An Efficient Approach for Plant Leaves Identification based on Texture Features

Sushil Kumar Saroj[a], Shiho Oshiro[b], Pratima Yadav[c], Nagendra Pratap Singh[d]

[ac]*Department of CSE, M.M.M. University of Technology, Gorakhpur, India*
[b]*Department of Engineering and Information Engineering,University of the Ryukyus,Okinawa, Japan*
[d]*Department of CSE, National Institute of Technology, Hamirpur, India*
sushil.mnnit10@gmail.com, e145756@ie.u-ryukyu.ac.jp, mail2pratima27@gmail.com, nps010175@gmail.com

Abstract: India is an agriculture major country. Agriculture plays vital role in GDP and culture of our country. India has found very large number and variety of plants. But various plants have same appearance, and because of which it is difficult to distinguish them. Nursing a plant according to its requirements is crucial. If, a plant is identified incorrectly and is supplied with wrong fertilizers can result in poor yield and productivity. Thus, identifying plant correctly is a prominent task. Therefore, we propose an approach to classify leaves of Cucurbita (commonly known as pumpkin) and Lagenaria siceraria (known as bottle guard) which are similar in appearance but are actually very different in texture. There are various approaches exist in a literature to identify the plant leaves. The propose approach using the Linear Discriminator classifier has performance 99.6% which is found better with respect to the other classifiers like K-NN, SVM etc.

Keywords- Leaf images, Feature extraction, GLCM, Tamura, Wavelet, Classification

1. Introduction

Plants have very important role in our environment and in our lives. As they help living beings to change the sunlight energy into nourishment, they are foundation to other form of life. Since, ancient times they have attracted people and the struggle to group them. The Swedish botanist Carolus Linnaeus in the eighteenth century provided with a systematic categorization of plants in wide range of ways. In 1973, L.R. Hicher was the first person to study the leaf features to classify them. From then, huge development has been seen in this field [1].

Plant disease are the major issue which farmers are facing nowadays and in order to cope up with those disease many researchers are carrying out various experiments. In order to provide any solution to plant disease, one should be able to classify the plant correctly. There are multiple plant species which are similar in appearance but differ in textures. One of the suitable examples is Cucurbita (pumpkin) and Lagenaria siceraria (bottle guard) tree leaves. It is easy to identify most plants from their flora or organic products, very less plants can be differentiated with the help of their leaves. One can be able to distinguish a plant by finding the properties of leaves such as the patterns, shapes and arrangements. Texture give vital characteristics of surface of any object with the help of aerial or satellite photographs, biomedical images, and many other types of images. Texture helps to detect any pattern present over the surface of any object.

2. Literature Survey

Dheeb et al. [2] performed segmentation of images with the help of k-mean technique and then passed those segmented images to neural network classifier and performed classification successfully with 93% precision and an average accuracy of 92.7%.

Afrat et al. [3] compared various classification techniques which are being used for leaves classification and acquired different accuracies on different features. They computed 98% accuracy with HOG, 96% accuracy with MSER and 98% accuracy with C-SHIFT. Chang et al. [4] used extended version of wavelet transform and designed a classification algorithm and calculated correction rate higher than 97%. Wldchen el at. [5] explained for distinguishing, investigating and comparing work in the field of plant species identification utilizing computer vision procedures. A precise audit was performed driven by inquiries and utilizing a well-defined process for information extraction and examination.

Arribas et al. [6] gave an automatic classification system of leaves images for sunflower using neural networks, which consists of 4 stages segmentation, feature extraction, feature selection and classification. The results explain that the system acquires higher accuracy using five selected discriminative features gaining 85% mean Correct Classification Rate and for the test set, over 90% an area under the ROC.

3. The Proposed Method

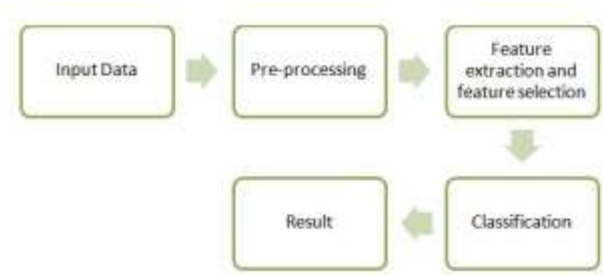

Fig. 1. Proposed methodology

The proposed strategy is the combination of the pre-processing, feature extraction, and classification based on chosen features utilizing machine learning classification methods. In pre-processing step to begin with, resize (measure up to estimate) all the images taken from different dataset collections at that point change over the color image into grayscale image by utilizing PCA based color to grayscale transformation strategy proceeded by contrast limited adaptive histogram equalization (CLAHE) due to the hierarchal steps conserve both color discriminability and the texture by utilizing basic linear calculations in subspaces with low computational complexity [7], [8] [9].

In following stage, obtain the color features and gray scale features of the image. Feature extraction is a procedure of determining new features for portraying and further processing of a image and furthermore it is identified with dimensionality reduction. Whereas features are the important quality of the image which helps in extraction of features such as color, edge, texture, shape, etc. In this paper we took a shot at a statistical component of the image, for example, GLCM, Tamura's features, Wavelet features, Law's Texture Energy (LTE) based features, and HOG features which are explained as follows:

3.1 Gray Level Co-occurrence Matrix (GLCM) Feature

GLCM is a statistical texture investigation method considering pixel-to-pixel and is one of the most general methods. Described by Haralick [10] in the early 1970s, analysis windows have been tried in numerous fields to quantify a given intra-image pattern. As a basic idea, the GLCM filter counts specific cell values at each position in the filter window with the right neighbour and pairs and calculates the frequency of occurrence in the image. The result is aggregated in GLCM, and statistical information is extracted and calculated from this matrix. By doing so, the filter value of the target cell is computed and describes the texture characteristics of the image.

To evaluate the GLCM, use the 5 x 5 sample filter this time and assume that there are images with gray levels from 1 to 4 (Fig. 1). First of all, as a basic operation, count is counted as (i, j) with vertical as i and horizontal as j, one as the right side and pair. As an example, pay attention to the red circle (1,1). (1, 1) has only one out of 20 pairs of 25 masses. Therefore, the cells with i = 1, j = 1 are 1. Continue to focus on (2, 2) in blue circle. (2, 2) is there are three in total, so the mass of i = 2, j = 2 is 3. Repeat this operation to fill all the tables (Fig.3). Next, pay attention to 1, 3, 4, 2 in the diagonal components. Make this diagonal component symmetrical. For example, understand that (1, 4) and (4, 1) are the same pair, and (1, 4) rewrites from 0 to 1. Since it is necessary to count gray portions in double, the numbers 1, 3, 4, 2 are rewritten to 2, 6, 8, 4. Repeat the other counts in this way.

			j		
	1	1	2	2	3
	1	2	2	3	3
i	2	2	3	3	4
	2	3	3	4	4
	3	3	4	4	1

Fig. 2. Sampling Filter

i \ j	1	2	3	4
1	1	2	0	0
2	0	3	4	0
3	0	0	4	3
4	1	0	0	2

Fig. 3. Obtained by counting the pair

i \ j	1	2	3	4
1	2	2	0	1
2	2	6	4	0
3	0	4	8	3
4	1	0	3	4

Fig. 4. Exchange left and right cell values

3.2 Tamura Feature

Tamura's features are based on psychophysical research on six characteristic elements that correspond to human visual perception. The six features are as follows.

- Coarseness
- Contrast
- Directionality
- Line Likeness
- Regularity
- Roughness

Coarseness, Contrast and Directionality were tested by Ma et al, but they were not very effective. So, Tamura modified it on its own. Howarth and colleagues were able to outperform the color features using the co-occurrence matrices and Gabor wavelets for the 2004 video data set evaluation.

Coarseness: Coarseness is related to the distance of the gray level spatial change, that is, the size of the primitive element forming the texture. Coarseness is designed to measure the difference between Coarseness texture and fine texture, and the evaluation method is shown below.

1) For each pixel p (x, y), let the size around the pixel be k = 0; 1; 2;.....; 5 and calculate the six averages for the window.

2) We take the average of non-overlapping neighbourhoods on the opposite side of the horizontal and vertical points in each scale Ek(x; y). Find the value of k that maximizes Ek(x; y) in either direction.

$$E_{\mathrm{k,a}}(p) = mod({A^1}_{\mathrm{k}} - {A^2}_{\mathrm{k}}) \qquad (1)$$

$$E_{\mathrm{k,b}}(p) = mod({A^3}_{\mathrm{k}} - {A^4}_{\mathrm{k}}) \qquad (2)$$

$$p(x, y) = E_{1,\mathrm{a}}, E_{1,\mathrm{b}}, E_{2,\mathrm{a}}, E_{2,\mathrm{b}} \ldots \qquad (3)$$

3) Compute Coarseness (Fcrs) by averaging Sbest for the entire image. Taking the size at each point shows the highest output when considering all directions together.

Contrast: The contrast is the variance of the brightness of the pixel and shows the method of measuring the gray level q. How the gray level q changes in the image I is measured, and the distribution of the gray level q is biased toward either of the black and white distribution on the histogram.

$$Contrast = \frac{\sigma}{(\alpha_4)^n} \qquad (4)$$

$$where = \begin{cases} n = 0.25 & (recommended) \\ \sigma^2 = (q-m)^2 P_{\mathrm{r}}(q|I) & (Variance) \\ \alpha_4 = \frac{1}{\sigma_1} \sum_{q_{\max}}^{q=0} (q-m)^4 P_{\mathrm{r}}(q|I) & (kurtosis) \end{cases}$$

Directionality: Directionality is the gradient orientation of pixels. The method of calculating the angle of edge intensity and directionality is as follows. The histogram of quantized direction values is shown in the following figure (Fig. 5).

Δx

-1	0	1
-1	0	1
-1	0	1

Δy

1	1	1
0	0	0
-1	-1	-1

Fig. 5. x and y = x; pixel difference in the y direction

The histogram of the quantized direction values is constructed by adjusting the number of edge pixels whose corresponding edge intensity and direction angle is larger than a predetermined threshold value. The histogram is relatively homogeneous for images with no strong direction and peaks for images with high directionality.

Line Likeness: It is defined as the average degree of coincidence in the edge direction scattered by the pixels and moves only by the distance d along the direction.

$$edgestrength = 0 : 5(|\Delta_{\mathrm{x}}(x,y)| + |\Delta_{\mathrm{y}}(x,y)|) \qquad (5)$$

$$directionality\ angle = arctan\frac{\Delta x}{\Delta y} + \frac{\pi}{2} \qquad (6)$$

Regularity: Regularity is given by following equation:

$$1 - r(\sigma_{\mathrm{coarseness}} + \sigma_{\mathrm{contrast}} + \sigma_{\mathrm{directionality}} + \sigma_{\mathrm{linelikeness}}) \qquad (7)$$

r is the normalization factor and σ is the standard deviation representing the feature of each partial image of the texture.

Roughness: Roughness is defined by the following equation.

$$Roughness = Coarseness + Contrast \qquad (8)$$

3.3 Wavelet Feature

Wavelet is extension and conversion of mother wavelet. It is a mathematical function useful for digital signal processing and image compression. In signal processing, wavelets can recover weak signals from noise and are found to be particularly useful in processing X-ray and magnetic resonance images in medical applications. Wavelet transformation is one means of analysing the characteristics of a signal, and it can be used in a mechanism similar to that of Fourier transform (FT). Fourier transformation does not exist inverse transformation, it is useful for analysing the signal at steady state, but it is not suitable for non-stationary one. Inverse transform exists as a feature of the wavelet, and it is possible to analyse time-frequency analysis and transient signals. Create wavelet groups of various width and time positions. Perform two kinds of operations on the mother wavelet. The first one performs shift and translation by parallel movement. The second one performs scaling and dilation by scaling. Wavelet transform calculation includes continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

Orthogonal Transform: Eliminate redundancy with delay of conversion and make complete reconstruction possible. The entire information of the signal is not repeated but is encoded once. It is better to introduce orthogonal transformation to discretize the parameters while preserving the information completely.

$$Motherwavelet = (t) \tag{9}$$

Scale = a, Shift = b,wavelet = ψ a,b(t)

$$\psi a, b(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{10}$$

Continuous Wavelet Transform: It was a time and effort to determine the window width by using the Fourier transform with window originally around 1981. there. We proposed WT to change the window width according to frequency and CWT was made. CWT is more frequently used for real-world signal analysis.

Mexican Hat Wavelet: Mother wavelet (t) is Mexican hat, which is the second derivative of the Gaussian function. Since, it is a real number function, you do not have to think about complex conjugation.

Mother wavelet

$$\psi(t) = (1-t^2)e^{-\frac{1}{2}t^2} \tag{11}$$

Wavelet

$$\psi_a, b(t) = \frac{1}{\sqrt{a}}(1-(\frac{t-b}{a})^2)e^{-\frac{1}{2}(\frac{t-b}{a})^2} \tag{12}$$

Wavelet transformation

$$W_\psi[x(t)] = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)(1-(\frac{t-b}{a})^2)e^{-\frac{1}{2}(\frac{t-b}{a})^2}dt \tag{13}$$

Discrete Wavelet Transform: It was theoretically developed around 1986 and gave a theoretical figure to binary DWT in connection with image processing and signal processing fields. DWT has a relatively large amount of compression, communication, and commentary. Redundancy is low, efficient coding is possible, frequent in transmission, compression, image processing, and the like. In order to reduce overlap, we use a binary discrete wavelet, discretize the parameters, and use orthogonal transformation to completely preserve the information.

Introduction of Binary Discrete Wavelet: The parameters are discretized, and the wavelet whose scale changes by the power of 2 is as follows.

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^j t - k) \tag{14}$$

Shrinks when j is large, and delays when k is large. The conversion parameter is discrete, but the signal to be handled is continuous.

High Pass Filter and Low Pass Filter: High pass and low pass filters are chosen so that they accurately halve the frequency range. LL (low - low), HL (high - low), LH (low - high), HH (high - high). A 2 o'clock array of coefficients containing data of four bands is obtained. The LL band can be broken up to any level, resulting in pyramid decomposition. The highest-level LL band is classified as the most important one and the other bands are classified as low importance. The inverse transform is used to reconstruct the various classes of data into the reconstructed image. First of all, it is divided into four bands (Fig. 6). Further decomposition of the LL band of FIG. 6 results in the following (Fig. 7). When only the LL band of Fig. 7 is further decomposed, it becomes as follows (Fig. 8). In this way, the decomposition level of LL can be arbitrarily determined. However, it is not right to decompose it a lot.

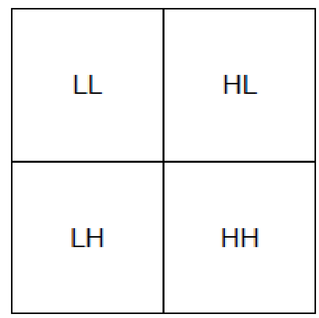

Fig. 6. Single level Decomposition

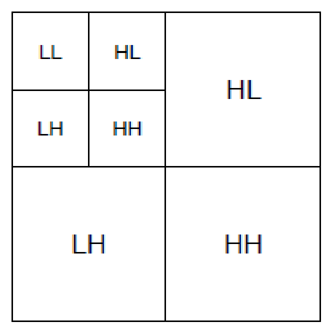

Fig. 7. Two level Decomposition

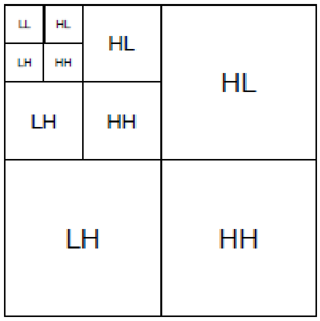

Fig. 8. Three level Decomposition

4. EXPERIMENTAL RESULTS AND DISCUSSION

In the proposed approach, the leaf image dataset contains 238 distinctive leaf images. The attached dataset in our examination is procured by ourself from the plants of our environment which comprise of crisp leaf images of pumpkin plant and bottle gourd plant. Out of 238 images 125 images are of pumpkin plant leaves and are caught by Oppo realme1 having 13MP camera with greatest goals of 1080 x 2160 pixels and rest of 113 images of bottle gourd leaves are caught by a Lenovo K3 Note having 13MP camera with a greatest goal of 4160 x 3120 pixels.

The database also contains some disease infected or partially dry leaves images. The sample dataset of leaf images and related classes are shown in Figure 9 and 10. For investigational examination, total 57 features are identified from each image. These 57 features are accumulation of 22 GLCM features from F-1 to F-22, 32 Wavelet features from F- 23 to F-54, 3 Tamura features from F-55 to F-57. For instance, all 57 features of one bottle guard leaf image and one pumpkin leaf image is specified in Table-I.

MATLAB R2017a is utilized for features extraction and characterization. With the assistance of different classifier like SVM, K-NN, linear discriminant and so forth we performed classification process and after studying the outcomes we concluded that the best classification outcome is registered with the help of linear discriminant classifier at 5-fold cross validation and 99.6% of accuracy has been recorded. The execution of proposed approach by utilizing of linear discriminant classifier is 99.6%, which is discovered better concerning alternate classifiers like k-NN, SVM, Quadratic discriminant, and Decision Tree classifiers.

In future, we can work with different features including shape and size to classify utilizing different classifiers and the proposed approach is utilized to classify the different vegetables and natural products by utilizing their leaves.

TABLE I
ALL 57 SELECTED FEATURES OF FIRST IMAGE OF FIG.9 AND FIG. 10 OF BOTTLE GUARD IMAGE (B35.JPG) AND PUMPKIN IMAGE (P44.JPG) RESPECTIVELY

Image Name	Features														
	F-1	F-2	F-3	F-4	F-5	F-6	F-7	F-8	F-9	F-10	F-11	F-12	F-13	F-14	F-15
Bottleguard B35.jpg	31.1432	0.2630	0.9600	0.9600	382.03	-30.10	0.2452	0.1531	2.4490	0.8801	0.8791	0.3376	31.1127	10.5811	82.3111
	F-16	F-17	F-18	F-19	F-20	F-21	F-22	F-23	F-24	F-25	F-26	F-27	F-28	F-29	F-30
	2.2483	0.2630	0.5826	-0.622	0.9435	0.9729	0.9960	12.0733	13.5155	13.4342	12.6801	10.7396	8.5687	6.3879	5.1665
	F-31	F-32	F-33	F-34	F-35	F-36	F-37	F-38	F-39	F-40	F-41	F-42	F-43	F-44	F-45
	4.1161	3.8808	6.4415	10.4455	10.2832	9.6051	9.3662	8.7245	0.1669	0.2636	0.2885	1.4216	3.6897	4.1792	4.0299
	F-46	F-47	F-48	F-49	F-50	F-51	F-52	F-53	F-54	F-55	F-56	F-57			
	3.3849	2.1836	2.1556	3.4550	1.8422	1.7502	1.9168	1.6858	1.5770	3.4259	2.9799	0.0569			
	F-1	F-2	F-3	F-4	F-5	F-6	F-7	F-8	F-9	F-10	F-11	F-12	F-13	F-14	F-15
Pumkin P44.jpg	35.3856	0.1984	0.9701	0.9701	524.21	-50.44	0.1694	0.1988	2.2517	0.9194	0.9181	0.3914	35.3063	11.3437	98.5846
	F-16	F-17	F-18	F-19	F-20	F-21	F-22	F-23	F-24	F-25	F-26	F-27	F-28	F-29	F-30
	2.0958	0.1984	0.4773	-0.688	0.9516	0.9815	0.9970	12.7045	11.2319	10.4400	9.8169	9.5748	8.7537	8.1062	7.5072
	F-31	F-32	F-33	F-34	F-35	F-36	F-37	F-38	F-39	F-40	F-41	F-42	F-43	F-44	F-45
	7.2837	7.6527	8.0499	8.6478	9.6852	10.7292	12.0706	12.5537	0.9905	3.2372	3.6334	4.0698	4.1734	4.2253	4.4764
	F-46	F-47	F-48	F-49	F-50	F-51	F-52	F-53	F-54	F-55	F-56	F-57			
	4.4170	4.2594	4.2084	4.1817	4.0614	3.8200	3.2350	1.5672	0.8148	3.8308	2.2297	0.0616			

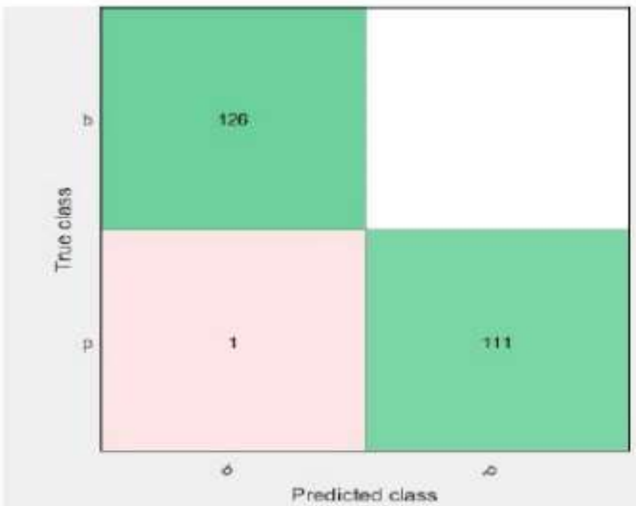

Fig. 9. Confusion matrix

Fig. 11. Pumpkin Leaf Images

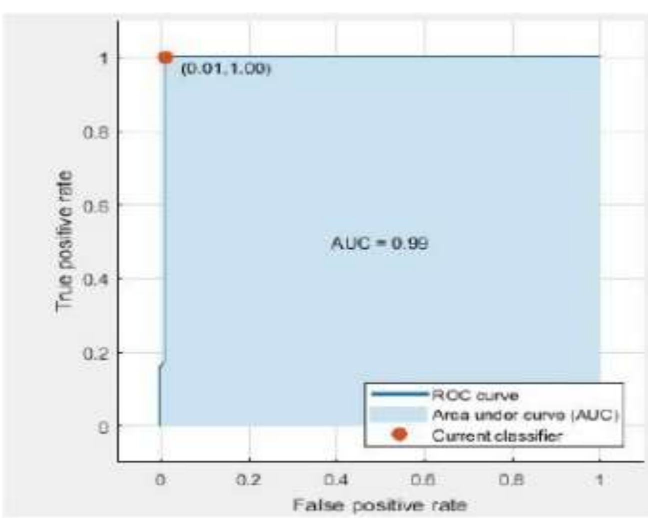

Fig. 10. ROC Curve

Fig. 12. Bottle Gourd Leaf Images

5. Conclusion

The proposed method was helpful for classification of pumpkin and bottle gourd plant leaves on the basis of the leaf texture using GLCM, Wavelet and Tamura features. In the proposed method, prior to extracting the feature, the leaf images were preprocessed and then machine learning based classification approach was used to classify the images. On the basis of experimental results, it was observed that the proposed method was proficient to distinguish between pumpkin and bottle gourd plant leaves images with accuracy 99.6% in case of linear discriminant classifier.

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