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Pattern Recognition of Clothes For Visually Impaired People and Colour Analysis of Clothes

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ABSTRACT

It's a challenging task for visually impaired people to recognize colours and pattern. As the rotation, illumination, and scaling of the images makes it complicated for identifying the exact pattern and colour. We have developed a system in which the images of four different pattern (plaid, striped, pattern-less, irregular) and around 11 colours can be identified with high accuracy up to 97%. This identification is done using radon signature descriptor and the Fuzzy C-means algorithm, which made it easy to extract the pattern from image. The support vector machine, helps in comparison with the database stored already. Our proposed system would help a lot for enriching the lives of the visually impaired people and helps them to live independently.

Keywords: Radon signature algorithm, fuzzy c-means algorithm, support vector machine, DWT

1. INTRODUCTION

According to world health organization,there are around 161 million people who are visually impaired people and around 36 million are blind. These people are struggling a lot in depending each and every for their needs. One of the basic need is choosing colour or pattern of a shirt they wear. The existing method have lots of problems in identifying the pattern and colour of an image due to rotation, scaling, illumination and intensity of the image. We observed that traditional texture finding system do not have higher levels of accuracy as compared to our proposed system with reference to cloth pattern recognition.

Our proposed system helps the visually impaired people to easily identify the colour and pattern. It is done in a very simple way. It just need a image of the cloth which the user is interested in and to be loaded to the system where the radon signature algorithm and the fuzzy c-means are readily identifies and extracts the pattern that the cloth image has and give the output in a sound format from the speakers connected to the computer where it tell the pattern of the image as striped, pattern-less, irregular or plaid and the colour(red, green, blue, orange, black, grey, white, purple, pink, cyan) of the image is displayed on the screen

Section II deals with the related works of our proposed work and section III describes about the proposed work and how it works and in section IV experimental results are discussed and section VI concludes the paper.

2. RELATED WORKS

Assistive system has been playing a major role helping the people in need.There are so many assistive system came up which helped the visually impaired people in day-to-day life. Clothing recommendation done by Hidayati et al suggests what kind of dress should be worn for blind people. But this system does not provide with any colour or cloth pattern, which would help them, decide what kind of colour and pattern to wear.

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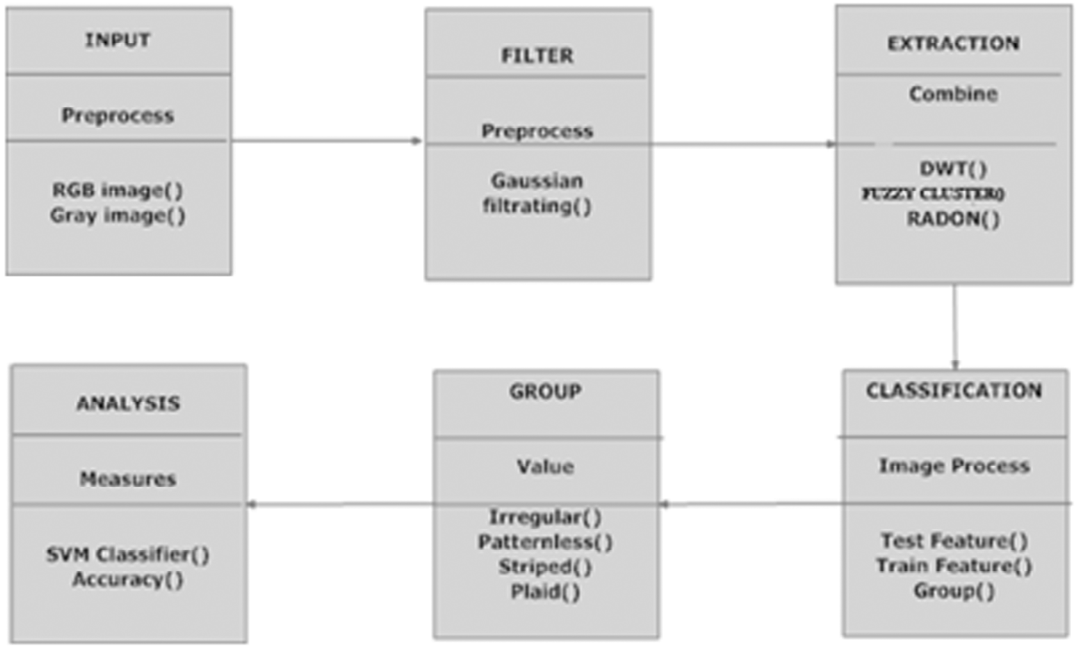

Figure 1: The processes involving the cloth pattern recognition

Pattern gives crucial data to numerous picture classification processes including cloth pattern recognition. Some early research on pattern recognition [1], [2], [10], [11], [12], [13] focused on the examination of worldwide two-dimensional (2D) picture analysis incorporating into plane revolution and scaling. Because of the absence of invariance to general geometric changes, these methodologies cannot adequately represent pattern images with huge 3-D changes, for example, perspective change and non-rigid texture distortion. Multifractal examination [15], [14] has accomplished great versatility to 3-D disfigurements. Texture representations in view of this strategy advantage from the invariance of fractal measurements to geometric

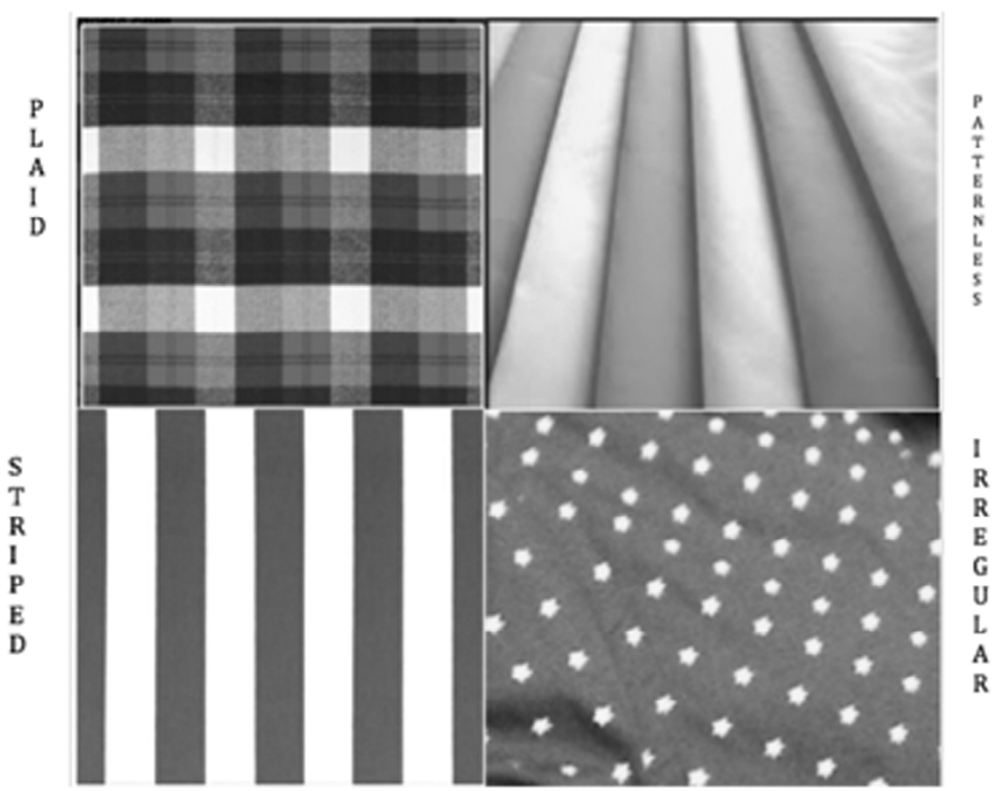

Figure 2: All the pattern which are detectable in this process

changes. For example, multi-fractal range (MFS) proposed by Xu et al. [8] joined fractal measurements of pixel sets gathered by thickness capacities and introduction formats. Numerous elements can catch properties of a picture in various perspectives. In the event that distinctive elements are profoundly corresponding, their blend will enhance the component representation. For instance, Lazebnik et al. [11] proposed a texture representation technique in light of relative invariant finders (Harris and Laplacian) and descriptors (RIFT and SPIN). Zhang et al. [9] likewise consolidated scale invariant component change (SIFT) and SPIN for texture grouping.

Dissimilar to existing conventional pattern images, cloth designs contain much bigger intra-class varieties inside every pattern variety. Albeit numerous PC vision and picture handling systems have been produced for texture investigation and classification, customary pattern examination strategies can't viably perceive attire designs. Here, we build up a camera-based framework particularly for outwardly debilitated individuals to help them perceive dress examples and hues.

3. FEATURE EXTRACTION OF IMAGE FOR CLOTH PATTERN RECOGNITION

Clothing pattern has a very few basic primitives. Due to large intra-class variation in properties like directionality and statistical properties which can be extracted using global features and are added up the local features which gives us the structural information. Coming up, we explain about the radon signature and fuzzy cluster(k-means) features

3.1. Radon Signature

Directionality property of an image plays a main role in finding a pattern of an image. For example we see the pattern of plaid and striped where both are anisotropic and for pattern-less and irregular it is isotropic. This directionality plays a important role in finding out the pattern and it is extracted using Radon Signature.

Radon Signature (RadonSig) is based on the Radon transform[8] which is commonly used to detect the principle orientation of an image. The image is then rotated according to this dominant direction to achieve rotation invariance. The Radon transform of a 2-D function f (x, y) is defined as

$$R(r,\theta)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)\,\delta(r-x\cos\theta-y\sin\theta)\,dx\,dy \tag{1}$$

where r is the perpendicular distance of a projection line to the origin and θ is the angle of the projection line. To retain the consistency of Radon transform for different projection orientations, we compute the Radon transform based on the maximum disk area instead of the entire image. R (r, θ) in (1) is a function with two parameters of r and è.The directionality of an image can be represented by Var (r, θ_i), the variances of r under a certain projection direction θ_i:

$$Var(r,\theta_i)=\frac{1}{N}\sum_{j=0}^{N-1}\left(R(R_j,\theta_i)-\mu(r,\theta_i)\right)^2 \tag{2}$$

$$\mu(r,\theta_i)=\frac{1}{N}\sum_{j=0}^{N-1}\left(R(r_j,\theta_i)\right) \tag{3}$$

where R (rj , θ_i) is the projection value at perpendicular distance of rj and projection direction of θi; μ (r, θi) is the expected value of R (r, θi); N is the number of sampling bins in each projection line. The RadonSig is formed by the variances of r under all sampling projection direction [Var(r,θ0),Var(r,θ1),...,Var(r,θT – 1)] where T is the number of sampling projection directions. It determines the feature dimension of Radon Signature. As the RadonSig is a nonsparse representation, we employ the L2-norm to normalize the feature vector.

The plaid designs have two rule introductions; the striped ones have one principle introduction; with respect to the patternless and the irregular images, they have no undeniable predominant course, however the directionality of the irregular images exhibits much bigger variations than that of the pattern-less image. In like manner, there are two prevailing crest values relating to two guideline introductions in the RadonSig of the plaid picture. The RadonSig of the striped picture has one crest esteem connected with the one guideline introduction. There is no predominant top worth in the irregular and the pattern-less cases. Yet, the RadonSig of the patternless picture is much smoother than that of the unpredictable picture.

3.2. Statistics of Wavelet Subband

The discrete wavelet change (DWT) deteriorates an image I into low-recurrence channel Dj (I) under a coarser scale and numerous high frequency channels under various scales $W_{k,j}(I)$; k = 1, 2, 3; j = 1, 2, ..., J, where J is the quantity of scaling levels. In this way, in every scaling level j, we have four wavelet sub-bands including one low-recurrence channel Dj(I) and three high-recurrence channels $W_{kj}(I)$. The high-recurrence channels $W_{k,j}(I)$; k = 1, 2, 3 encode the discontinuities of a picture along level, vertical, and slanting directions, separately. In this paper, we apply J = 3 scaling levels of DWT to decay every cloth picture.

Statistical features are very much adjusted to break down compositions which need background clutter and have uniform measurable properties. DWT gives a speculation of a multi-resolution spectral analysis device. Along these lines, we remove the measurable components from wavelet subbands to catch worldwide factual data of pictures at various scales. It is standard to figure the single vitality quality on each subband [24]. In this paper, we utilize four factual qualities including fluctuation, vitality, consistency, and entropy to all wavelet subbands. Along these lines, the STA is an element with the measurement of 48 (3 × 4 × 4). The four standardized factual qualities extricated from every wavelet subband can be figured by the accompanying equations:

$$variance = \sum_{i=0}^{L-1} (z_i - m)^2 \; p(z_i) / (L-1)^2 \tag{4}$$

$$energy = \sum_{i=0}^{L-1} (z_i - m) \, p(z_i) / (L-1) \tag{5}$$

$$uniformity = \sum_{i=0}^{L-1} p(z_i) \tag{6}$$

$$entropy = \sum_{i=0}^{L-1} p(z_i) \log_2 \, p(z_i) \tag{7}$$

Where zi andp(zi), i = 0,1, 2, ..., L – 1 istheintensitylevel and corresponding histogram; L is the number of intensity levels; m = L – 1 z p (z) is the average intensity level.

3.3. Fuzzy Cluster

Picture division can be characterized as the procedure of blending pixels having comparative components into the same gatherings, or locales. The divided picture is then the union of unmistakable gatherings, where pixels of homogeneous locales are related to the same gatherings. Various systems have been proposed in the writing, where shading, composition or edges elements are utilized to depict every gathering

Let X = {x_1, · , x_n} be a n tests information set and accept that every specimen x_k is spoken to by an arrangement of p elements. A parcel of X into c bunches is an accumulation of commonly disjoint subsets Xi of X such that $X_i U \cdot \cdot\cdot U X_c = X$ and $X_i \cap X_j = \varnothing$ for any i ≠ j. Segments can be spoken to by (c × n) hard segment frameworks U whose general term is $U_{ik} = 1$ if $X_k \in X_i$, and 0 generally. To get an allotment grid U, one can utilize the supposed Hard c-Means (HCM) calculation which minimizes the inside group separations:

$$J = \sum_{i=1}^{n} \sum_{x \in xi} \|x - v\|^2 \tag{8}$$

Where k stands for the usual Euclidean distance and v_i are thecluster centers gathered into a matrix V for convenience. The objective function can be rewritten as

$$J = \sum_{k=1}^{c} \sum_{i=1}^{c} u_{jk} \|x_k - v_j\|^2 \tag{9}$$

$$J = \sum_{k=1}^{c} \sum_{i=1}^{c} u_{jk} \|x_k - v_j\|^2 \tag{10}$$

$$V_i = \frac{\sum_{k=1}^{n} u_{ik}^m X_k}{\sum_{k=1}^{n} u_{ik}^m} \tag{11}$$

$$U_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|} \right)^{2/(m-1)}} \tag{12}$$

The choice to first initialize a random partition matrix or the cluster centers is let to the user, both being used in the literature. The algorithm stops when the centroids stabilize, i.e. the matrix norm between two successive V is below a given threshold. Equivalently, the entire procedure can be shifted one half cycle, so that initialization and termination is done on U. Naturally, in terms of speed and storage, there are some advantages to initialize and terminating with V. Application to image segmentation consists in taking X as the entire set of pixels x of an image I, each of them being described by p features.

4. SYSTEM AND INTERFACE DESIGN

The camera-based cloth pattern analysis help visually impaired individuals to coordinates with a help of a camera, a receiver, a PC, and a Bluetooth earpiece for sound depiction of cloth patterns and hues. A camera mounted upon a couple of shades is utilized to catch cloth pictures. The cloth pattern and colours are depicted to visually impaired people by a verbal presentation with minimal diversion to hearing. Bone directed headphones or little remote Bluetooth speakers can be utilized to ensure protection and minimize foundation sounds. The battery level will likewise be checked and a sound cautioning is given if the battery level is low.

Sound yield: As for sound showcase, we utilize a working sys-tem speech office that is standard in cutting edge versatile PC frameworks and cell phones. We at present use Microsoft Speech Software Development Kit, which bolsters scripts. Various design alternatives are likewise accessible as per individual inclination, for example, speech rate, volume, and voice sex.

5. CLOTH PATTERN RECOGNITION AND COLOUR ANALYSIS

The extracted features from local and global features are combined using support vector machines (SVM). The colours are identified by quantizing them in presence of HIS (hues, intensity and saturation). By analyzing both of these results we get to know about the colors and patterns of a cloth.

5.1. Clothing Pattern Recognition

We apply three feature extraction to get the pattern out of the cloth image. Discrete Wavelet Transform helps us to decompose the image and is formed by vector dimension 48 and then the Radon Signature divides the image to an angle 3 degree per sample provided and get 60 sample angle which are divided in 0 degree to 180 degrees

These are then combined at the SVM with RBF kernel to get the resultant output as we desire

5.2. Cloth Colour Identification

The key thought is to quantize shading space taking into account the connections between saturation, intensity, and hues. Specifically, for every cloth picture, our shading ID strategy quantizes the pixels in the picture to the accompanying 11 hues: red, orange, yellow, green, cyan, blue, purple, pink, dark, dim, and white.

The discovery of shades of white, black, and grey depends on the saturation range S and intensity range I. On the off chance that the intensity I of a pixel is bigger than an upper power limit I^U, and the saturation S is not exactly an saturation threshold S_T, the shade of the pixel is "white." Similarly, the shade of a pixel is resolved to be black if the power I is not exactly a lower power bound I^L and saturation S is less than threshold saturation S_T. For the remaining estimations of I while S is less thanS_T, the shade of a pixel is distinguished as grey. For different hues (i.e., red, orange, yellow, green, cyan, blue, purple, and pink), the tint qualities are utilized. The shade H can be envisioned as a 360° shading wheel. We quantize the shade of red in the scope of 345° – 360° and 0° – 9°, orange as 10° – 37°, yellow as 38° – 75°, green as 76° – 160°, cyan as 161° – 200°, blue as 201° – 280°, purple as 281° – 315°, and pink as 316° – 344°.

6. CLASSIFICATION OF THE IMAGE

We assess the execution of the proposed strategy on distinctive datasets: the CCNY Clothing Pattern dataset with vast intra-class varieties to assess our proposed technique and the best in class surface characterization strategies. Our analyses concentrate on the assessment and approval of 1) the corresponding connections between the proposed worldwide and nearby component channels; 2) the prevalence of our proposed technique over the cutting edge texture grouping approaches with regards to cloth design analysis; and 3) the speculation of our methodology on the customary surface arrangement.

6.1. Datasets

CCNY clothing pattern dataset: Our proposed system data set contain 628 images of pattern (striped, plaid, pattern-less, irregular in number of 127,128,127,129).It contains image resolution sampled to 140 × 140.

6.2. Experiments and Discussions on Clothing Pattern Recognition

1. *Experimental setup:* We have a fixed number of images in our dataset which contains all the categories of images we have in our experiment. The results are audible in a ear piece or speaker where all the process of the pattern finding and colour analysis is done in the MAT lab which contains all the features extraction process

2. *Effectiveness of Different Features and Combinations:* We evaluate relationship between the local and global features which include the Radon Signature and the Discrete Wavelet Transform in the global features and the Fuzzy Cluster in the local one. When we analyze the features Fuzzy Cluster and Discrete wavelet Transform individually the features were in good accuracies but for Radon signature it is worse. Combinations of features had good yields in accuracies. Fuzzy+Radon signature is better than Fuzzy + Discrete wavelet transforms and so on. On finalizing we found out that the results combining all the three features give extra-ordinary results.These results found out are then combined in the SVM, which helps in finding the pattern and colour analysis of the image in which the image pattern is know.

The figure 3 represents about the intensity per pixel which is identified by using the radon signature feature which depicts the pattern to be realized.

The figure 4 tells us about Discrete Wavelet Transform which decomposes the image and bring out the pattern which is on the fore ground of the image.

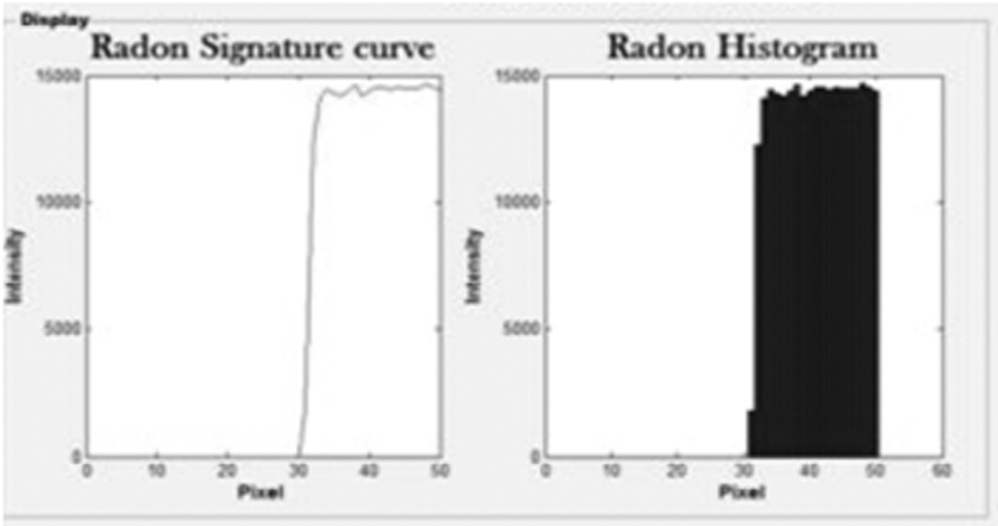

Figure 3: Radon signature curve and histogram

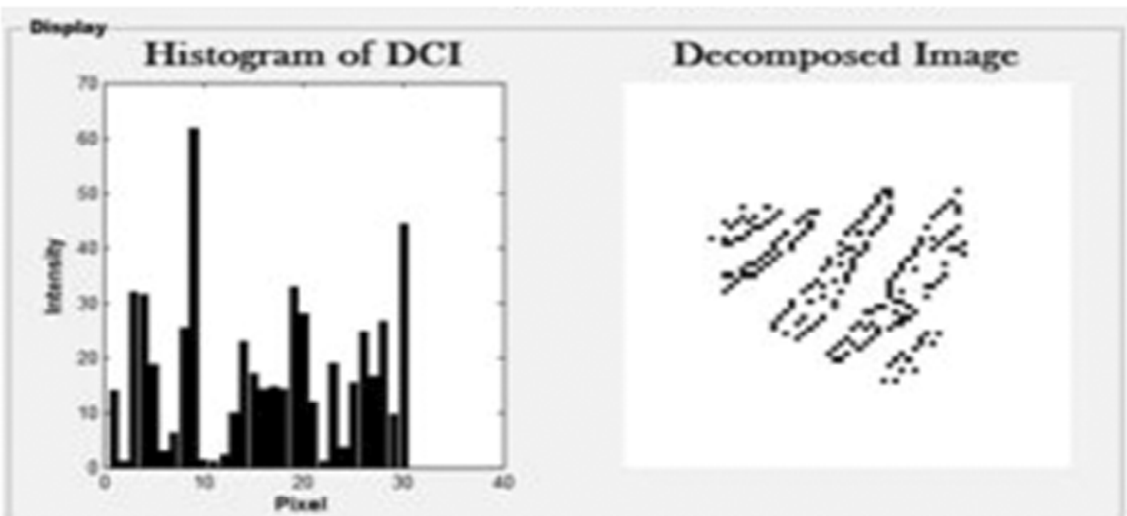

Figure 4: DWT graph: Pixel VS Intensity

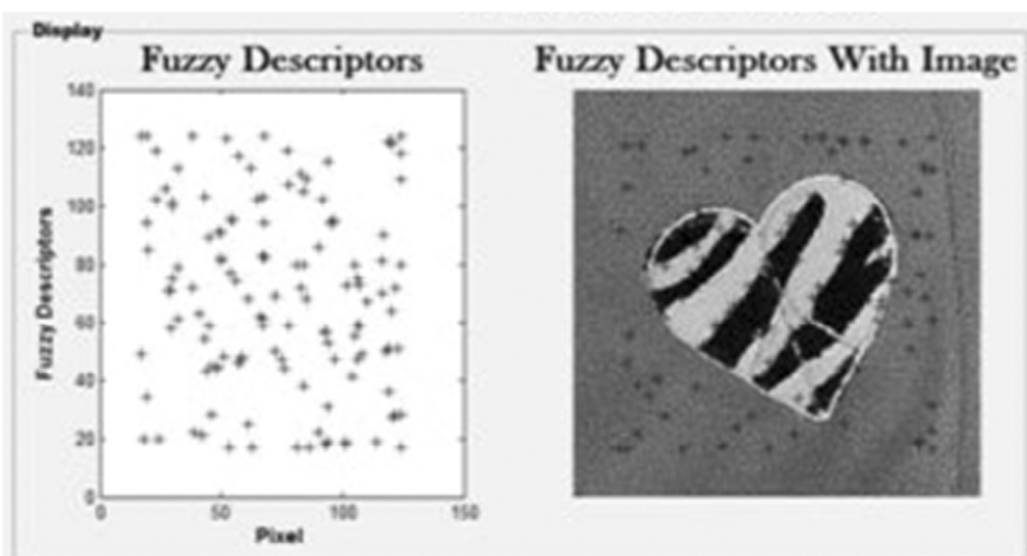

Figure 5: Pixel VS Fuzzy Cluster Descriptors

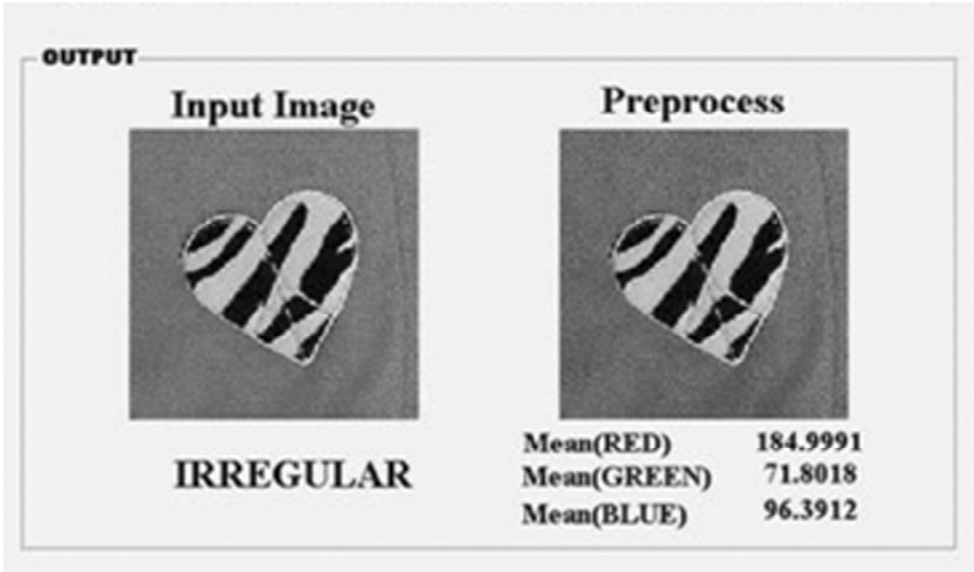

Figure 6: Classification *of the image*

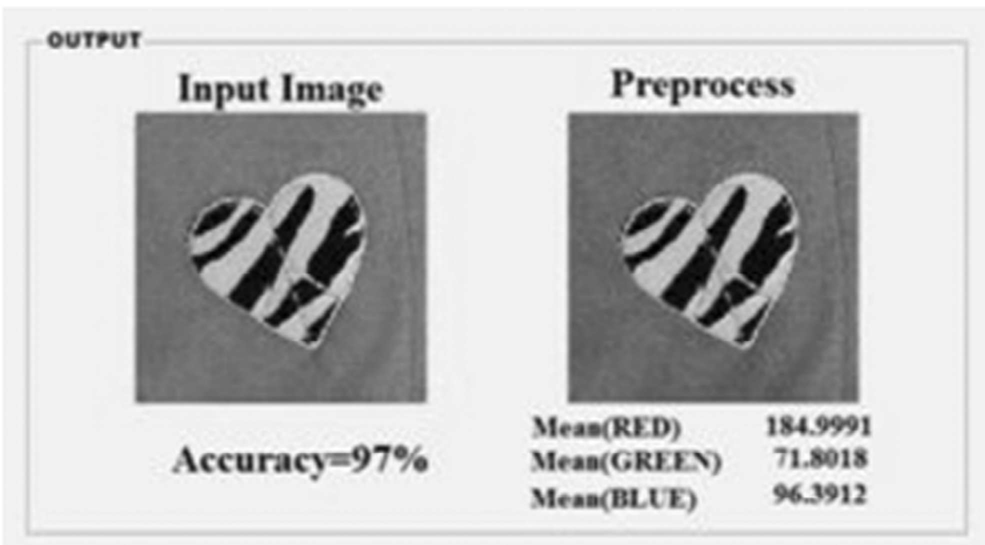

Figure 7: Accuracy when comapared with the exsisting method

The figure 5 tells the same intensity value of the same colours are identified in each pixel and are grouped accordingly to find out the RGB composition of the image.

The image is classified when all the above feature are combined to give a output with the help of support vector machine where these are compared with the set of values which are in the data base accordingly

The exsisiting method had a accuracy of about 94 percent where as our proposed system can yield accuracy upto 97 percentage

7. CONCLUSION

We have performed research on the analysis of cloth pattern to help the visually impaired people to enhance their lifestyle and for better living. With the help of global (Radon Signature and Discrete Wavelet Transform) and the local features(Fuzzy Cluster) with which we performed various extraction processes to extract the pattern and analyze the colours and the support vector machine which deals with combination of all the features we used and supporting the process to get the best result and analysis. All the four patterns and the eleven colours can be identifiesd. Our proposed system is far more accurate than the traditional systems and give the best result.

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