Species and Variety Classification of Leaves from Images

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Summary
Content Based Image Classification has produced many successful and automated applications in agricultural science like fruits and vegetable classification, wood type detection, plant disease detection, soil type recognition and cashew grade classification. In this paper, classification of the leaves is carried out. The proposed framework creates a fixed size descriptor of size 1632. The descriptor is composed of Local Binary Pattern, Generalized Co-occurrence Matrix properties, and edge detection. Once a feature vector is constructed, classification is performed using linear Support Vector Machine. The system is tested using leaves database having 40 leaf species. The proposed system is implemented in MATLAB and achieves the average accuracy of 99%.

Key words:
Classification, Edge Detection, Generalized Co-Occurrence Matrix, Histogram, Local Binary Pattern, Support Vector Machine.

1. Introduction

In this era, Content Based Image Retrieval system has become a significant research issue. Many image databases are now available in the areas of agriculture, medicine, fashion, entertainment, education and manufacturing to name the few. Content-Based Image Retrieval is an efficient searching as well as indexing approach. The knowledge seekers surf websites using Laptops, PCs, Tablets or Smartphones. Use of images by e-commerce sites, product and service industries, etc. is not new nowadays. The QBIC System of IBM [1], the Chabot of U.C. Berkeley, the Photobook of Massachusetts Institute of Technology (MIT) [2], VisualSEEK [3] and MARS [4] are popular examples of CBIR software systems. The text-based retrieval system involves manual annotation of images. The vast amount of laborious task and different human perception of the same image are two major issues with manual annotation [5][6][7].

The Images are the significant source of information in the agriculture industry. Image categorization relies on a mixture of structural, statistical and, spectral approaches. The Structural approaches focus on the appearance of an object in an image. The Statistical approach relies on both the average value and the variance. The Spectral approach depends upon the spectral space representation such as Fourier spectrum. We must handle issues properly such as the illumination and the background colour while a camera is used for species classification. The leaves contain different texture, shape, and the size. The development of an automated solution using these kinds of features is desirable in contexts like the robotic agriculture. We can also extend online recognition of the plant species on the mobile device also for the non-skilled users.

Figure 1 shows a flowchart of Content-Based Image Retrieval system. A query image, which is an image file, is used as input to the CBIR system. The set of features is extracted from an input image file. Each image, stored in the database, is represented as a feature vector. A matching between the feature vector of the query image and extracted feature vectors is carried out. Based on the similarity measures, the system retrieves the required image files from the database and presents it in the form of the result.

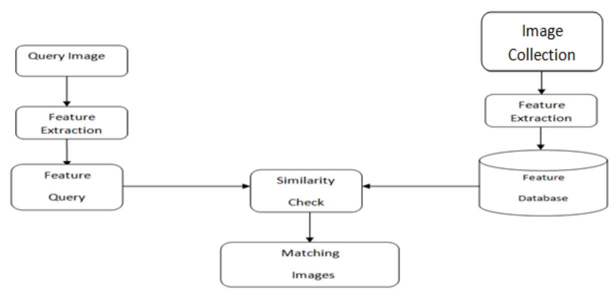

Fig. 1. Content Based Image Retrieval System

2. Literature Survey

Bolle et al. [8] coined the name 'Veggie-Vision' for the recognition of the fruits and the vegetable. They used colour, texture, and density as features. They reported an accuracy around 95% in some scenarios. The system 'Veggie-Vision' was developed in the year 1996.

Rocha et al. [9] [10] presented a unified approach which can combine many features and classifiers. They approached the multi-class classification problem as a set

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of binary classification problems. One can mix together diverse features and the classifiers at different stages of the classification. They have achieved good classification accuracy in some scenarios, but they used the first two responses. As an example, the method shows poor results for the Fuji Apple class.

The cashew nut is the most popular and important crop in India. India is the largest exporter of processed cashew nut. Thakkar et al. [11] applied the CBIR in the agricultural science. They performed automatic grading of whole cashew kernel based on the Fuzzy Logic. The system consists of phases like image smoothing, segmentation, feature extraction, fuzzification of features, and fuzzy classification.

Dubey et al. [12] performed species and variety classification of fruits and vegetables using Improved Summation and Difference Histogram (ISDH) technique. They performed k-means approach with value '2' for the variable 'k' to segment the image into the foreground and background. The dataset contains fifteen different classes with a total of 2633 images. Forty images from every class are used to train the Multi-Class Support Vector Machine and the remaining images from every class are used to test the developed system. In the Multi-Class Support Vector Machine, accuracy is 95% for the 'Fuji Apple', for 'Nectarine' accuracy is 97%, for 'Spanish Pear' accuracy is 96% and for the remaining classes, accuracy is about 98%.

Dubey et al. [13] performed disease classification of fruits using Improved Summation and Difference Histogram (ISDH) technique. They performed k-means approach with value '4' for the variable 'k' to segment defected area. Blotched, Rotten, Scabbed and Normal are different types of disease present in the apple. There is a total of 391 images. Sixty images from each class are used to train the multiclass Support Vector Machine and the remaining images from each class are used to test the SVM. The ISDH method was compared with the state of the art techniques like Global Colour Histogram, Colour Coherence vector, and Unser's descriptor. An average accuracy obtained is 92% in an RGB colour space and 97% in an HSV colour space. They reported an accuracy of 99% when Gradient features were combined with ISDH features. The authors used 67% of the total images from the database in the training process.

Dubey et al. [14] performed species and variety classification of fruits and vegetables using the Global Colour Histogram, Colour Coherence Vector, Colour Difference Histogram, Structure Element Histogram, Local Binary Pattern, Local Ternary Pattern, and Complete Binary Pattern Techniques. They performed k-means approach with value '2' for the variable 'k' to segment the image in the foreground and background. The dataset consists of fifteen different classes with a total of 2633 images. Sixty images from each class are used in the training while the remaining are used in the testing using the Multi-Class Support Vector Machine. The authors achieved 93% accuracy.

Object-based classification of the summer crops using several machine learning methods was carried out by Pena, J.M. et al [15]. They derived several spectral and textural features from the segmentation of bi-temporal ASTER images and compared performances of the C4.5 decision tree, logistic regression, SVM and multilayer perceptron (MLP) neural network. As a single classifier, SVM and MLP obtained maximum overall accuracy of 88%. They also performed hierarchical classification. The first binary classifier separates the crop into 'Woody' and 'Herbaceous' classes. The second classifier classifies 'Woody' crop further into 'Almond', 'Walnut', and 'Vineyard'. Similarly, the second classifier classifies 'Herbaceous' into six classes. They also observed high computation time and model complexity as compared to the C4.5 decision tree classifier.

An evaluation of a set of shape features, suggested by Pauwels et al. [16], was carried out using the Linear Discriminant Analysis by Silva Pedro FB et al. A dataset containing 15 classes and 171 leaf samples was constructed and achieved an accuracy of 87%. The eccentricity, aspect ratio, elongation, solidity, stochastic convexity, isoperimetric factor, maximal indentation depth, and Lobed ness features were considered for an evaluation. The dataset was evaluated using the Pearson's Correlation, Principal Component Analysis, Linear Discriminant Analysis, and Hierarchical Clustering methods. They divided the whole dataset into 70%(training)and 30% (testing). They performed Linear Discriminant Analysis on the randomized training and testing sets and achieved the 12.7 % mean misclassification rate along 1000 executions [17].

3. Proposed Framework

The block diagram of figure 2 depicts both pre-processing and feature extraction processes together. In the beginning, we have retrieved R, G, and, B planes from the RGB image. The RGB image is converted into HSV image to extract H, S and V planes. We have computed the Generalized Co-occurrence Matrix properties using various distance and direction measures for every plane of an RGB image. The Local Binary Pattern histogram with bin size 256 is computed for R, G and B planes of an RGB image. We have used Canny Edge Detector algorithm with 0.25 as the threshold value so that the algorithm retains the most prominent edges. For all the planes of an RGB image, edge points have been extracted using Canny edge detector. For every edge point, both the average and the variance have been calculated using 5x5 neighbourhood. We have computed the histogram of the mean values and a histogram of the variance values for every plane. We have extracted the sixteen bins Centre Symmetric Local Binary Pattern, the sixteen bins histogram of an image and properties of the Generalized Co-occurrence Matrix from an HSV image.

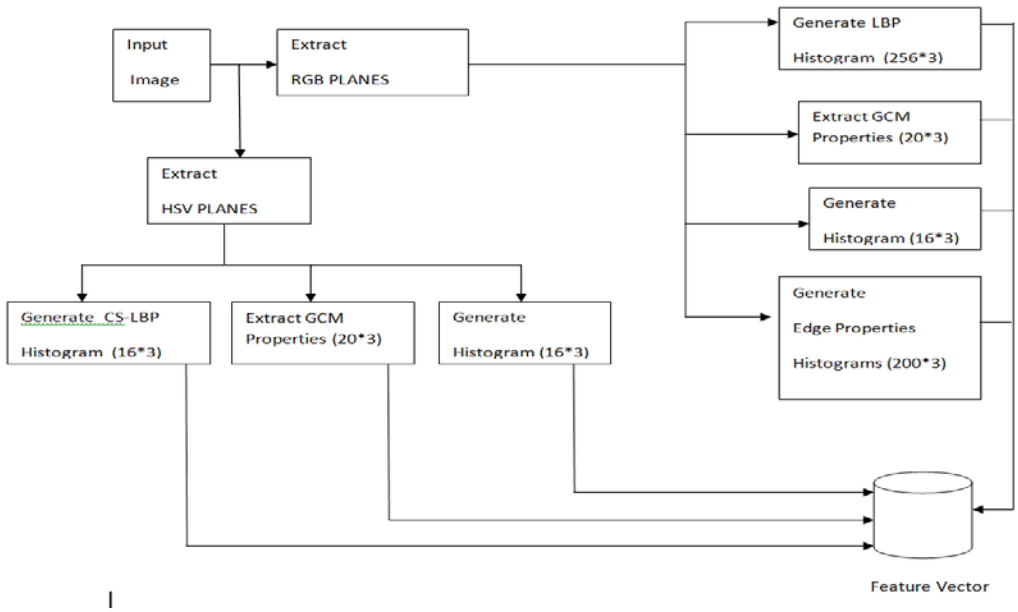


Fig. 2. Feature Vector Generation

The Generalized Co-occurrence Matrix is useful to extract texture of the image. Generalized Co-occurrence Matrix properties such as contrast, correlation, energy and homogeneity, with four different distances and two directions, are computed as described in Table 1. This generates 120 (20*6) additional features for each plane of HSV and RGB image. GCM is represented as 4-tuple (i, j, d, ϴ) [18]. Here, 'd' is the distance between pixels p1 and p2. Gray levels of p1 and p2 are 'i' and 'j' respectively. 'ϴ' is the angle between pixels p1 and p2.

Contrast:

$$\sum_{i,j} |i-j|^2 p(i,j) \quad (1)$$

Correlation:

$$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\,p(i,j)}{\sigma_i \sigma_j} \quad (2)$$

Energy:

$$\sum_{i,j} p(i,j)^2 \quad (3)$$

Homogeneity:

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (4)$$

P (i, j) represents an intensity at position (i, j), 'µ' denotes mean and σ indicates the standard deviation in the above equations.

Table 1: Generalized Co-occurrence Matrices

Number of Gray levels	Distance	Direction
128	3	Horizontal
128	9	Horizontal
128	15	Horizontal
128	64	Horizontal
128	64	Vertical

The Local Binary Pattern captures texture information using the local neighbourhood. The LBP produces 256 distinct binary patterns. The histogram of the LBP has been separately calculated for the planes of the RGB image. The LBP histogram adds 768 (256*3) additional features into the feature vector.

$$LBP(x,y) = \sum_{i=0}^{n-1} s(n_c - n_i)\; 2^i \quad (5)$$

s(x) = 1 if x >=0

0 otherwise

The variable 'nc' represents an intensity of a centre pixel of the 8-neighbourhood in the image. The variable 'ni' indicates the ith pixel of the neighbourhood. In the Centre Symmetric-LBP (CS-LBP), the centre-symmetric pairs of the pixel are compared. The CS-LBP generates 16 distinct binary patterns. In our proposed system, a histogram of CS-LBP is generated for all the planes of an HSV image and generates 48 (16*3) more features.

4. The Dataset

Table 2: Leaf Database: Plant species (class) and specimens available (#)

Class	Scientific Name	#	Class	Scientific Name	#
1	Quercus suber	12	21	Fraxinus sp.	10
2	Salix atrocinera	10	22	Primula vulgaris	12
3	Populus nigra	10	*23*	Erodium sp.	11
4	Alnus sp.	8	24	Bougainvillea sp.	13
5	Quercus robur	12	*25*	Arisarum vulgare	9
6	Crataegus monogyna	8	26	Euonymus japonicus	12
7	Ilex aquifolium	10	27	Ilex perado ssp. azorica	11
8	Nerium oleander	11	28	Magnolia soulangeana	12
9	Betula pubescens	14	29	Buxus sempervirens	12
10	Tilia tomentosa	13	30	Urtica dioica	12
11	Acer palmatum	16	31	Podocarpus sp.	11
12	Celtis sp.	12	32	Acca sellowiana	11
13	Corylus avellana	13	33	Hydrangea sp.	11
14	Castanea sativa	12	34	Pseudosasa japonica	11
15	Populus alba	10	35	Magnolia grandiora	11
16	Acer negundo	10	36	Geranium sp.	10
17	Taxus bacatta	5	37	Aesculus californica	10
18	Papaver sp.	12	38	Chelidonium majus	10
19	Polypolium vulgare	13	39	Schinus terebinthifolius	10
20	Pinus sp.	12	40	Fragaria vesca	11

The dataset contains the leaves of 40 different plant species. Every leaf specimen have been photographed using the coloured and contrasting background surface to generate an image. The Apple iPad 2 device has been used as a camera. The recorded 24-bit RGB images have a resolution of 720x920 pixels [19]. Figure 3 [19] is an example of within class shape variations for the Quercus suber specimen. Figure 4[19] provides an overview of the general aspect of the typical leaves of each plant. Table 2[19] provides details of each leaf species with available samples. Total images in the database are 443. Specimens Nerium oleander(8), Podocarpus sp.(31) and Pseudosasa japonica(34) displayed in figure 4 are good examples of inter-class variations. The red colour background is selected for the green leaves. For the acer palmatum leaves, a grey background has been used. The choice of colours is arbitrary.

Fig. 3. Example of shape variation in specimens of Quercus suber

5. Experimental Results

We have resized all the images of the database into 384x512 for the purpose of Content Based Image Classification. Here, we have adopted classification accuracy calculated by a linear SVM classifier both on the training set as well as on the testing set. The database was divided into the five disjoint partitions to perform five-fold cross-validation. We performed ten repetitions of training the SVM on 4/5 (80%) of the set and testing on the remaining 1/5(20%) [19]. Overall fitness ‘Er’ is the average of the five-fold cross-validation accuracy. The fitness function is defined as follows:

$$Er = (1- (\sum(SVM[accuracy(i)])/n)))*100 \% \quad (6)$$

In our case, the value of n is 5. accuracy(i) represents the accuracy of fold 'i' by the SVM. We have evaluated our proposed method using 64-bit MATLAB 2013a, 8GB of RAM running on the Windows 8.1 OS with i7 5th generation processor. The performance of the system is evaluated based on Error Rate, Precision, Recall, Accuracy and F-Score [20].

Precision= tp / (tp + fp) (7)
Recall= tp / (tp + fn) (8)
Accuracy= (tp + tn) / (tp + tn + fp + fn) (9)
F-score= 2 * ((Precision * Recall) / (precision +recall)) (10)

In the above equations, the variable 'tp' indicates 'true positive', the variable 'fp' indicates 'false positive', the variable 'tn' indicates 'true negative' and the variable 'fn' indicates 'false negative'. The F-score is also known as the harmonic mean of the precision and the recall. The Confusion Matrix properties obtained using fifteen leaf classes are given in Table 3. Table 4 and Table 5 covers the Confusion Matrix for 15 classes and Confusion Matrix properties for 40 classes respectively. Figure 5 depicts the Receiver Operating Characteristic curves for the fifteen classes of the database. The Receiver Operating Characteristic curves, for the forty classes of the database, are shown in Figure 6.

Fig. 4. Leaf Database

Table 3: Confusion Matrix properties (15 Classes)

Leaves Class	Accuracy	Sensitivity	Specificity	Precision	Recall	Fscore
Quercus suber	1	1	1	1	1	1
Salix atrocinera	1	1	1	1	1	1
Populus nigra	0.98	0.80	1	1	0.80	0.88
Alnus sp.	1	1	1	1	1	1
Quercus robur	0.98	0.83	1	1	0.83	0.90
Crataegus monogyna	0.98	0.75	1	1	0.75	0.85
Ilex aquifolium	0.98	0.80	1	1	0.80	0.88
Nerium oleander	1	1	1	1	1	1
Betula pubescens	0.98	0.85	1	1	0.85	0.92
Tilia tomentosa	0.99	0.92	1	1	0.92	0.96
Acer palmatum	1	1	1	1	1	1
Celtis sp.	0.99	0.91	1	1	0.91	0.95
Corylus avellana	0.97	0.76	0.99	0.90	0.76	0.83
Castanea sativa	1	1	1	1	1	1
Populus alba	0.90	0.90	0.90	0.37	0.90	0.52
Average	**0.98**	**0.90**	**0.99**	**0.95**	**0.90**	**0.91**

Table 4: Confusion Matrix (15 Classes)

Leaves Class															
Quercus suber	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Salix atrocinera	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0
Populus nigra	0	0	8	0	0	0	0	0	0	0	0	0	0	0	2
Alnus sp.	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0
Quercus robur	0	0	0	0	10	0	0	0	0	0	0	0	0	0	2
Crataegus monogyna	0	0	0	0	0	6	0	0	0	0	0	0	0	0	2
Ilex aquifolium	0	0	0	0	0	0	8	0	0	0	0	0	0	0	2
Nerium oleander	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0
Betula pubescens	0	0	0	0	0	0	0	0	12	0	0	0	0	0	2
Tilia tomentosa	0	0	0	0	0	0	0	0	0	12	0	0	0	0	1
Acer palmatum	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0
Celtis sp.	0	0	0	0	0	0	0	0	0	0	0	11	0	0	1
Corylus avellana	0	0	0	0	0	0	0	0	0	0	0	0	10	0	3
Castanea sativa	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0
Populus alba	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9

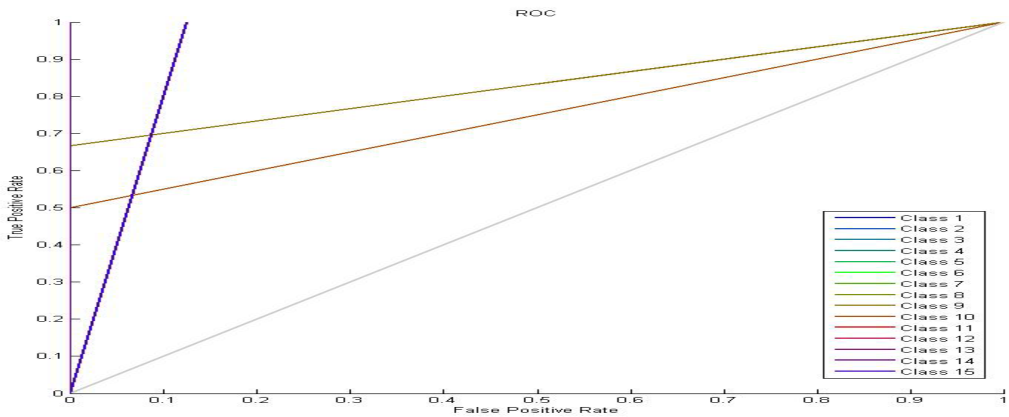


Fig. 5. Receiver Operating Characteristic Curve (15 classes)

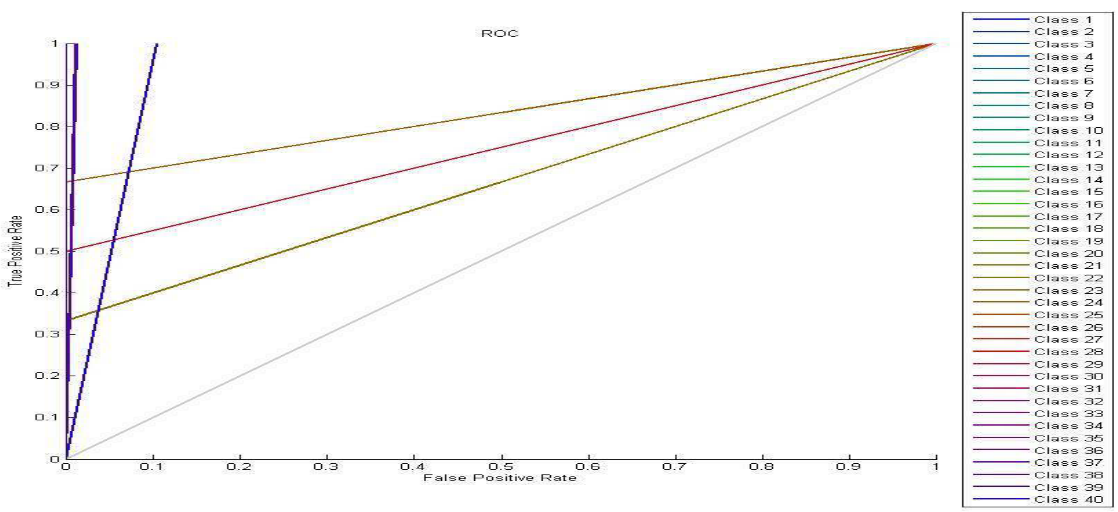


Fig. 6. Receiver Operating Characteristic Curve (40 Classes)

Table 5 Confusion Matrix properties (40 CLASSES)

Leaves Class	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**Fscore**
Quercus suber	1	1	1	1	1	1
Salix atrocinera	0.99	0.90	1	1	0.90	0.94
Populus nigra	0.99	1	0.99	0.90	1	0.95
Alnus sp.	0.99	0.87	1	1	0.87	0.93
Quercus robur	0.99	0.83	1	1	0.83	0.90
Crataegus monogyna	0.98	0.25	1	1	0.25	0.40
Ilex aquifolium	0.99	0.80	1	1	0.80	0.88
Nerium oleander	1	1	1	1	1	1
Betula pubescens	0.99	0.85	1	1	0.85	0.92
Tilia tomentosa	0.99	0.92	1	1	0.92	0.96
Acer palmatum	1	1	1	1	1	1
Celtis sp.	0.99	0.91	1	1	0.91	0.95
Corylus avellana	0.99	0.84	1	1	0.84	0.91
Castanea sativa	0.99	0.91	1	1	0.91	0.95
Populus alba	0.99	0.80	1	1	0.80	0.88
Acer negundo	0.99	0.80	1	1	0.80	0.88
Taxus bacatta	0.99	0.60	0.99	0.75	0.60	0.66
Papaver sp.	1	1	1	1	1	1
Polypolium vulgare	0.99	1	0.99	0.92	1	0.96
Pinus sp.	1	1	1	1	1	1
Fraxinus sp.	1	1	1	1	1	1
Primula vulgaris	0.99	0.83	1	1	0.83	0.90
Erodium sp.	0.99	0.90	0.99	0.90	0.90	0.90
Bougainvillea sp.	0.99	0.92	1	1	0.92	0.96
Arisarum vulgare	0.99	0.66	0.99	0.85	0.66	0.75
Euonymus japonicus	0.99	0.75	1	1	0.75	0.85
Ilex perado ssp. azorica	0.99	0.81	0.99	0.90	0.81	0.85
Magnolia soulangeana	0.99	0.75	1	1	0.75	0.85
Buxus sempervirens	1	1	1	1	1	1
Urtica dioica	0.99	0.91	1	1	0.91	0.95
Podocarpus sp.	1	1	1	1	1	1
Acca sellowiana	0.99	1	0.99	0.91	1	0.95
Hydrangea sp.	0.99	0.90	1	1	0.90	0.95
Pseudosasa japonica	1	1	1	1	1	1
Magnolia grandiora	1	1	1	1	1	1
Geranium sp.	0.99	0.60	1	1	0.60	0.75
Aesculus californica	1	1	1	1	1	1
Chelidonium majus	0.99	0.90	1	1	0.90	0.94
Schinus terebinthifolius	0.99	0.90	1	1	0.90	0.94
Fragaria vesca	0.90	1	0.90	0.21	1	0.34
Average	**0.99**	**0.88**	**0.99**	**0.96**	**0.88**	**0.90**

6. Conclusion

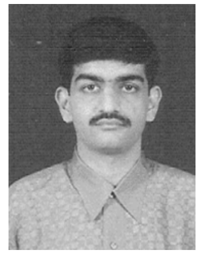
The leaves database is a fine grain dataset. As compared to the set of shape features, suggested by Pauwels et al., the proposed approach which is based on Histogram, Generalized Co-occurrence Matrix, Local Binary Pattern and, Canny edge detector performs well on the leaves dataset. The developed system, using the MATLAB, generated 89% average recall and 96% average precision accuracy. We have also received 99.99% average accuracy. The misclassification error is around 1% as compared to 12% obtained using Linear Discriminant Analysis reported by Silva Pedro FB et al.

References

[1] Niblack C. and Barber R., "The QBIC Project: Querying Images by Content using Colour, Texture and Shape," in Proceedings of SPIE Storage and Retrieval for Image and Video Databases, CA, Vol. 1908, pp. 173-187,1993.

[2] Pentland A., Picard R., and Sclaroff S., "Photobook: Content-Based Manipulation of Image Databases," International Journal of Computer Vision, vol. 18, no.3, pp 233-254, 1996

[3] Smith J. and Chang S., "Visualseek: A fully automated Content-Based Image Query System," in Proceedings of the 4th ACM International Conference on Multimedia, USA, pp. 87-98, 1996
[4] Marwaha P., and Sachdeva S., "Content-Based Image Retrieval in Multimedia Databases," International Journal of Recent Trends in Engineering, vol.1 no.2, pp.210-213,2009
[5] D.Feng., W.C. Siu, and H. J. Zhang, "Fundamentals of Content Based Image Retrieval" , Multimedia Information Retrieval and Management- Technological Fundamentals and Applications, New York, Springer, 2003
[6] Gudivala, V.N., and Raghvan, V.V. "Content Based Image Retrieval Systems", IEEE Computer, vol. 28, September, 1995
[7] Ashok Kumar, D. and Esther, J. "Comparative Study on CBIR based by Colour Histogram, Gabor and Wavelet Transform", International Journal of Computer Applications, Vol.17, No.3, March 2011
[8] Bolle, R.M., Connell, J.H. Haas, N., Mohan, R. and Taubin,G. (1996), 'Veggie-Vision': a produce recognition sytem', Proceedings of Third IEEE workshop on Applications of Computer Vision, pp. 1-8, Sarasota, USA
[9] Rocha, A. and Goldenstein, S. (2007) 'PR: more than meets the eye', Proceedings of the Eleventh IEEE International Conference on Computer Vision, pp.1–8.
[10] Rocha, A., Hauagge, C., Wainer, J. and Siome, D. (2010) 'Automatic fruit and vegetable classification from images', Computers and Electronics in Agriculture, Vol. 70, No. 1,pp.96–104
[11] Thakkar, M. R. , Bhatt, M. S. & Bhensdadia, C.K. (2011, March). "Fuzzy logic based computer vision system for Classification of whole cashew kernel". In Internation Conference on Advances in Communication, Network and Computing, pp.415-420. Springer Berlin Heidelberg.
[12] Dubey, S.R. & Jala, A. S. (2013) Species and variety detection of fruit and vegetables from images. International Journal of Applied Pattern Recognition, 1(1), 108-126
[13] Dubey, S.R. & Jala, A. S. (2014) Fruit dessease recognition using improved sum and difference histogram from images. International Journal of Applied Pattern Recognition, 1(2), 199-220.
[14] Dubey, S.R. & Jala, A. S. (2015) Fruit and Vegetable recognition by fusing colour and texture features of the image using machine learning. International Journal of Applied Pattern Recognition, 2(2), 160-181
[15] Pena, Jose M., Pedro A. Gutierrez, Cesar Hervas-Martinez, Johan Six, Richard E. Plant, and Francisca Lopez-Granados. "Object-based image classification of summer crops with machine learning methods." Remote Sensing 6, no. 6 (2014): 5019-5041.
[16] Pauwels, E.J., de Zeeuw, P.M., Raguelova, E.: Computer-assisted tree taxonomy by automated image recognition. Eng. Appl. of AI 22(1) (2009) 26-31.
[17] Silva, Pedro FB, Andre RS Marcal, and Rubim M. Almeida da Silva."Evaluation of features for leaf discrimination". In International Conference Image Analysis and Recognition, pp. 197-204. Springer Berlin Heidelberg, 2013.
[18] Waikar, Sharvari M., and K. B. Khanchandani, 2014. "Determination of Image Features for Content-based Image Retrieval using Interactive Genetic Algorithm." IMAGE 89.17
[19] https://archive.ics.uci.edu/ml/datasets/Leaf
[20] Han, Jiawei, Micheline Kamber, and Jian Pei. Data mining: concepts and techniques. Elsevier, 2011.
[21] Manimala, S., and K. Hemachandran. "Image Retrieval-Based on Colour Histogram and performance Evaluation of similarity Measurement." Assam University Journal of science & Technology 8: 94-104



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