ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

FEATURE EXTRACTION FROM SEGMENTED JASMINE FLOWER IMAGES

Dr. S. Krishnaveni, Dr.A.Subramani

1 Assistant Professor, M.V.M.Govt. Arts College for Women, Dindigul, Tamilnadu, India(e-mail: seetharamankrishnaveni@gmail.com

2 Assistant Professor, M.V.M.Govt. Arts College for Women, Dindigul, Tamilnadu, India(e-mail: subramani.appavu@gmail.com)

ABSTRACT

Feature extraction is a sort of dimensionality reduction that efficiently represents region of an image as a compact feature vector or the process in which certain features of interest within an image are detected and represented for further processing. This research work proposes a hybrid feature descriptor based on color, texture, and shape. The feature set includes two color features: Average Color Difference (ACD) & Color and Edge Directivity Descriptor (CEDD), a texture feature using Local Binary Pattern (LBP) and shape feature using Zernike Moments (ZM). Image descriptors derived from different color spaces often exhibit different properties, among which are high discriminative power and relative stability over the changes in photographic conditions such as varying illumination, hence, the color features are derived from different color spaces like YIQ, HSV and L*a*b. Then the feature vectors are normalized and fused to improve the classification performance.

KEY WORDS Average Color Difference (ACD), Color and Edge Directivity Descriptor (CEDD), Local Binary Pattern (LBP), Zernike Moments (ZM).

INTRODUCTION

This paper presents a hybrid image descriptor based on color, texture, and shape for jasmine image classification. The color cue is often applied by the human visual system for object and scene image classification. Indeed, color images, which contain more discriminative information than grayscale images, have been shown to perform better than grayscale images for image classification tasks. Image descriptors defined in different color spaces usually help improve the identification of object, scene and texture image categories [1]. Color histogram

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

and global color features and local invariant features often provide varying degrees of success against image variations such as rotation, viewpoint and lighting changes, clutter and occlusions [2].

The color, shape and texture features are very common in image processing applications [5,6]. Most of the time the combination of all three features are used, or sometimes subset this combination also be applied [8] proposed an invariant moments based shape descriptors for object recognition, the experiments are carried out with plant leaves [14] extracted invariant moments and texture features for leaves classification with General Regression Neural Network (GRNN).

FEATURE EXTRACTION

It is studied that the combination of color, texture and shape features could be a better feature descriptor for image classification, hence, this work makes use of the same combination of features for jasmine flower classification.

Average Color Differences

The Average Color Differences (ACD) are an extension of the semi-variogram to color images . The variograms is a notation which generalizes the covariance . Here it is used to generalize the color images than the covariance. To compute a variogram of an image $f(x)$, a direction ® and a unit displacement vector h in this direction must be selected. For various multiples of vector h, written qh, the following value,

$$V(a,) = \frac{1}{2}\varepsilon\left[f(x) - f_{\beta}(x + qh)\right]^2 \quad (1)$$

is plotted against q, where $f_{\beta}(x + qh)$ is the displacement of image □ in direction 〈 by distance q. The expectation value ∑ of the grayscale differences squared is measured only in the region in which the original and displaced images overlap. It is an integrative multi-channel strategy in which the difference in the above equation is replaced by Euclidean distance in the CIE

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

L*a*b color space, which is designed in such a way that this distance corresponds to the perceptual between two color expressed in CIE L*a*b coordinates.

The ACD method estimates the color differences as a function of the distance between pixels. Given two generic pixels $v_i = (c_{1i}, c_{2i}, c_{3i}, x_{1i}, x_{2i})$ and $v_j = (c_{ij}, c_{2j}, c_{3j}, x_{1i} + nd_1, x_{2i} + nd_2)$, the average color diffference between v_i and v_j is defined as follows:

$$ACD(n, d_1, d_2) = \frac{1}{2} E \left\{ \left[\sum_{h=1}^{3} \quad (c_{hi} - c_{hj})^2 \right]^{1/2} \right\} \qquad (2)$$

Where E indicates the expected value. Four variograms corresponding to the displacements $(d_1, d_2) = \{(1,0), (1,1), (0,1), (-1,1)\}$, for n = 1, … , 50 were considered to estimate ACD as proposed in [4]. The variograms corresponding diagonal directions (1, 1) and (-1, 1) have been rescaled by $1/\sqrt{2}$ to ensure that all the variograms span the same length. For rotation invariance the average variograms over the four displacements were computed, which results in a feature vector of dimension 50. The ACD is estimated on the L*a*b color space as suggested in [4].

Color and Edge Directivity Descriptor

The CEDD is a composite image descriptor that captures and relates shape, texture and color from an image [3]. CEDD could be estimated either with full image or an image block. Initially the jasmine image is converted from RGB to YIQ color space to extract texture information. An Edge Histogram Descriptor (EHD) is applied to the YIQ color image to construct a histogram of 6 bins, five corresponding to the types of edges found in the image plus one for no edges of any type found [13]. Then, a given threshold, an edge may fall in more than one of the five directional bins. This determines its texture, of the edge does not fall in any edge category then it belong to the last bin, corresponding to no edges.

The global feature or grayscale intensity distribution of an image could be well represented by an image histogram in general. The most notable advantage of histogram is they are invariant to translation and rotation, further the normalized histogram makes it invariant to scale. The invariance properties makes histograms more suitable for image indexing and retrieval applications. Another important image feature is edge information, which are helpful to understand the objects and shapes presents in the image.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

The edge features simulates the human visual system, as they focused to contours and boundaries in an image. Combining edge and histogram representation results in edge histogram descriptor, originally proposed for MPEG-7 coding (Park et al., 2000). MPEG-7 seeks for the local edge information to minimize the memory requirement, hence the edge histograms will make use of less number of bins and stores the metadata effectively. The edge localization process starts by partitioning the image into 4×4 sub-image as shown in Figure 1. In the next step, for each sub-image, the edge information is estimated to generate the edge histogram. Edges are identified with various edge operators, where the sub-images are further partitioned into small regions called Kernels (image-block).

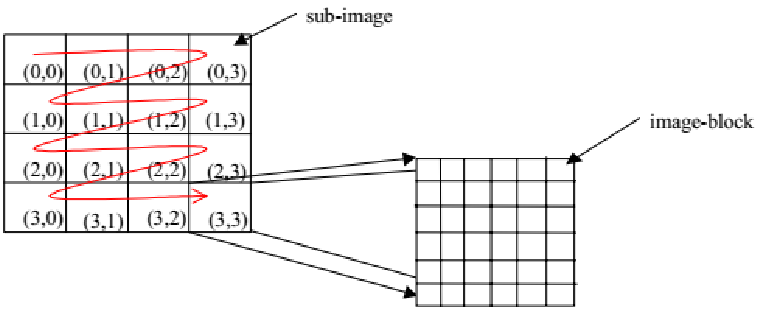

Figure 1. Definition of sub-image and kernel

There are totally five type of edges identified for each kernel to construct the edge histogram descriptor. For each kernel, four directional edges and a non-directional edge information is collected, the orientation for the directional edges include 90, 180, 45 and 135 degree. Suppose a kernel consists an irregular edge, then it is noted as a non-directional edge.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

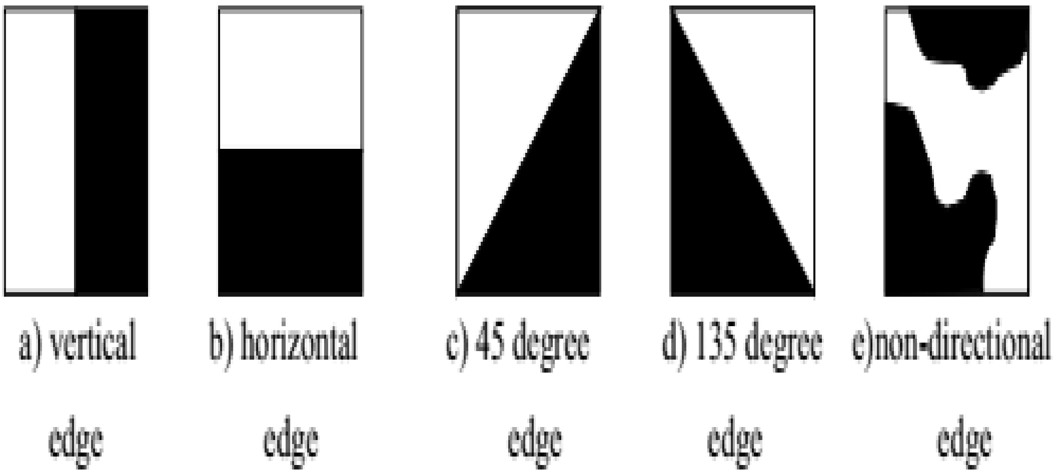

Figure 2: Five types of edges

Once the edge information is extracted from the kernels, a count is made to estimate the total number of edges available for each edge type for each sub-image. These counts are plotted in the edge histogram, for each edge type one bin will be reserved, hence the histogram will contain five bins, and this is for one sub-image. The initial partition of 4×4 results, 16 sub-images, and 5-bins for each sub-image makes the histogram consisting 16×5=80 bins.

The four directional and a non-directional edge information is extracted from each kernel as described below. Initially each kernel is further divided into 2×2 sub-kernels as illustrated in Figure 3. Then the mean intensity value for each sub-kernel is estimated and convolved with edge operators to identify the edge magnitudes. Based on equation (4.19)-(4.23), the edge strength is measure for each edge type, the edge type which has a maximum strength and greater than a predefined threshold strength (T_s) is assigned for the current kernel. In specific, the kernels are labelled from 0 to 3 as shown in Figure 3, for the k^{th} sub-kernel of the $(i, j)^{th}$ kernel, the mean gray level $I_k(i,j)$ should be estimated.

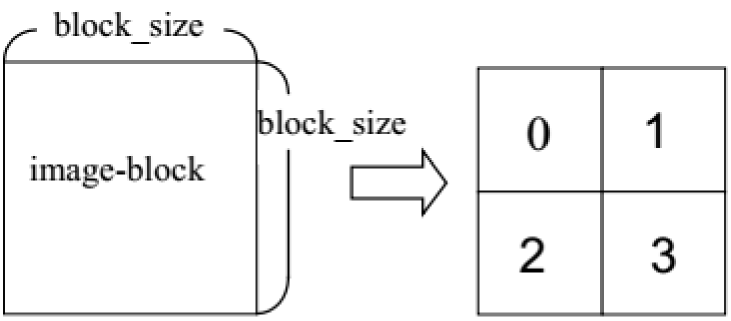

Figure 3 Sub-blocks and their labelling

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

By applying the directional edge filters as shown in Figure 4, the edge information are estimated.

1	-1
1	-1

(a)

1	1
-1	-1

(b)

$\sqrt{2}$	0
0	$\sqrt{-2}$

(c)

0	$\sqrt{2}$
$\sqrt{2}$	0

(d)

2	-2
-2	2

(e)

Figure 4: Operators for Edge Detection. (a) ver_edge_filter, (b) hor_edge_filter, (c) dia45_edge_filter, (d) dia135_edge_filter, (e) nond_edge_filter

With that directional and non-directional edge data for each sub-kernel, the edge strengths are measured as given in the following equation.

$$ver\_edge\_stg(i,j) = \; k = 03|A_k(i,j) \times ver\_edge\_filter(k)| \qquad (3)$$

$$hor\_edge\_stg(i,j) = \; k = 03|A_k(i,j) \times hor\_edge\_filter(k)| \qquad (4)$$

$$dia45\_edge\_stg(i,j) = \; k = 03|A_k(i,j) \times dia45\_edge\_filter(k)| \qquad (5)$$

$$dia135\_edge\_stg(i,j) = \; k = 03|A_k(i,j) \times dia135\_edge\_filter(k)| \qquad (6)$$

$$nond\_edge\_stg(i,j) = \; k = 03|A_k(i,j) \times nond\_edge\_filter(k)| \qquad (7)$$

Among the five edge strengths, the edge type with maximum strength which is higher than the selected threshold is confirmed for the kernel's edge type, defined as

$$\max\{ver\_edge\_stg(i,j),\ hor\_edge\_stg(i,j),\ dia45\_edge\_stg(i,j),\ dia135\_edge\_stg(i,j),\ nond\_edge\_stg(i,j)\} > T_s$$

With that edge information, the color descriptors are extracted and combined to derive the Color Edge Directivity Descriptor. In order to extract the color information, a set of fuzzy rules

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

undertake the extraction of a Fuzzy-linking histogram that was proposed in [3]07). This histogram stems from the HSV color space. Twenty rules are generated to a three-input fuzzy system in order to produce eventually a 10-bin quantized histogram. Each bin corresponds to a preset color. The number of blocks assigned to each is stored in a feature vector. Then, four extra rules are applied to a two input fuzzy system, in order to change the 10-bins histogram into 24-bins histogram, importing thus information related to the hue of each color is presented. Color information processed to every edge type yields a 6×24 = 144 bins histogram.

Texture Feature using Local Binary Patterns

Local Binary Patterns (LBP) based texture feature extraction is widely used as texture descriptor in recent years [10]. LBP is a parameter free approach, which represents local structures of image effectively by comparing each pixels with its adjacent neighbors. The major advantage of LBP texture descriptor is that it is invariant to illumination changes and moreover this method requires less computation effort [9]. The simplicity and effective performance make this feature extraction method suitable for real time applications like face image analysis, image retrieval, environment modeling, surveillance, object detection, satellite image analysis and biomedical image exploration. Among different applications, the face image analysis domain has large number of evidences for the successful implementation of LBP features.

The key features of LBP such as invariance to illumination changes and computational efficiency, motivate this research work to make use of LBP for extracting textural features from jasmine images. The conventional LBP based texture feature extraction is used in this research work. The LBP operator assigns label to each pixels in the image with decimal numbers, known as Local Binary Patterns or LBP codes. These codes encode the local structure around every pixel in the image. Figure 4.5 illustrates the procedure of constructing LBP codes for an image. Initially, for each pixel, 8 adjacent pixels from 3×3 neighborhood positions are extracted, where the current pixel is considered as center. The center/current pixel value is subtracted with each of its 8-adjancent, then the sign of the subtracted results are compared to check whether they are positive or negative. The negative cells are marked as 0, whereas the positive number cells are marked with 1. With this binary window, a binary number is generated by combining all

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

these binary codes in a clockwise direction starting from top-left one, the corresponding decimal number is estimate to label the pixel. The concatenated binary numbers are knows as Local Binary Patterns (LBP). A histogram of 256 bins is constructed for this encoded image and the same has been used texture feature vector.

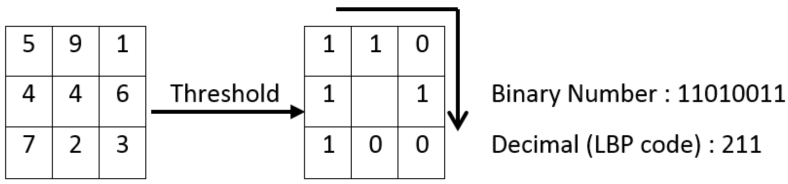

Figure 5 An example of the basic LBP Operator

4.1.1 Shape Feature using Zernike Moments (ZM)

To compute the Zernike moments of a jasmine image, the range of the image should be mapped to the unit circle first with its origin at the image's center [12]. The pixels residing outside the unit circle are ignored in the computation process. For this implementation of Zernike moments, binary images with spatial resolution of 500×500 are used. All of these binary images are normalized into a unit circle with fixed radius of 250 pixels. The following text describes the procedure to extract shape features from an image using Zernike moments.

In the initial stage Jasmine image is converted into the binary image, then it is mapped over a unit disc image in polar coordinate with (x', y') as the center of the unit disc, and the distance of image pixels are estimated as

$$d = \sqrt{(x2 - x')^2 \frac{1}{2} + (y2 - y')^2 \frac{1}{2}} \qquad (8)$$

In the next step, the polar angle ⎝ and the distance vector 〉 for any (x,y) pixel in □(x,y) in polar coordinates as

$$\rho = \sqrt{(x - x')^2 + (y - y')^2 / d} \qquad (9)$$

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

$$\theta = tan^{-1}\left[\frac{x-x'}{y-y'}\right] \quad (10)$$

This step maps pixel coordinate (x1, x2) to (-1, +1) and (y1, y2) to (-1, +1) in polar. In this way almost all the pixels in image bound box are inside unit circle except some foreground pixels. For a Zernike basis function with order (n,m) given over the unit disc is defined as

$$Z_{nm}(\rho, \theta) = R_{nm}(\rho)\; exp\; exp\; (jm\theta)\;\; , \rho \leq 1 \quad (11)$$

Where, $j = \sqrt{-1}, \theta = tan^{-1}y/x,$ 〉 is the length of the vector from the origin to the pixel (x,y); ⎝ is the angle between the vector 〉 and x-axis in counter-clockwise direction. R_{nm}(〉) is a radial polynomial function defined as:

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} \quad (-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \quad (12)$$

Where n is a positive number, |m| ≤ n, n−|m| should be an even number. When the image is mapped onto unit disc, take desired value of order of moment, i.e., n and m compute real and imaginary parts of the Zernike moment using radial polynomials.

$$A_{nm} = \frac{n+1}{\pi}\sum_x \quad \sum_y \quad f(x,y)V^*_{nm}(x,y), \;\; x^2 + y^2 \leq 1 \quad (13)$$

Where * is the complex conjugate operator. In this research work, the radius is set as 250, this normalization step allows the scale invariance for the descriptor. Thirty-six Zernike moments of order zero to ten in n and m are then extracted from the normalized image, and the magnitudes are used as the descriptor. The total number of moments used in the shape descriptor was determined experimentally.

RESULTS AND DISCUSSIONS

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

The Average Color Differences (ACD), Color Edge Directivity Descriptor (CEDD), Local Binary Pattern (LBP) and the Zernike Moments (ZM) are extracted from the segmented jasmine image. The four set of features are fused together to form the complete feature vector:

$$J = \{ACD_{1\times50}, CEDD_{1\times144}, LBP_{1\times256}, ZM_{1\times36}\} \quad (14)$$

The feature subscript indicates the dimension of each feature descriptors, in total, the complete feature vector has the dimension of 1×486. Table 1 and 2 presents the sample color feature values from ACD and CEDD descriptors from a jasmine flower image. Table 3 quantifies the LBP feature values derived from the same jasmine flower image, and Table 4 presents the Zernike moments for the jasmine flower image.

Table 1 ACD Feature Descriptors for Jasmine Flower Classification

0.000198	0.001312	0.00263	0.003981	0.005394
0.000496	0.001414	0.002722	0.004104	0.005528
0.000809	0.001571	0.002835	0.00423	0.005653
0.001088	0.001759	0.002966	0.004359	0.005775
0.001289	0.00195	0.003114	0.004495	0.005898
0.001389	0.002124	0.003273	0.004638	0.006028
0.001397	0.00227	0.003429	0.004787	0.006163
0.001348	0.002386	0.003579	0.004942	0.006306
0.001292	0.002476	0.00372	0.005099	0.006457
0.001273	0.002553	0.003853	0.005251	0.006457

Table 1 describes the sample color feature values from ACD descriptors from a jasmine flower image.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

Table 2 CEDD Feature Descriptors for Jasmine Flower Classification

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1

Table 2 describes the sample color feature values from CEDD descriptors from a jasmine flower image.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

Table 3 LBP Feature Descriptors for Jasmine Flower Classification

3502	568	1155	1435	521	188	1109	3521
978	148	149	215	833	155	1862	4754
325	36	82	77	78	20	79	144
649	46	97	86	881	71	1550	2151
797	123	230	225	86	33	149	253
197	17	22	32	157	18	179	250
811	67	100	95	59	19	93	166
2545	149	154	136	2833	148	2089	1773
470	86	106	131	47	22	74	160
121	29	14	21	77	22	131	243
95	20	19	28	15	10	8	22
119	9	20	9	100	19	100	157
866	75	118	104	58	26	89	155
181	19	18	30	95	14	105	204
2627	131	145	143	108	30	111	172
6439	227	202	182	3156	180	1381	1618
1222	1171	247	3944	181	186	267	9115
402	261	46	435	222	188	302	8427
79	57	24	166	25	20	20	348
111	89	20	165	90	102	129	2622
163	168	32	300	31	37	17	392
33	22	11	33	21	48	25	480
113	87	12	166	10	12	21	233
185	128	20	179	137	136	160	1955
807	1027	163	3649	85	126	149	4889
163	162	20	247	91	153	177	3891
130	78	25	181	16	20	7	246
128	96	17	163	75	128	122	2216
1820	1912	162	2646	119	182	128	3014
224	158	18	230	147	176	135	2788

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

3884	2076	171	1587	138	131	110	2078
4424	1637	233	1220	1784	1254	1070	38440

Table 3 describes the sample color feature values from LBP descriptors from a jasmine flower image.

Table 4 Zernike Moments Feature Descriptors for Jasmine Flower Classification

9424237	-917939	652273.1	-105719
-339515	-356219	-53909.8	-198212
-3139494	-253535	-758836	168050.8
-3139494	2031152	-1271726	-756045
549720.7	980230	-780417	-321721
506497.9	980230	-1271726	-14844.5
-1047136	2031152	-758836	-14844.5
2052913	461121.5	189733.6	-321721
-1047136	335918.6	-944356	-756045

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

Table 4 presents the sample color feature values from ACD descriptors from a jasmine flower image.

In general, the feature descriptors are real numbers that represent image patterns. These features are further fused for performing image classification. Fusion at feature level is challenging for the following reasons:

- The features obtained from the different descriptors are heterogeneous. Some may measure distances while other compute similarities.
- The different feature vectors need not be in the same range.

Feature Level Fusion

This paper follows the combination approach to pre-classification (measurement level) fusion. [7] have developed a theoretical framework for combining the evidence obtained from multiple classifiers using schemes like the sum rule, product rule, max rule, min rule, median rule and majority voting. In order to implement these rule-based schemes, initially the feature vectors are converted into posteriori probabilities for a better separation between normal and defected flower.

Consider a problem of classifying a feature vector D into one of 'm' classes based on different classification algorithms. Let x_i be the feature vector presented to the *i*th classifier. Let the outputs of the individual classifier algorithm be P(⎤j|x_i), i.e., the posterior probability of the pattern D belonging to class ⎤$_j$ given the feature vector x_i. Let c □ {1, 2, ... , m} be the class to which the input pattern D is finally assigned.

The performance of the normalized feature vectors fused (J) with weighted sum rule are analyzed with conventional Support Vector Machine (SVM). Table 5 presents the classification results derived from feature vectors of various normalization methods. Comparatively the QQ normalization method outperforms the other, hence these normalized feature vectors are used for further experimental analysis.

Table 5 Classification Performance of Feature Normalization Methods

Normalization Methods	Specificity	Sensitivity	Precision
Min-Max	0.8700	0.8201	0.8094

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

Z-Score	0.8230	0.8246	0.8022
Median MAD	0.7962	0.7577	0.8177
Double Sigmoid	0.7989	0.7587	0.8133
Tanh	0.7454	0.6867	0.7001
Two-Quadrics (QQ)	**0.8805**	**0.8707**	**0.8311**
Logistic	0.8716	0.7267	0.8253
Quadric-Line-Quadric (QLQ)	0.8529	0.7877	0.8172

CONCLUSION

The combination of color, texture, shape feature descriptors are best known for image classification. One such combination of feature descriptor is estimated here for jasmine flower classification. The feature set consists of two color features: Average Color Differences (ACD), Color Edge Directivity Descriptor (CEDD), a texture feature using Local Binary Pattern (LBP), and a shape descriptor based on Zernike Moments (ZM). These feature descriptors are extracted from the segmented jasmine image, fused and normalized to derive it as single feature set for classification.

References

[1] Banerji, S., Verma, A., & Liu, C, "Novel color LBP descriptors for scene and image texture classification", Proceedings of the 15th International Conference on Image Processing, Computer Vision, and Pattern Recognition, Las Vegas, Nevada, pp. 537 – 543, 2011.

[2] Burghouts, G. J., & Geusebroek, J. M, "Performance evaluation of local color invariants", Computer Vision and Image Understanding, Vol. 113, Issue. 1, pp. 48 – 62, 2009.

[3] Chatzichristofis, S., & Boutalis, Y, "A hybrid scheme for fast and accurate image retrieval based on color descriptors", Proceedings of the International Conference on Artificial Intelligence and Soft Computing, Spain, 2007.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, Nov 2022

[4] Hanbury, A., Kandaswamy, U., & Adjeroh, D. A, "Illumination – invariant morphological texture classification", Proceedings of the Mathematical Morphology, Springer, pp. 377 – 386, 2005.

[5] Hiremath, P. S., & Pujari, J, "Content Based Image Retrieval based on Color, Texture and Shape features using Image and its complement", International Journal of Computer Science and Security, Vol. 1, Issue. 4, pp. 25 – 35, 2007.

[6] Jyothi, B., Latha, Y. M., & Reddy, V, "Medical image retrieval using multiple features", Advances in Computational Sciences and Technology, Vol. 3, Issue. 3, pp. 387 – 396, 2010.

[7] Kittler, J., Hatef, M., Duin, R. P., & Matas, J, "On combining classifiers", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 20, Issue. 3, pp. 226 – 239, 1998.

[8] Mercimek, M., Gulez, K., & Mumcu, T. V, "Real object recognition using moment invariants", Sadhana, Vol. 30, Issue. 6, pp. 765 – 775, 2005.

[9] Ojala, T., Pietikäinen, M., & Harwood, D, "A comparative study of texture measures with classification based on featured distributions", Pattern recognition, Vol. 29, Issue. 1, pp. 51 – 59, 1996

[10] Ojala, T., Pietikäinen, M., & Mäenpää, T, "Multiresolution gray – scale and rotation invariant texture classification with local binary patterns", IEEE Transactions on Pattern Analysis & Machine Intelligence, Vol. 7, pp. 971 – 987, 2002.

[11] Park, S. J., Park, D. K., & Won, C. S, "Core experiments on MPEG-7 edge histogram descriptor", MPEG document M, Vol. 5984, pp. 22 – 34, 2000.

[12] Rao, P. B., Prasad, D. V., & Kumar, C. P, "Feature extraction using Zernike moments", International Journal of Latest Trends in Engineering and Technology, Vol. 2, Issue. 2, pp. 228 – 234, 2013.

[13] Won, C. S., Park, D. K., & Park, S. J, "Efficient Use of MPEG-7 Edge Histogram Descriptor", ETRI journal, Vol. 24, Issue. 1, pp. 23 – 30, 2002.

[14] Zulkifli, Z., Saad, P., & Mohtar, I. A, "Plant leaf identification using moment invariants & general regression neural network", IEEE Proceedings of the 11th International Conference on hybrid intelligent systems, pp. 430 – 435, 2011.