fibers with riffle texture analysis to extract fiber surface structure options for classifying cashmere and superfine merino sheep wool fibers. Here, the options square measure extracted from brightness variations caused by the shell scale height, form and interval provides a good approach for characterizing totally different animal fibers and after classifying them Rahul Mehta, *et al.*, 2011 have projected a Color-texture based mostly image retrieval system. During this work, color extraction and comparison area unit performed exploitation typical. Color histograms (CCH) and, therefore, the

Quadratic Distance Metric (QDM) and the feel extraction and comparison area unit performed exploitation the thought of Pyramid Structure ripple remodel Model (PSWTM) and, therefore, the euclidian distance.

Shervan Fekri Ershad, 2011 given a paper on color texture classification approach supported combination of primitive pattern units and applied mathematics options. To extend the accuracy of classification, planned approach is dilated to color pictures to utilize the power of approach in analyzing every RGB channels, singly. This approach may be a general one and it might be employed in totally different applications and also the technique has been tested on the stone texture.

Farsi, H, *et al*., 2013 have given a paper on color and texture feature-based image retrieval by victimization hadamard matrix in separate wave rework. During this study, the authors propose a brand new methodology supported combination of Hadamard matrix and separate wave rework (HDWT) in hue-min-max-difference color area. A median normalised rank and combination of preciseness and recall area unit thought of as metrics to judge and compare the projected methodology against totally different strategies. Piotr Szczypinski, *et al*., 2014 have given a paper on texture and color based mostly image segmentation and pathology detection in capsule scrutiny videos. This paper presents associate in-depth study of many approaches to beta analysis of wireless capsule scrutiny pictures (WCE). It is incontestable that versatile texture and color based mostly descriptors of image regions.

Nitin Jain, *et al*., 2014 have projected a way on color and texture feature extraction for Content based mostly Image Retrieval. This paper presents 2 options, color and texture and, therefore, the extraction algorithms. Regularity, radial asymmetry, smoothness and coarseness square measure a number of the feel properties perceived by human eye square measure thought of during this work. Texture feature extraction supported Gabor filter is conferred.

From the literature survey, it is found that, most of the work is applied on characterization and defect detection in material materials. The work on examination of cotton quality is found. The options like color and intensities are thought of. In color recognition, the reminder colors become necessary. Thus, the motivation for the work associated with identification of various reminder basic colors in material materials.

PROPOSED METHODOLOGY

The proposed methodology consists of two phases, namely, feature extraction and classification. The block diagram shown in Figure 2 gives overall approach used to classify the basic colours and their shades in fabric images. We have used two classifiers for the purpose of comparison. In rule based approach, the images are classified into three basic colours. In turn, each of the basic colour fabric images is classified into ten different shades. In K-nearest neighbour approach, the images of basic colours are classified into ten different shades.

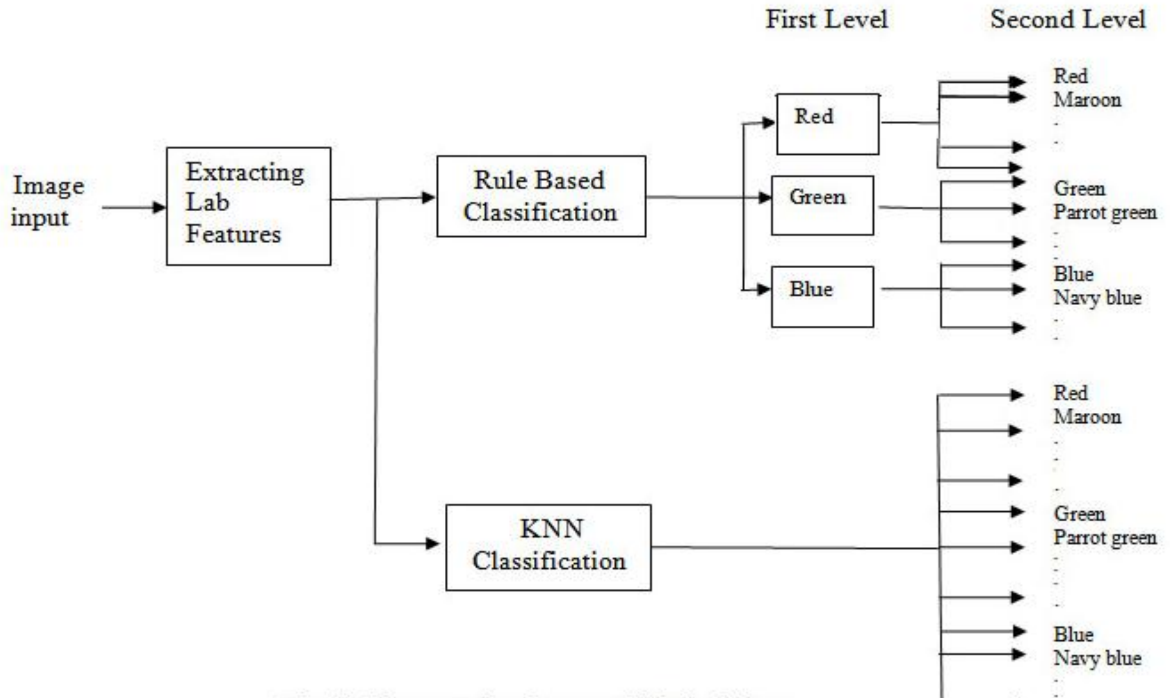

Fig. 2: Phases in the Proposed Methodology.

Different shades of basic colours, namely, Red, Green and Blue are acquired using a digital camera having resolution of 12 Mega pixels. The images are captured with constant light intensity of 1000 lux and a constant object distance of 0.5 meter. We have used 900 images of different shades of basic colours. The images are collected from the garment shops and also from textile industries. The number of images of each of the basic colours considered in the work is given in Table 1.

Table 1: *Number of Basic Colour Fabric Images.*

Basic Colour	Number
Red	300
Green	300
Blue	300

Feature Extraction

The CIE Lab colour model is used in the work. The CIE Lab colour space is better suited to many digital image processing manipulations than the RGB space, which is typically used in image editing programs. The Lab features of images are extracted. It is observed that in the red fabric images, ‘a’ component is predominant compared to ‘L’ and ‘b’ components. The ‘a’ component is smaller than ‘L’ and ‘b’ in green fabric images. In case of blue fabric images, ‘b’ is smaller than ‘L’ and ‘a’. The same observation is found for different shades of basic colours. In order to identify the specific shade, the mean and deviation parameters are obtained. Feature values of different shades of red, green and blue colours are shown in Tables 2–4 respectively. Let L_i mean represent mean of Luminance for the i^{th} shade for i= 1 to 10 and σ_i represent the corresponding standard deviation. Similarly, a_i mean and b_i mean represent the mean values of ‘a’ and ‘b’ components respectively.

Table 2 gives different shades of red colour fabric images considered in the work. It is observed that the a_i mean is maximum for sunset orange and is minimum for chocolate. The L_i mean is maximum for lavender shade and minimum for light pink shade. The L_i mean is found to be minimum for lavender dark and maximum for sunset orange.

Table 2: *Feature Values (L_i Mean, a_i Mean, b_i Mean) for Red Colour Shades.*

S. No.	Shades	L_i Mean	a_i Mean	b_i Mean	Std. Deviation		
					σ L_i	σ a_i	σ b_i
1	Pink	134.14	190.30	164.54	9.21	1.93	6.35
2	Reddish Brown	136.74	170.63	159.60	5.69	10.76	6.38
3	Sunset Orange	139.94	194.39	191.61	4.80	1.38	2.84
4	Lavender Dark	132.39	189.37	123.01	7.65	3.05	33.46
5	Lavender	142.70	177.68	136	3.04	0.17	0.78
6	Chocolate	140.14	141.06	145.29	7.53	18.89	7.78

7	Light magenta	125.70	182.06	142.74	4.78	0.91	0.73
8	Rani pink	130.30	185.20	125.71	2.17	0.41	1.69
9	Red	129.46	191.88	178.18	2.85	3.05	23.81
10	Light Pink	127.55	193.72	122.96	2.41	3.82	19.37

Table 3 gives different shades of green colour fabric images used in the work. It is observed that the L_i mean component is maximum for turquoise green and is minimum for light sea green. The a_i mean component is maximum for cement green shade and minimum for turquoise green shade. Further, the b_i mean component is found to be minimum for turquoise green shade and maximum for yellowish green shade.

Table 3: *Feature Values (L_i Mean, a_i Mean, b_i Mean) for Green Colour Shades.*

S. No. (i)	**Shades**	**L_i Mean**	**a_i Mean**	**b_i Mean**	**Std. Deviation**		
					σ L_i	σ a_i	σ b_i
1	Leaf Green	149.48	106.30	140.60	5.42	2.57	2.43
2	Yellowish Green	149.19	120.00	186.13	15.00	3.18	5.8
3	Light bottle Green	153.60	120.21	130.47	2.82	0.24	0.68
4	Pista Green	149/63	106.19	112.84	5.83	2.65	0.95
5	Sea Green	147.21	108.77	125.14	2.51	1.62	6.58
6	Medium-Aqua Green	153.17	99.96	134.30	2.87	2.04	7.16
7	Turquoise Green	158.62	94.22	110.85	5.00	4.13	1.30
8	Bottle Green	157.59	95.31	166.29	5.31	3.71	18.65
9	Cement Green	156.62	124.00	131.83	5.23	13.22	21.63
10	Light Sea Green	140	110	138	4.62	5.18	7.2

Table 4 gives different shades of blue colour fabric images considered in the work. The L_i mean component for blue, sky blue, light renold blue and bright blue is found to be more when compared with the L_i mean values of other shades. It is observed that, the a_i mean is maximum for dark blue shade and is minimum for light renold blue. Further, it is observed that, the b_i mean is maximum for dark blue shade and minimum for bright blue shade.

Table 4: *Feature Values (L_i Mean, a_i Mean, b_i Mean) for Blue Colour Shades.*

S. No. (i)	**Shades**	**L_i Mean**	**a_i Mean**	**b_i Mean**	**Std. Deviation**		
					σ L_i	σ a_i	σ b_i
1	Sky Blue	145.48	124.20	72.82	4.29	8.26	7.96
2	Light Renold Blue	152.27	110.20	89.85	4.84	9.94	11.45
3	Lavander Blue	141.10	132.62	90.38	3.75	4.04	12.51
4	Renold Blue	150.27	122.10	114.94	5.03	5.98	23.27
5	Ash Blue	152.31	125.29	125.89	6.37	5.30	28.08
6	Blue	142.75	133.16	90.69	3.99	0.96	10.96
7	Ash gray Blue	157.06	125.06	128.10	7.69	4.97	25.38
8	Navy Blue	141.70	130.40	114.88	6.27	1.98	19.36
9	Bright Blue	141.96	148.40	74.62	3.32	5.20	4.78
10	Dark Blue	134.64	134.32	85.41	8.02	1.86	9.39

In rule based classification, the mean and the standard deviation of lab features are used to classify
different shades of basic fabric colours. The Lab_{avg} value is calculated using the equation (1):

$$Lab_{avg} = \frac{\sum_i^n Lab_i}{n} \quad \text{------------------------(1)}$$

Where n represents the number of pixels in an image.

The Mean value (Lab_{Mean}) is computed using the equation (2)

$$Lab_{Mean} = \frac{\sum_1^N Lab_{avg}}{N} \quad \text{-----------------------(2)}$$

N is the number of images of each shade.

The standard deviation (σ) is computed using the equation (3).

$$\text{Standard deviation } (\sigma) = \sqrt{\frac{\sum \left(Lab_{avg} - Lab_{Mean}\right)^2}{N-1}} \quad \text{----------------- (3)}$$

In K-nearest neighbour classification (taking the value of k=1), Lab features are used to classify the different shades of basic fabric colours. The average Lab values are stored in a feature vector table during training phase. The index value associated with each image is also stored in an array. Once, all the differences between Lab feature values of data to be tested and the Lab features stored in feature vector table are calculated, the minimum distance (difference) is computed. The image with zero difference or smallest difference in the average Lab feature value is decided to be correctly recognized image.

Rules based Classification

The set of rules for classifying the basic colours and their different shades is shown in Box 1. Consider the red coloured fabric image. It is observed that the dominant component in Lab mean value is 'a'. Further, the range of Lab values for different shades of basic colours are observed. The mean and the standard deviation are used as features. The rules for classification of red coloured fabric images are given in Box 2. The rules, namely, Rule 1 through Rule 9 are devised taking into consideration the standard deviation. Similarly, the rules for classifying shades of green and blue fabric images are given in Box 3 and Box 4 respectively.

```
if ((a > L)  and (a > b))                                        //Rule 1
        Classify the colour as "Red  colour"
else if ((a< L)  and (a< b))
        Classify the colour as " Green  colour"                   //Rule 2
else
        Classify the colour as "Blue  colour"
```

Box 1: *Rules for Classification of Basic Colours.*

if ((a>L) and (a>b))

if (($L_1 \in [L_1mean \pm \sigma L_1]$) and ($a_1 \in [a_1mean \pm \sigma a_1]$) and ($b_1 \in [b_1mean \pm \sigma b_1]$)) //Rule 1

Classify the colour as " Pink"

else if (($L_2 \in [L_2mean \pm \sigma L_2]$) and ($a_2 \in [a_2mean \pm \sigma a_2]$) and ($b_2 \in [b_2mean \pm \sigma b2]$)) //Rule 2

Classify the colour as " Reddish Brown"

else if (($L_3 \in [L_3mean \pm \sigma L_3]$) and ($a_3 \in [a_3mean \pm \sigma a_3]$) and ($b_3 \in [b_3mean \pm \sigma b_3]$)) //Rule 3

Classify the colour as " Sunset Orange"

else if (($L_4 \in [L_4mean \pm \sigma L_4]$) and ($a_4 \in [a_4mean \pm \sigma a_4]$) and ($b_4 \in [b_4mean \pm \sigma b_4]$)) //Rule 4

Classify the colour as " Lavender Dark"

else if (($L_5 \in [L_5mean \pm \sigma L_5]$) and ($a_5 \in [a_5mean \pm \sigma a_5]$) and ($b_5 \in [b_5mean \pm \sigma b_5]$)) //Rule 5

Classify the colour as " Lavender"

else if (($L_6 \in [L_6mean \pm \sigma L_6]$) and ($a_6 \in [a_6mean \pm \sigma a_6]$) and ($b_6 \in [b_6mean \pm \sigma b_6]$)) //Rule 6

Classify the colour as " Chocolate"

else if (($L_7 \in [L_7mean \pm \sigma L_7]$) and ($a_7 \in [a_7mean \pm \sigma a_7]$) and ($b_7 \in [b_7mean \pm \sigma b_7]$)) //Rule 7

Classify the colour as " Light Magenta"

else if (($L_8 \in [L_8mean \pm \sigma L_8]$) and ($a_8 \in [a_8mean \pm \sigma a_8]$) and ($b_8 \in [b_8mean \pm \sigma b_8]$)) //Rule 8

Classify the colour as " Rani Pink"

else if (($L_9 \in [L_9mean \pm \sigma L_9]$) and ($a_9 \in [a_9mean \pm \sigma a_9]$) and ($b_9 \in [b_9mean \pm \sigma b_9]$)) //Rule 9

Classify the colour as " Red"

else

Classify the colour as " Light Pink"

Box 2: *Rules for Classification of Shades of Red Colours.*

if ((a<L) and (a<b))

if (($L_1 \in [L_1mean \pm \sigma L_1]$) and ($a_1 \in [a_1mean \pm \sigma a_1]$) and ($b_1 \in [b_1mean \pm \sigma b_1]$)) //Rule 1

Classify the colour as "Leaf Green"

else if (($L_2 \in [L_2mean \pm \sigma L_2]$) and ($a_2 \in [a_2mean \pm \sigma a_2]$) and ($b_2 \in [b_2mean \pm \sigma b2]$)) //Rule 2

Classify the colour as "Yellowish Green"

else if (($L_9 \in [L_9mean \pm \sigma L_9]$) and ($a_9 \in [a_9mean \pm \sigma a_9]$) and ($b_9 \in [b_9mean \pm \sigma b_9]$)) //Rule 9

Classify the colour as "Cement Green"

else

Classify the colour as " Light Sea Green"

Box 3: *Rules for Classification of Shades of Green Colours.*

```
if ((b>L)  and (b<a))
    if ( (L1∈ [L1mean ± σ L1]) and ( a1 ∈ [a1mean ± σ a1] ) and ( b1 ∈ [b1mean ± σ b1 ] ))          //Rule 1
            Classify the colour as " Sky Blue"
    else  if ( (L2 ∈ [L2mean ± σ L2] ) and ( a2 ∈ [a2mean ± σ a2] ) and ( b2 ∈ [b2mean ± σ b2 ]))      //Rule 2
            Classify the colour as " Light Renold Blue"
:
    else  if ( (L9 ∈ [L9mean ± σ L9]) and ( a9 ∈ [a9mean ± σ a9] ) and ( b9 ∈ [b9mean ± σ b9 ]))       // Rule 9
            Classify the colour as " Bright Blue"
    else
            Classify the colour as " Dark Green"
```

Box 4: *Rules for Classification of Shades of Blue Colours.*

K-Nearest Neighbour Classification

In K- nearest neighbour classification, Lab features are used to classify the different shades of basic fabric colours. The Lab features are stored in a feature vector table during training phase. During testing phase, distances between Lab features of image to be tested and the Lab features stored in the feature vector table are calculated using the Euclidian distance formula given in equation (4).

$$\text{Dist} = \sqrt{\sum (TestData - TrainData)^2} \quad \text{--(4)}$$

RESULTS AND DISCUSSION

In the classification process, 70% of samples are used for training and 30% of samples are used for testing. A graph of recognition rate for basic colours in case of rule based classification and KNN classification is shown in Figure 3. The average recognition rate of basic colours is found to be 97% and 94% respectively. It is observed that, the recognition rate using rule based classifier is more compared to KNN classifier.

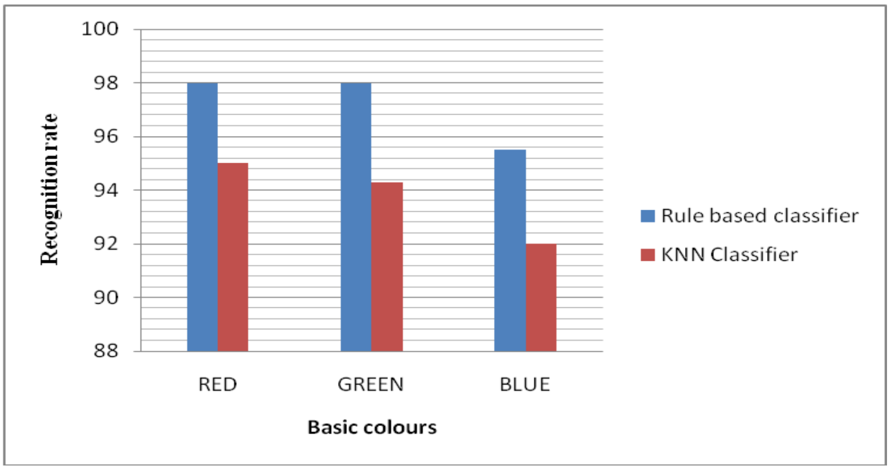

***Fig. 3:** Recognition Rates for Basic Colours using Rule Based Classifier and KNN Classifier.*

A plot of recognition rate for different shades of red colour using rule based classification and KNN classification is shown in the graph shown in Figure 4. The average recognition rate is found to be 98% and 95% respectively. The recognition rate for lavender shade is less using KNN classifier.

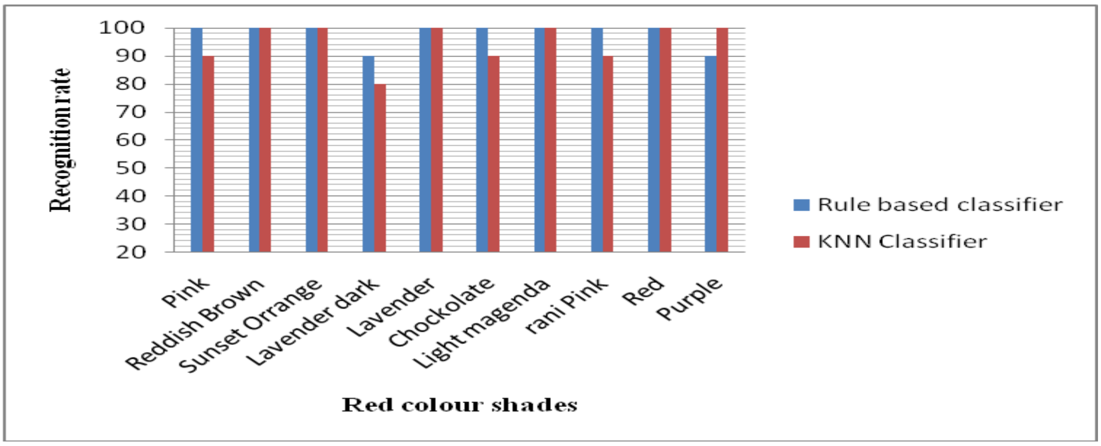

***Fig. 4:** Recognition Rate for Shades of Red Colour using Rule Based Classifier and KNN Classifier.*

A plot of recognition rate for different shades of green colour using rule based classification and KNN classification is as shown in Figure 5. The average recognition rate is found to be 98% and 94.3% respectively. The recognition rates for yellowish green and medium aqua green are found to be minimum in case of rule based classifier.

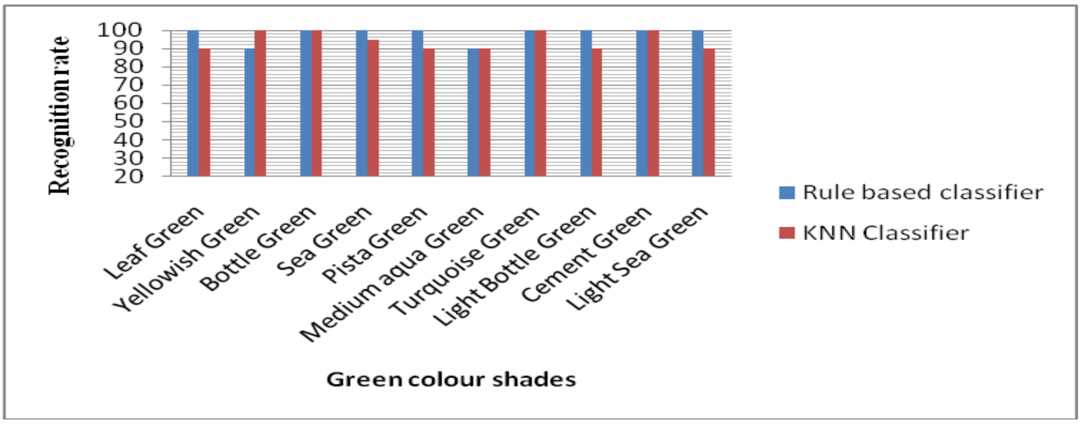

***Fig. 5:** Recognition Rate for Shades of Green Colour using Rule based Classifier and KNN Classifier.*

A plot of recognition rate of different shades of blue colour using rule based classification and KNN classification is shown in Figure 6. The average recognition rate is found to be 95.5% and 92% respectively. In case of rule based classifier, the recognition rate of bright blue is found to be minimum. The recognition rates for renold blue and ash blue shades are found to be minimum in case of KNN classifier.

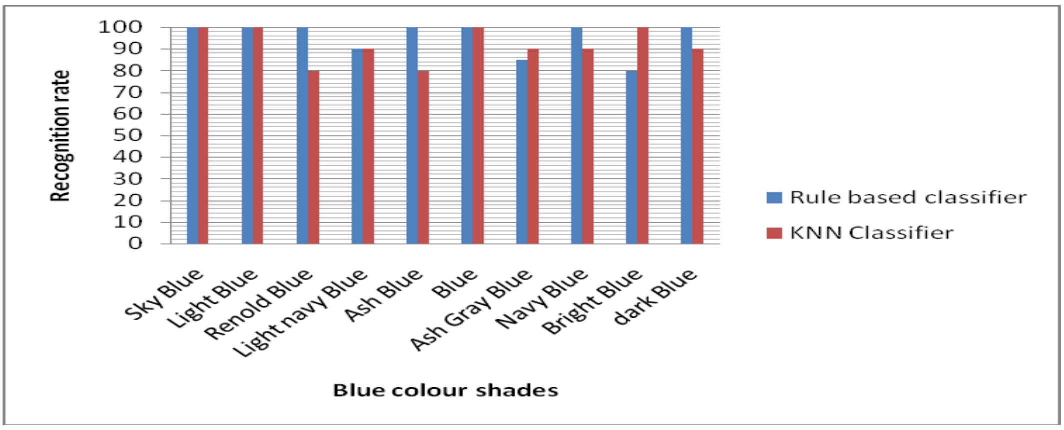

***Fig. 6:** Recognition Rate for Shades of Blue Colour using Rule based Classifier.*

It is observed that, the rule based classifier gives better results to classify the basic colours into red, green and blue colours compared to K-nearest neighbour classifier. The results are shown in Figure 3. Further, it is found that rule based approach gives better recognition rates to classify different shades of red, green and blue colour fabric images. The recognition rates for shades of red, green and blue fabric images using rule based approach and K-nearest neighbour approach are shown in Figures 4–6 respectively.

CONCLUSION

The proposed methodology is used to classify the different shades of basic colours in fabric images. The recognition rate of basic colours is found to be 97% using rule based classifier. The recognition rates for the different shades of red, green and blue colours are 98%, 98% and 95.5% respectively using. The recognition rate for shades of basic colours is found to be 94% using K-nearest neighbour classifier. The recognition rates for the different shades of red, green and blue colours are 95%, 94.3% and 92% respectively. The work finds applications in automation in apparel industry, namely, readymade garments, knit-ware, formal-ware, cotton dress materials etc.

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