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IDENTIFICATION OF PLANT LEAF RECOGNITION USING OPTIMIZE TEXTURE METHOD

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Abstract: Today work proposes an approach for the plant identification from their digital leaf images using multiple visual features to organize heterogeneous plant types. Recognizing the fact that plant leaves can have a types of recognizable features like color (green and non-green) and shape (simple and compound) and texture (vein structure patterns), a single set of features may not be efficient enough for complete recognition of heterogeneous plant types. Here we present a review paper for analysis of various approaches to find better one from them. This paper explains only about the leaf recognition methods and its performance metric.Here we are also proposed a new methodology for plant leaf recognition with texture analysis.

Keyword: Shape-wise plant classification, Color wise plant classification, Moment Invariant, Texture analysis.

I. INTRODUCTION

Plant is greatly important sources for human's living and development whether in industry, food stuff or medicines. It is also significantly important for environmental protection. Recognition of natural objects in the surrounding environment has been of great importance for the humankind from everlasting. The desire to understand and describe the living nature lead scientists to create systems of biological classification, counting an enormous number of categories and species. For illustration: while the 10th edition of Linneaus'sSystemaNaturae describes about 6000 plant species, currently the number of published and accepted plant species in the world is over 310000 [1]. However, many plant species are still unknown yet and with the deterioration of environments, these unknown species might be at the margin of extinction. So it is necessary to correctly and quickly identify the plant species in order to preserve its genetic resources.

II. LITERATURE WORK

The various research and journal papers have studied related to plant recognition using different approaches. According to our research, Many of the papers have been analyzed which focus on the problem of better identification of plants by leaf using texture analysis. Few reviews of summary described here and implicated with their respective author. JyotismitaChaki, Ranjan Parekh, Samar Bhattacharya [2] proposed that the current work proposes an approach for the recognition of plants from their digital leaf images using multiple visual features to handle heterogeneous plant types. Plants play an important role in Earth's ecology as they help to provide sustenance, shelter, medicines, fuel. Nowadays plants however suffer from the threat of extinction as forest areas are rapidly diminishing with each passing day. Shanwen Zhang, Yingke Lei, Chuanlei Zhang, Yihua Hu [3] has explained plant classification based on the leaf images is an important and tough task. For leaf classification problem, in this paper, a new weight measure is presented, and then a dimensional reduction algorithm, named semi-supervised orthogonal discriminant projection (SSODP), is proposed.
N.Valliammal, Dr.S.N. Geethalakshmi [4] has defined; Plants play an important role in both human life and other lives that exist on the earth. Due to environmental deterioration and lack of awareness, many rare plant species are at the margins of extinction. Despite the great advances made in botany, there are many plants yet to be discovered, classified, and utilized; unknown plants are treasures waiting to be found.

Proposed Method for Plant Recognition:
This paper presents an easy leaf recognition algorithm. Wediscusses image preprocessing and acquisition which includes the image enhancement and segmentation and high frequency feature extraction of a leaf images. Also introduces the texture analysis and extraction of feature descriptors to classify leaf images i.e. parametric calculations as shown in Figure. In this design preprocessing, enhancement, segmentation and texture analysis steps are described. The detail algorithms to perform these steps are also discussed.

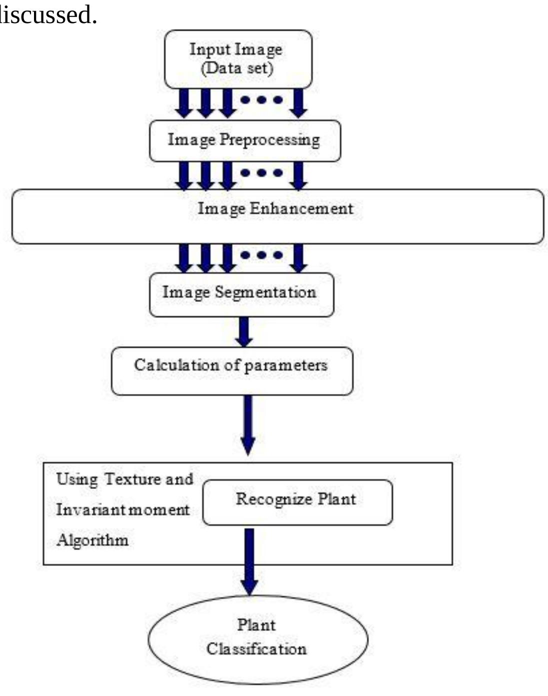

Fig.1: Proposed Model

Image Pre-Processing:

The first thing which comes in our mind is that the margin of leaf which is essential for our preprocessing algorithm. We enhance our images by first converting into gray scale and then make 3*3 window and move this window from left to right and top to bottom calculates average of window in every move from left to right and top to bottom. If average of window pixel is greater than gray image pixel value d(x,y) then replace pixel value with average value otherwise value obtained by Gaussian function which is obtained by

y = y + (y*c) / (1+ (1/ (2.71828^y))

Image Segmentation:

The purpose of segmentation is separation of leaf objects from background so that we can properly use the image features. The output of image segmentation is a binary image in which the leaf objects are numerically displayed with 1 and the background with 0. For segmentation we applied binary mathematical morphological algorithm [5],[6] based on shape of image. In morphological operation, opening in which erosion followed by dilation using 8 connected neighborhood has been performed. After applying above operation we get leaves of image shown in Fig. 2 of the complete image. Again to get branch we have performed dilation followed by erosion to segment image. The result is shown in Fig. 3.

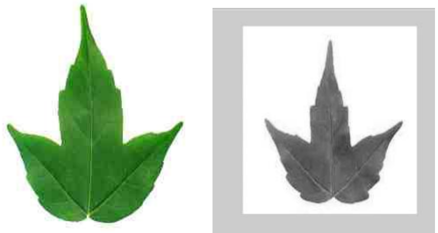

Fig.2: Original Image(Left)and Enhanced Image(Right)

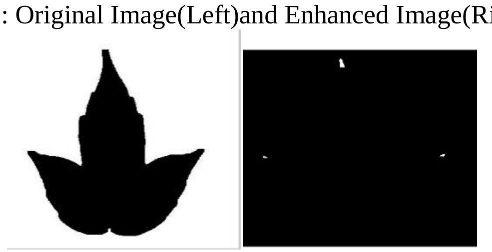

Fig.3: Image Segmentation

Texture Method:

Texture could be defined as a structure composed of a large number of more or less ordered similar elements or patterns without one of these drawing special attentions.

For texture analysis we calculated the parameters of leafs

Factors of Leaf :

Smooth Factor

The effect of noises to image area is used to illustrate the smoothness of leaf image. Smooth factor is the ratio between area of leaf image smoothed by 5 × 5 rectangular averaging filter and the one smoothed by 2 × 2 rectangular averaging filter.

Aspect Ratio

It is the ratio of length L to width W i.e. L/W.

Leaf Area

Area is the actual number of pixels in the region. The area of leaf in a preprocessed image is the number of white or '1' pixels.

Rectangularity

Rectangularity illustrates the similarity between a leaf and a rectangle. It is defined as LW/A, where L represents length, W denotes the width and A is the leaf area.

Circularity

Circularity is ratio involving area of the leaf A and square of perimeter P of the leaf. It can be defined as A/P2.

Eccentricity

A scalar value which specifies the eccentricity of the ellipse has the same second moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value ranges between 0 and 1.

Solidity

Solidity is defined as ratio between the area of the leaf and the area of its convex hull. It is defined as the S (area of leaf/ area of convex).

Moment Invariant:

Moment invariants have been frequently used as features for image processing, remote sensing, shape recognition and classification. Moments can provide characteristics of an object that uniquely represent its shape. Invariant shape recognition is performed by classification in the multi dimensional moment invariant feature space. Several techniques have been developed that derive invariant features from moments for object recognition and representation. Traditionally, moment invariants are computed based on the information provided by both the shape boundary and its interior region (Hu, 1962, Prokop and Reeves, 1992). The moments used to construct the moment invariants are defined in the continuous but for practical implementation they are computed in the discrete form. Given a function f(x,y), these regular moments are defined by:

$$M_{pq} = \iint x^p\, y^q f(x,y)dxdy$$

Mpq is the two-dimensional moment of the function f(x,y). The order of the moment is (p+q) where p and q are both natural numbers. For implementation in digital from this becomes:

$$\mathrm{M}_{pq} = \sum_X \sum_Y x^p y^q\, f(x,y)$$

To normalize for translation in the image plane, the image centroids are used to define the central moments. The co-ordinates of the center of gravity of the image are calculated using equation (2) and are given by:

$$\bar{x} = \frac{M_{10}}{M_{00}} \bar{y} = \frac{M_{01}}{M_{00}}$$

The central moments can then be defined in their discrete representation as:

$$M_{pq} = \sum_{X} (x - \bar{x})^p (y - \bar{y})^q$$

The moments are further normalized for the effects of change of scale using the following formula:

$$n_{pq} = \mu_{pq} / \mu_{00}^{\gamma}$$

Where the normalization factor: γ=(p+q/2)+1. From the normalized central moments a set of seven values can be calculated and are defined by:

$$\emptyset_1 = \eta_{20} + \eta_{02}$$
$$\emptyset_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$\emptyset_3 = (\eta_{30} - \eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2$$
$$\emptyset_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{03} - \eta_{21})^2$$
$$\emptyset_5 = (3\eta_{30} - 3\eta_{12})\ (\eta_{30} + \eta_{12})\ [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})\ (\eta_{21} + \eta_{03})\ [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$
$$\emptyset_6 = (\eta_{20} - \eta_{02})\ [(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})\ (\eta_{21} + \eta_{03})$$
$$\emptyset_7 = (3\eta_{21} - \eta_{03})\ (\eta_{30} + \eta_{12})\ [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})\ (\eta_{21} + \eta_{03})\ [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

Theses even invariant moments, ϕ_I, 1≤I≤7, set out by Hu, were additionally

Texture Method:
Texture could be defined as a structure composed of a large number of more or less ordered similar elements or patterns without one of these drawing special attentions.

Implementation and Evaluation
We prepare our database for the experimental use. The database contains various leaves with various shapes, colors and size. Experiment was done with these different leaves of different classes and tested in our classifier. First we read different leaf images of plant and finally match the new input image with our previous class or tree. We checked the accuracy that it matches the actual image or not. For all the 96 leaves of different 14 plants taken, which are completely different in their shape, color. The various parameters like volume fraction are found to be from 0.938967 to 0.989385 which is within 10 percent variation as shown in figure.

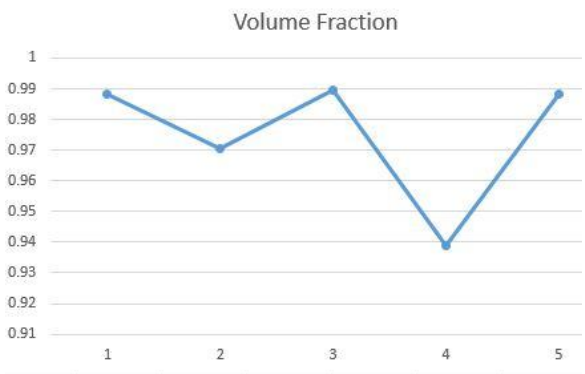

Fig: Volume fraction of various leaf.

Explanation of Dataset:

Class	Name	No Of Leafs
Class1	Chestnut leaf	2
Class2	Golden rain tree	5
Class3	Trident maple	15
Class4	Chinese redbud	10
Class5	Horse chestnut	14
Class6	Bamboo	14
Class7	Rose	4
Class8	Eenbruinigherfstblad	5
Class9	Autumn leaf	4
Class10	Pipe	4
Class11	Golden Maple Leaf	4
Class12	Japan Arrowwood	5
Class13	Castor aralia	5
Class14	Canadian poplar	5

Table 4.1: details about dataset

Experiment Result:
For the first we test the image and then take image as input for matched the target image for get accuracy of the system.
Test Image:

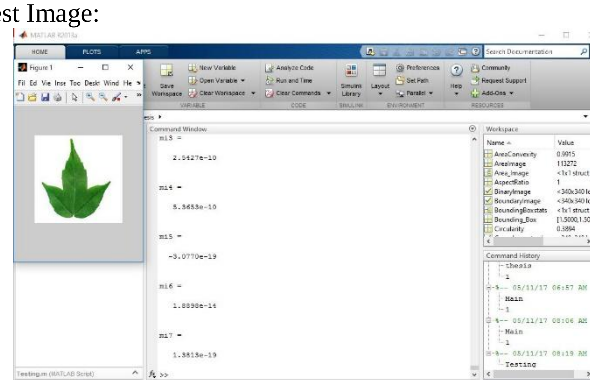
Fig: Tested Image with Mi values

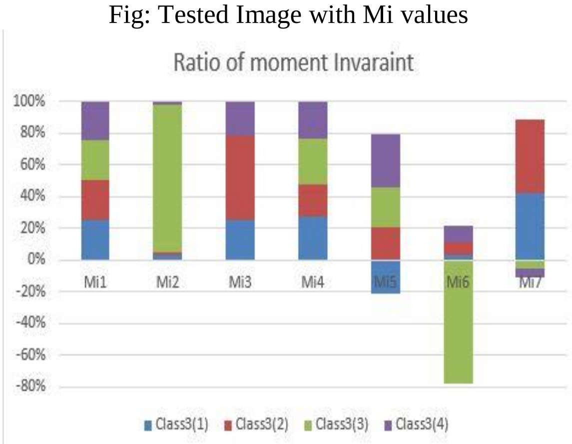

Fig: Ratio of Moment Invariant for same plant

Here we analysis that Mi1,Mi4 and Mi5 are vary use for match the image correctly. Because variation of values very less.

Result Based on Accuracy:
For the accuracy of the model first take input image and match with target image. Repeat these process many time and analysis that by table values.

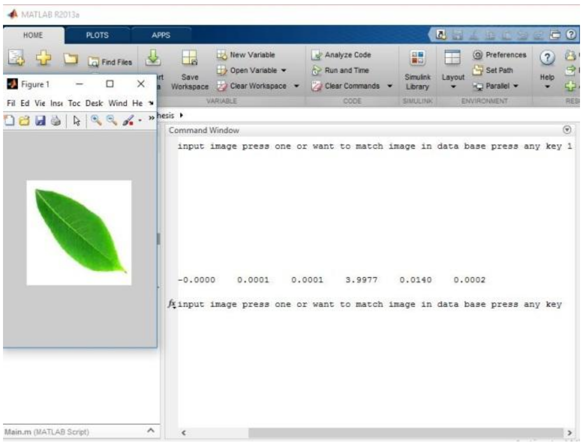
Fig: Input process of Single Image

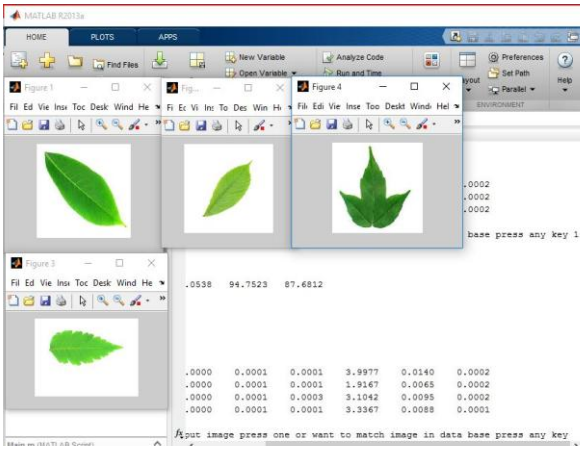
Fig: Input Process with multiple Image

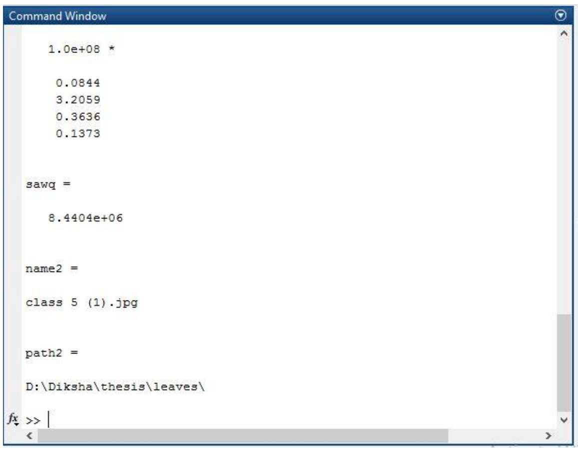

Fig: Process for Match Image with Input Image

Table: Details about accurate classified leaf from dataset

Class	Name	No Of Leafs	Wrongly Classified	Correctly Classified
Class1	Chestnut leaf	2	0	2
Class2	Golden rain tree	5	0	5
Class3	Trident maple	15	2	13
Class4	Chinese redbud	10	1	9
Class5	Horse chestnut	14	2	12
Class6	Bamboo	14	1	13
Class7	Rose	4	0	4
Class8	Eenbruinigher fstblad	5	0	5
Class9	Autumn leaf	4	1	3
Class10	Pipe	4	0	4
Class11	Golden Maple Leaf	4	0	4
Class12	Japan Arrowwood	5	0	5
Class13	Castor aralia	5	0	5
Class14	Canadian poplar	5	0	5

According to table values:
Accuracy = Total no of correctly Classified Leaf / Total No leaf in dataset
= 89/96
= 0.9270
Percentage of accuracy = 0.9270*100
= 92.70.

III. CONCLUSION

It has been found that 4 parameters that are area convexity, volume fraction, moment invariant, Texture analysis provide better results. We conclude that it is an alternative for classifying structurally complex images. They offer exceptional invariance features and reveal enhanced performance than other moment based solutions. Hence, the system is useful for the botany researchers when he wants to recognize a damaged plant because it depends on the textural features not on the color features which is naturally changing during the seasonal succession.

Future Scope: For the better recognition rate we have search new parameters. The various featured parameters may have some variation Noise into consideration so we can improve recognition rate.

REFERENCES

[1] H. Fu, Z. Chi, D. Feng, and J. Song, "Machine learning techniques for ontology-based leaf classification," IEEE 2004 8th
[2] S. Zhang, Y. Lei, C. Zhang, Y. Hu, "Semi supervised orthogonal discriminant projection for plant leaf classification", Springer Pattern Analysis and Applications, pp.1-9, 2015.
[3] N.Valliammal, "Hybrid Image Segmentation Algorithm for Leaf Recognition and Characterization", IEEE International Conference on Process Automation, Control and Computing, pp.1-6, 2011
[4] H. Kebapci, B. Yanikoglu, G. Unal, "Plant Image Retrieval Using Color, Shape and Texture

Features", The Computer Journal, pp. 1-16, 2010.

[5] J. Du, D. Huang, X. Wang, and X. Gu, "Shape recognition based on radial basis probabilistic neural network and

[6] Application to plant species identification," in Proceedings of 2005 International Symposium of Neural Networks, ser.

[7] LNCS 3497. Springer, 2005.R. C. Gonzalez, R. E. Woods, "Digital Image Processing". Prentice Hall, 2004.Amlekar M., Manza R.R., Yannawar P., Gaiwad A.T., Leaf Features Based Plant Classification Using Artificial Neural Network, IBMRD's Journal of Management and Research, Vol 3, No 1 2014,224-232.

[8] Tuceryan M., Jain A. K., "Texture Analysis" The Handbook of Pattern Recognition and Computer Vision, by C.H. Chen, L.F. Pau, P.S.P. Wang (eds.) World Scientific Publishing Co., 1993

[9] Slansky, J., "Image Segmentation and Feature Extraction" IEEE Trans. on SMC, vol. Smc-8, pp. 237-247.

[10] Haralick, R. M., "Statistical and Structural Approaches to Texture" Proceedings of the IEEE, vol. 67, pp. 786-804

[11] Zucker, S. W., Kant, K. "Multiple-Level Representations for Texture Discrimination" Proceedings of the International Conference on Pattern Recognition and Image Processing, pp. 609-614, Dallas,TX, 1981

[12] Hawkins, J. K., "Textural Properties for Pattern Recognition" Picture Processing and Psychopictorics, B. Lipkin and A. Rosenfeld (editors), Academic Press, New York, 1969.

[13] Duda R. O. and Hart P. E., Pattern Classification and Scene Analysis, New York: John Wiley □ □ Sons,(Preliminary Edition),1996

[14] Cover,T. M., Hart P. E. " Nearest Neighbor Pattern Recognition " IEEE Trans.On IT vol. It-13, January 1967,pp 21 – 27

[15] Fix,E., Hodges J.L. "Discriminatory Analysis: Non parametric Discrimination: Small Sample Performance " project 21 - 49 - 004 Report Number 11 USAF School of Aviation Medicine,Randolph Field,Texas,1952,pp 280 – 322.

[16] JyotismitaChaki, Ranjan Parekh, Samar Bhattacharya "Plant Leaf Recognition Using a Layered Approach" Microelectronics, Computing and Communications (MicroCom), 2016 International Conference, IEEE 2016.

