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Plant Identification and Classification Using Multiwavelet Transform

Shanmugaraja P[1*], Chokkanathan K[2], Thangaraj K[3], Ilanchezhian P[4], Balakrishnan N[5]
[1,3,4,5] Sona College of Technology, Salem, Tamilnadu, India
[2]Madanapalle Institute of Technology and Science, Madanapalle, Andhra Pradesh, India
*shanmugarajap@gmail.com

ABSTRACT
Identification of a plant is very much essential for the study of plant varieties. A computerized system is required for specifying the characteristics of the plant varieties. The proposed work helps in effective identification and classification of the plant species using its computational model. This proposed system considers all the features of a plant especially the leaf's shape and venation for the classification of the plant species.The disadvantages of scalar wavelets areovercome with the help of multiwavelets which involves scalar wavelets into the vector space. Because of this scheme the pitfalls of scalar wavelets are fulfilled. The characteristics of multiwavelets made them suitable for applying them in image processing to a great extent.

Keywords

Plant Identification, Plant classification, Multiwavelet transform.

INTRODUCTION

Trees plays a major role in protection of the environment. Saplings becomes plants and plants becomes trees during their life cycle. Our planet earth is preserved by trees by maintain the ecological balance. In our study we take plants for identification. Plants contains leaves, stems, and roots. Leaf plays a major role in the lifetime of a plant [1]. Food and air are provided to the plant for its growth by leaves. Photosynthesis is one of the important reactions that happens in leaves. Leaves get the food from the light source. Leaves also sweat like humans by releasing excess water from the stems. Plants contains other parts which are seasonal and tend to grow only during some parts of the year. Leaves are easy to be processed using the computer system. Plant identification is done based on the leaf structure. It is very important to categorize plants in order to identify its characteristics. Manual identification is a tedious process, and it differs according to the individual's knowledge and perception. Sampling of images is easy which helps us to determine the pattern. Plants can be differentiated using the size and shape of the leaves[2]. Recent technologies like image processing, machine learning and pattern recognition make plant identification an easier process. Even though plant has multiple parts leaves are used for classifying the plants. Feature selection is one of the important key concepts in identifying various species of plants in the world.

PROPOSED APPROACH

IMAGE PREPROCESSING

For processing the images, they need to be resized to 512*512. They are in the space of RGB. Vein feature extraction is the preliminary process done in this method. As shown in Figure 1b for preliminary process gray scale images are used. The second process is to extract RGB planes for the purpose of segmentation[3]. Using the extracted planes an OR operation is performed. The result of this operation is a binary image. Figure1cis an image whose colour is black with white background. Figure.1dshows an image with noise removed using morphological filling by complementing the resultant. Figure.1f represents the boundary of a

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leaf image. The boundary image is retrieved by using the intensity variation. Original image is subtracted from the image which is dilated and complemented to extract the leaf boundary. Figure 1g,1h,1i shows how the colour details are retrieved from the RGB plane. Figure 1e shows the features of texture as grey scale image.

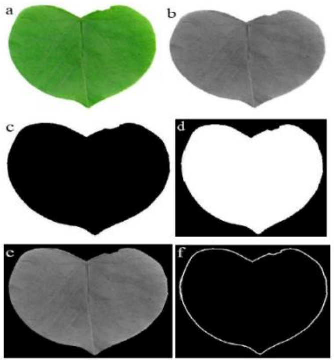

Fig. 1. A. RGB input B. Gray ScaleC. Binary D. Binary complementedE.Cropped Gray scale F. Boundary extracted G.Cropped R component H.Cropped G component I. B component cropped image

FEATURE EXTRACTION OF LEAF BIOMETRIC

Feature extraction is a tedious process, and it requires a pre-processing step on the image. With the help of digital image, the leaf image features can be extracted. The purpose of pre-processing an image is to improve the quality of the data and this improvisation helps feature enhancement[4]. By applying morphological operations on the gray scale the vein features can be extracted. Fig 3 shows the image which is free from gray overlap which lies between the background and the veins found on the leaf. This is the result of morphological processing. In this model initially the gray scale image is converted from RGB . Radius ranges from 1- 4. Operations are performed on the gray scale leaf image. Disk shape structuring element is used Flatley. The converted image is obtained by removing the margin from the leaf image and it is binarized. After performing all these stages the vein features are extracted from the leaf image.

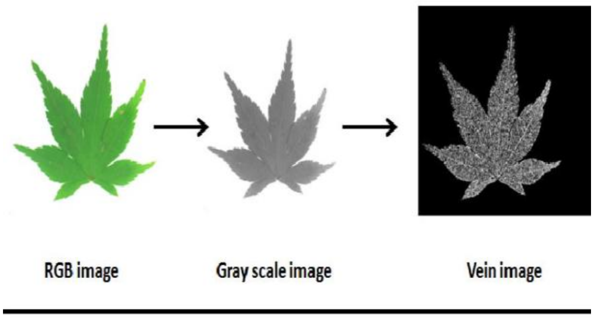

Figure. 3. Vein features morphology operations

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Feature Classification

The proposed architecture use KSVM for classification and for feature extraction we use multiwavelets coefficients. According to the study done by us wavelet feature provides rich information for extracting tissues from leaves. Along with wavelet feature prostate features also provides complete details about edges and lines. These details can be extracted with different orientation and scales[5]. Extracting features from the whole image is clumsy so the features are extracted from the sub images. More images of square shape are obtained from the original gray scale image. Windows with larger sizeprovide stable information while extracting low frequency information. On the other hand, for preserving locality of the information smaller windows are used.

Initially feature vector representations are created with the help of sub window with multiwavelet coefficients. KVSM classification machine is used in the later stage to train them. Given the data KSVMs classifiers will maximize the generalization. It also results in minimization of structural risk. In tissue classification and object detection their performance is very high when compared with other methods.

Multiwavelet Coefficients

Wavelets functions are developed for the purpose of data sorting based on their frequencies. This function is responsible for converting to frequency domain. The result of this operation produces vector space with orthogonal basis [6]. The success percentage of wavelets has enormously increased in the past decade by finding the solutions for unsolvable problems. Multiwavelets on the other hand are the extension of wavelets with a common basis, scaling and functions.Translates of N scaling and wavelet functions generate a basis for multiresolution analysis in multiwavelets.

The functions are show below.

1. [(I)(p)=[()1(p), ()2(p),.)IN(p)] – N scaling function
2. [(x) ['P 1(x),Q2(x),... QN(x)] – N wavelet function

In the proposed method N is set to 2. The resultant of this value changes the equation two scale dilation into

D (X) = (k x 2) (4 F2YL(k)) (1)

Below equation represents two-scale wavelet equation

T(x) = T 2IH(k)(2x k)(2)

In a 2-channel multifilter lowpass (L) and highpass(H) can be interpreted like scalar wavelets. The multiwavelets used in this work are created by J.Geronimo et al[8]. When compared with scalar wavelet case this multiwavelet contains two different types of scaling functions, two types of wavelets and has remarkable properties[12]. All these properties highlight the usage of multiwavelet function. D1 & D2 are the two scaling functions which have a poor support from [0,1] and [0, 2] [7]. Wave functions exhibit both symmetric and asymmetric properties and Scaling functions exhibit only symmetric properties. They have orthogonal

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characteristics and results in approximation of second order. Results first level of decomposition is shown in the following table 1.

Table 1. Results of the block H2L1

L_1 L_1	L_2 L_1	H_1 L_1	H_2 L_1
L_1 L_2	L_2 L_2	H_1 L_2	H_2 L_2
L_1 H_1	L_2 H_1	H_1 H_1	H_2 H_1
L_1 H_2	L_2 H_2	H_1 H_2	H_2 H_2

In the block H2L1 low pass coefficients are in the horizontal direction of the first scaling function and equivalent coefficients of second wavelet[11]. The next level takes the submatrix for decomposition in a similar manner. This proposed work uses two different schemes for getting two input rows. We use oversampling factor for feature extraction in which two identical rows are used. This method pre-processes

D (X) = (2x k) 4 F2YL(k)

the equation using a scalar signal-based property in the continuous multiwavelet transform. The difference between the two schemes is less computation is required for the first scheme when compared with the second one. Results are compared by applying both the schemes for both levels of decomposition.

EXPERIMENTS AND RESULTS

In the proposed system 50transrectal ultrasound images are used in the study. For extracting prostate and non-prostate patches,the boundaries of them are delineated by human interventions. After this boundary identification it is clear that prostate tissues fall inside the boundary whereas non prostrate tissues fall outside the boundary. This identification is explained using the formula P E {1 -1,+1}. Here negative value indicates the non-prostate tissue and positive value indicates prostate tissue. In order to deal with the turbulent boundary layers (i.e near the delineated boundaries) prostate contours are used. If 76% of the pixels fall inside, then it’s a prostate whereas if the same percentage of the pixels fall outside then a patch p is non prostate.If a patch doesn’t satisfy the above condition, then it is removed from the sample training data set. The proposed methodology is evaluated using the error rates with three fold cross validation method. The training data set is randomly split for three times. 80 % of both the patches were used for training KVSM network. The remaining 20% are used for validation comparison.

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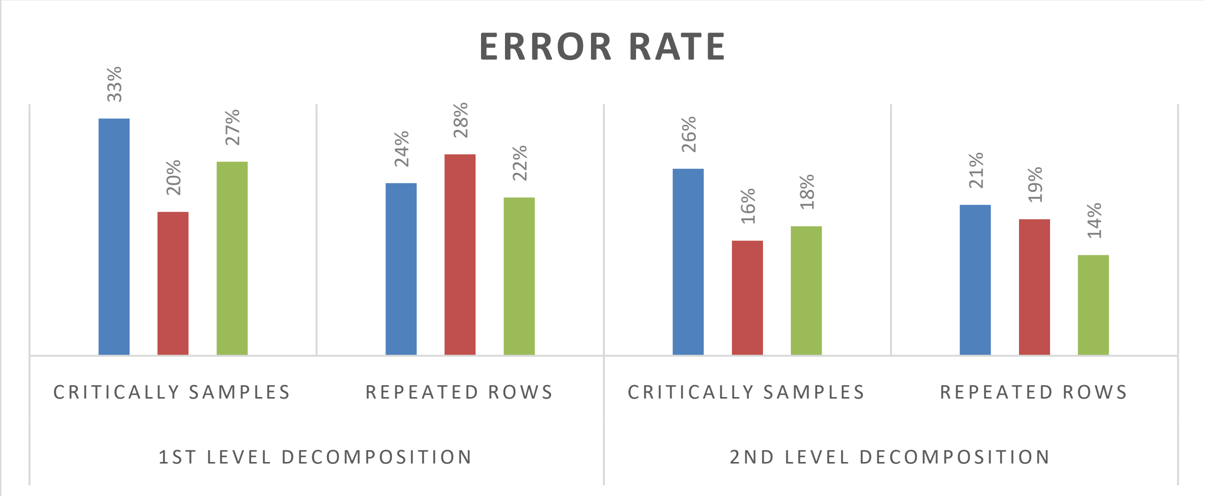

Figure 4.0 . Decomposition Levels

The results shows that repeated rows performed well when compared with critical samples. The first level decomposition results in classification of over sampled data. 2nd level decomposition is much better than the 1st level decomposition. The classification process is enhanced with the help of the multiwavelet feature vector.

CONCLUSION

The proposed methodology uses KSVM classifier for identification and classification of leaf images from a plant. When compared with other methods the proposed method results in higher performance . Feature extraction used here are texture, shape and color of the vein with the help of using multiwavelet transformation. Maximum accuracy is obtained with the help of combined classifier. The proposed methodology is compared with KSVM, Decision tree and Naïve bays method. The performance accuracy of the proposed methodology is more than that of the other methods.

REFERENCES

[1] A. Ghanei, H. Soltanian-Zadeh, A. Ratkesicz and F. Yin, "A threedimensional deformable model for segmentation of human prostate from ultrasound image", Medical Physics, Vol. 28, pp. 2147-2153, 2001.

[2] N. Hu, D. Downey, A. Fenster, and H. Ladak, "Prostate surface segmentation from 3D ultrasound images", IEEE International Symposium on Biomedical Imaging, pp. 613-616, Washington, D. C., 2002.

[3] S.D. Pathak, V. Chalana, D.R. Haynor, "Edge-Guided Boundary Delineation in Prostate Ultrasound Images", IEEE Tr

[4] Sapna Sharma and Dr. Chitvan Gupta, “A Review of Plant Recognition Methods and Algorithms”, IJIRAE, ISSN: 2349-2163 Issue 6, Vol June 2015.

[5] Sachin D. Chothe, V.R.Ratnaparakhe “Plant Leaf Identification System”, International Journal on innovative Research in Science, Engineering and Technology Vol.4, Special Issue 6, May 2016.

[6] Nisar Ahmed, Usman Ghani Khan and Shahzad Asif, “AN Automatic Leaf Based Plant Identification System”, 5th International Multidisciplinary Conference, 29-31 Oct.

Received 25 April 2021; Accepted 08 May 2021.

[7] Andrade, M., Mayo, S. J., Kirkup, D., & Van Den Berg, C., "Comparative morphology of population of Monstera Adans. (Araceae) from natural forest fragments in northeast Brazil using elliptic Fourier analysis of leaf outlines", Kew Bulletin, 63, 193–211, 2008.

[8] X. Wang, D. Huang, J. Dua, H. Xu and L. Heutte, Classification ofplant leaf images with complicated background, Appl. Math. Comput.,vol.205, pp.916-926, 2008.

[9] J. Du, D. Huang, X. Wang and X. Gu, Computer-aided plant speciesidentification (CAPSI) based on leaf shape matching technique, Trans.Inst. Meas. Control, vol.28, pp. 275-284, 2006.

[10] Nam Y., Hwang E., and Kim D., A similarity-based leaf image retrievalscheme: Joining shape and venation features, Computer

[11] Shanmugaraja, P**,**Vasanthi, S; Balamurugan, D ; Chandrasekar, S**,** 'Design and Implementation of Transport Relay Translator and its security mitigations', International Journal of Engineering and Technology, vol. 5, no. 4, pp. 3439-3442, ISSN : 0975-4024 , 2013

[12] Shanmugaraja, P ;Chandrasekar**, S**, Accessible Methods to Mitigate Security Attacks on IPv4 to IPv6 Transitions', European Journal of Scientific Research, vol. 77, no. 2 , pp. 165-173, ISSN : 0975-4024 ,2012.

[13] S. Zhang and Y. K. Lei, Modified locally linear discriminant embedding for plant leaf recognition, Neurocomputing, vol.74, pp.2284-2290,2011.