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Preprocessing and Multi Feature Extraction Method for Automated Plant Species Identification

A.M. Bojamma[1] and Chandrasekar B.S.[2]
[1]Research Scholar, Department of Computer Science, Jain University, Bengaluru (Karnataka), India.
[2]Director, Center for Distance Education & Virtual Learning (CDEVL) Jain University, Bengaluru (Karnataka), India.

(Corresponding author: A.M. Bojamma)
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ABSTRACT: Image preprocessing and feature extraction are some of the very important and mandatory stages for image classification-based applications. Preprocessing and feature extraction play an important role in obtaining high accuracy rates during classification. The challenges like not having the required dataset and the trails in extraction of features like color texture, shape is addressed in this study. In this work we have created a dataset of the plants which are indigenous to the Western Ghats region of India. The preprocessing stage involves application of Gaussian filter for reduction of noise. Gaussian filter enhances image structure at different stages, Otsu's binarization technique has been applied for thresholding. We have extracted shape descriptors like area, perimeter, aspect ratio, circularity, rectangularity. Color moments and also the texture-based feature extraction using Haralick's method are applied on the dataset. The results obtained are presented and the methods are evaluated on the Western Ghats dataset. This study emphasizes on the importance of feature extraction process.

Keywords: Color Features**,** Feature Extraction, Image Processing, Leaf Dataset, Otsu's Binarization, Preprocessing, Western Ghats, Shape Features, Texture Features, computer vision.

Abbreviations: GLCM: Grey Level Co-occurrence Matrix.

I. INTRODUCTION

Knowledge of the species is crucial for conservation of the biodiversity of a region. The conventional manual techniques used to identify plants is a cumbersome, complex and time-consuming process. It requires the skills of an experienced botanist to identify rare and endangered species of plants. It can be a huge hurdle for novices or beginners who would want to acquire species knowledge, which is hard to overcome.

On the positive side, the field of computer vision has made progress in various applications including that of automated species identification. The availability of tools, relevant techniques and technologies such as mobil devices, high resolution digital cameras, powerful machine learning algorithms and computer vision applications which have enhanced and automated the image processing and pattern recognition have made a greater impact in this field. They are not only a viable option but also very accurate, fast and readily available for the general public [1, 2]. The draw back in some of the older studies is not having a standard dataset pertaining to a particular region of study.

Image processing is one of the effective ways of conducting studies on plants for identification purpose. This field is used widely in agricultural and bio medical research where images are converted to digital format and required useful information is extracted from the image for identification and classification purposes. For plant species identification it is required that one or more characteristics of a plant needs to be taken into consideration. Typically we humans use one or more than one of the following characteristics : the plant as a whole including features like size shape, its flowers (color of the flower, size, inflorescence, etc.) it can be its stem, fruits (size, season of growth, color) and its leaves (shape, texture, margin, pattern of the veins) [3].

Majority of the automated plant species classification approaches have relied on leaf as a primary characteristic for identification due to the availability of leaves throughout the year. Most researchers in this field have given predominant importance to global features [4, 5] like the leaf base the leaf tip. The margin of the leaf. Very few researchers have worked on the local features of the leaf like base, petiole [6, 7].

General approach for leaf image classification: the primary goal of an automated identification system is to learn to recognize the images and use the results obtained for identification purposes. The leaf identification system encompasses the following stages.

Stage 1: The image acquisition stage: During this stage the image of the whole plant or its organs like leaf, flower are obtained. The images can be captured using cameras inbuilt into mobile phones or using a digital camera.

Stage 2: The preprocessing stage: The main aim of the preprocessing stage is to remove the distortions or the noise factor from the image. The preprocessing stage generates a binary image of the plant organ. During this stage the preprocessing unit receives a raw image and generates an output image which is suitably modified for the next stage of feature extraction [8].

Stage 3: Feature Extraction Stage: This stage refers to a phase in plant identification where different key features are extracted from the meaningful regions of the image. The extraction can include both local and global descriptors like geometric parameters - length, breadth, area, diameter etc. it can be extraction of color descriptors, texture descriptors or contour-based descriptors. These extracted features characterize some key feature of the plant captured in the images [9].

Stage 4: Classification stage: In the classification step, all extracted features are concatenated into a feature vector, which is then classified using machine learning algorithms.

II. RELATED WORK

Efficiency of recognition systems has a direct correlation to the feature extraction process with feature selection being a primary criterion for high performance systems. In automated plant identification systems features both local and global have been extracted for recognition purpose. It is essential that there is focus on the feature extraction phase as the efficiency of recognition systems. Dimensionality reduction of information is the primary goal of feature extraction [8]. In leaf identification system the primary features studied are leaf shape [12], texture margin, veins. Some researchers have extracted features in combination like shape and vein [10], color and texture etc. [11]

Aimen and Khan *et al.,* (2015) have extracted morphological features, Fourier descriptors and also have proposed a new feature called shape defining feature for use in the algorithm [12].

Nam and Hwang *et al.*, (2005) use chain codes, Fourier transform MPP (Minimum Perimeter Polygons), are used to identify the shape of the leaf. Chain codes is used to identify the boundary of the leaf. Fourier transform is used to convert the function from the space domain to the frequency domain. Polygonal approximation method to identify curvature descriptions [13].

Chaki *et al.*, (2015) have calculated nine shape features from the preprocessed image which include four basic parameters like leaf area, leaf perimeter, major axis and minor axis(corresponding to the axes of an ellipse) a feature vector was created with additional five features that were derived from primary features [14].

Novotný and Suk (2013) have used simple and morphological shape descriptors (SMSD) and Fourier descriptors for feature extraction. Features are computed from both boundary of the leaf and its texture. Two of most popular descriptors - image moments and Fourier descriptors were used extensively for testing [15].

Nesaratnam and BalaMurugan (2015) all have extracted features from the segmented leaf using Hu moments. Image moments are widely used as they provide better understanding of the shape than any other geometrical feature [16].

Zulkifli *et al.*, (2011) have used three moment invariants techniques: Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI) and Tchebichef Moment Invariant (TMI) for this study. The results obtained by these three techniques were compared and it was found that TMI was most effective. TMI with the GRNN classifier gave a 100% classification rate [17].

Histogram of oriented gradients (HOG) is a representation of shape, and use PCA+LDA for dimensionality reduction. HOG descriptors are reminiscent of edge orientation histograms in the article authored by Du and Wang (2011) [18].

RSC, a novel algorithm for feature extraction is proposed by Prasad and Singh (2107) [19]. Relative Sub-image coefficients are the features extracted from leaf images and is used for classification. 300 features are extracted from each layer of color component in a colored leaf image.

Voncarlos *et al.*, (2017) have used the Local Binary Pattern (LBP), Histogram of Gradients (HOG), Speed of Robust Features (SURF) and Zernike Moments (ZM) for feature extraction purposes to obtain different feature descriptors of a leaf image generating feature vectors, which are used to train a pool of Classifiers [20].

In the paper titled "Feature Selection for Texture-Based Plant Leaves Classification" Elnemr [21] has used Curvelet Transform Descriptors (CTD), Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) texture features extraction methods have been used to extract edges along curves and texture features.

III. CREATION OF DATASET

The Western Ghats are identified as one of the ecological hotspots of the world. It is one among the 34 global diversity hotspots in the world with extraordinarily rich bio diversity. Large number of plant species are facing extinction due to human intervention and urbanization in this region. We have made an attempt to create a dataset for the endangered plant species of Western Ghats. Dr. Shivarama Karantha Nisargadhama Pilikula, botanical garden, is home for the rare and endangered species of the Western Ghats. We, the authors have collected leaf samples and have created a dataset from the arboretum in Pilikula. The botanical garden comprises of arboretum, medicinal gardens and Garden of threatened plants (RET Garden).

No standard databases of leaves form the Western Ghats were available for conducting the experiments. The leaves were collected from their natural habitat and the selection of leaves and plants were quite random. The images of the front side of these leaves were captured using a high-resolution camera.

Table 1: A sample of the leaf dataset with local and botanical names.

S. No.	Botanical Name	Vernacular Name in kannada
1.	Aegle Marmelos	Bilvapathre
2.	Ailanthus Triphysa	Guggul Dhupa
3.	Aristolochia Indica	Isvaberusa
4.	Bauhinia Racemosa	Aralukadumandara
5.	Calophyllum Inophyllum	Surahonne, Honne Mara
6.	Diospyros Bourdillonii	Kari Mara
7.	Flacourtia Montana	Hennu Sampige
8.	Garcinia Indica	Punarapuli
9.	Hiptage Benghalensis	Madhvi
10.	Justicia Betonica	Kaadu Kanakaambara
11.	Lagerstroemia Reginae	Maruvachalumara
12.	Mangifera Indica	Mavina Mara
13.	Putranjiva Roxburghii	Amani Putrajiva
14.	Saraca Asoca	Abhanga
15.	Zygipus Rugosa	Kotta Mullu

The images of individual leaves were then transformed in to a uniform resolution of 1200*2000 dpi. 51 different species of plants have been collected from the region. The local names and the corresponding botanical names of some of the studied leaves are given in the table.

Fig. 1. Leaf Images from the dataset.

IV. MATERIALS AND METHODS

A. Preprocessing

The acquired images for classification are often found to have varying degrees of noise and can come from different sources, they require to be cleaned up and standardized for further usage in machine learning applications. This step is very important step in development of computer vision algorithm.

Most of the image enhancement techniques like contrast enhancement, brightness enhancement, sharpness enhancement can be achieved at this level. Once a best image preprocessing technique is applied on the images, we can see considerable improvement in the efficiency of the feature extraction algorithm as well as the detection rate of and classification algorithm.

In our paper we have followed the following preprocessing technique:

Firstly, the original image is resized 1200*2000 dpi to obtain equal sized standardized images. The resized image is then converted from the BGR format to the RGB format for further processing. The resultant RGB image is then converted to greyscale image using the formula: New grayscale image = ((0.3 * R) + (0.59 * G) + (0.11 * B)). The color images once converted to gray scale images will reduce the computational complexity and takes up less space in memory. With the conversion, the color image of the leaf is now in the grayscale.

The gray scale image however is very much inclusive of noise. The noise in the images can impact the accuracy of the feature extraction algorithm. It is imperative that the noise from the image should be removed. In order to remove the noise, we have applied the gaussian blur techniques also known as gaussian smoothening technique. The image is convolved with a gaussian filter. The Gaussian filter being a non-uniform low-pass filter reduces the high-frequency components in the image. This technique is widely used in computer vision to blur the images and reduce the noise present in the image.

The next stage of preprocessing is segmentation. The segmentation stage further reduces the noise present in the image by separating the foreground objects from the background.

Simple Thresholding and the Otsu's binarization thresholding methods are applied in segmentation. In our paper initially we have subjected the image to binary inverse thresholding and have further used the Otsu's method of binarization or thresholding. We obtain a binary image as a resultant output.

Inverted binary thresholding:

$$\text{dst}(x) = \begin{cases} 0, & \text{if } scr(x,y) > \text{thresh} \\ \text{maxval}, & \text{otherwise} \end{cases}$$

Otsu's algorithm tries to find a threshold value (t) which minimizes the weighted within-class variance given by the relation:

$\sigma^2 w(t)=q_1(t)\sigma_1^2(t)+q_2(t)\sigma_2^2(t)$

Where class probabilities are estimated as:

$$q_1(t) = \sum_{i=1}^{t} P(i) \quad \& \quad q_2(t) = \sum_{i=t+1}^{I} P(i)$$

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \quad \& \quad \mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)}$$

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \quad \& \quad \sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)}$$

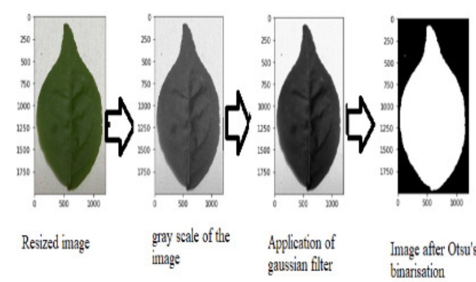

Fig. 2. Stages in preprocessing.

The final stage of preprocessing involves the morphological transformation on the image. Closing morphological operations are performed so that any damaged leaves are closed and can be further used for feature extraction. The result of applying the preprocessing techniques is represented in Fig. 2.

B. Feature Extraction

Higher level information from an image can be obtained by applying the feature extraction techniques. The shape, texture and color features were extracted from the leaf images for identification.

Shape features: In this paper we have extracted the area, perimeter, circularity, rectangularity and aspect ratio. Contour feature extraction, Image moments are calculated in order to calculate the features like the area and perimeter of the leaf.

The aspect ratio of the leaves is calculated using the formula: aspect ratio= width/height.

The circularity is calculated using the formula: circularity = ((perimeter)**2)/area.

Rectangularity of the leaf is calculated using the formula: rectangularity = width *height/area.

Color Features: To extract the colors the preprocessed image is split into three color channels of red, green and blue. The mean and standard deviation of these colors of the respective leaves are obtained by the below given formulas

$$SD = \sqrt{\frac{\sum |x-\mu|^2}{N}}$$

μ= ∑x/n

Mean = sum of all data points/number of data points.

Texture features: Texture is a key component of human vision perception. The spatial distribution of gray values is analyzed using statistical texture methods by computing the local features at each point in the image. In this technique the GLCM is computed first and the texture features based on GLCM are calculated.

Haralick's features are generated from grey level co-occurrence matrix (GLCM). We have extracted the Haralick's features for all four adjacency matrices are constructed for a single image. The mean is calculated for all 4 types of GLCM.

Features like contrast, correlation, inverse difference moments and entropy are obtained and their corresponding means are calculated.

Contrast is the measure of intensity variation of the reference pixel from its neighbor.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2\, p_d(i,j).$$

Entropy is the randomness or the degree of disorder present in the image. The value of entropy is the largest when all elements of the co-occurrence matrix are the same and small when elements are unequal:

$$\text{Entropy} = -\sum_i \sum_j p_d(i,j) \ln p_d(i,j).$$

Correlation feature shows the linear dependency of gray level values in the co-occurrence matrix:

$$\text{Correlation} = \sum_i \sum_j p_d(i,j) \frac{(i-\mu_x)(i-\mu_y)}{\sigma_x \sigma_y},$$

where $\mu_x ; \mu_y$ and $\sigma_x ; \sigma_y$ are the mean and standard deviations and are expressed as

$$\mu_x = \sum_i \sum_j i\, p_d(i,j)$$

$$\mu_y = \sum_i \sum_j j\, p_d(i,j)$$

$$\sigma_x = \sqrt{\sum_i \sum_j (i-\mu_x)^2\, p_d(i,j)}$$

$$\sigma_y = \sqrt{\sum_i \sum_j (j-\mu_y)^2\, p_d(i,j)}.$$

V. EXPERIMENTAL RESULTS

The results obtained after feature extraction has been shown in tabular format. Color features like area, perimeter physiological length, physiological width, aspect ratio, rectangularity and circularity are calculated. The mean and standard deviation of red, blue and green components of the image are calculated in the color features. The texture features that are calculated are contrast, correlation, inverse difference momentum and entropy are calculated.

Table 2: Extracted Shape Features.

Plant species	area	perimeter	Phy_length	phy_width	aspect_ratio	rectangularity	circularity
Aegle marmelos_1	56.5	28.72792	9	10	0.9	1.59292	14.60696
Aegle marmelos_2	62	29.31371	9	10	0.9	1.451613	13.85957
Aegle marmelos_3	4	8	3	3	1	2.25	16
Aegle marmelos_4	160.5	47.2132	15	15	1	1.401869	13.88839
Aegle marmelos_5	14.5	14.24264	5	5	1	1.724138	13.98985
Aegle marmelos_6	89	34.97056	11	12	0.916667	1.483146	13.7409
Aegle marmelos_7	52.5	27.89949	9	9	1	1.542857	14.82632
Aegle marmelos_8	72	34.396	12	10	0.586439	1.522327	17.78087
ailanthus triphysa_1	1426015	4952.994	1200	1696	0.707547	1.427194	17.2033
ailanthus triphysa_2	1559478	5199.026	1080	1967	0.549059	1.362225	17.33264
ailanthus triphysa_3	1487735	5174.129	1174	1927	0.609237	1.520632	17.99488
ailanthus triphysa_4	1455628	5176.406	1128	1961	0.575217	1.519625	18.40799
ailanthus triphysa_5	1503356	5149.109	1106	1930	0.573057	1.419877	17.63609
ailanthus triphysa_6	1525749	5194.908	1113	1949	0.571062	1.421752	17.68775
ailanthus triphysa_7	1452709	5098.322	1062	1975	0.537722	1.44382	17.89271
ailanthus triphysa_8	1425767	5162.562	1169	1974	0.592199	1.618502	18.69314

Table 3: Extracted color features.

Plant species	mean_r	mean_g	mean_b	stddev_r	stddev_g	stddev_b
Aegle marmelos_1	136.4134	146.715	118.2223	71.19693	62.36932	84.1533
Aegle marmelos_2	136.5839	146.0833	117.3296	69.92749	60.83593	82.74859
Aegle marmelos_3	137.8797	145.7612	119.0164	70.80346	62.11517	82.6997
Aegle marmelos_4	136.1926	143.6937	118.1359	72.06939	63.47439	81.64315
Aegle marmelos_5	135.9118	144.6186	116.5466	72.26637	63.79333	84.41486
Aegle marmelos_6	125.3268	134.9538	103.0942	70.56221	62.1331	82.87598
Aegle marmelos_7	125.6572	133.5658	106.8811	71.14501	62.63841	80.79326
Aegle marmelos_8	124.0384	133.7075	99.86197	71.09785	62.99068	83.518
ailanthus triphysa_1	108.8101	111.1142	93.08499	82.39704	75.30204	78.32643
ailanthus triphysa_2	99.59075	102.8175	85.01725	86.48105	80.49109	83.01519
ailanthus triphysa_3	112.3836	120.6054	91.12757	79.64858	70.17453	82.28399
ailanthus triphysa_4	117.8827	125.889	94.84249	76.58693	66.79275	80.48288
ailanthus triphysa_5	99.62331	103.9764	85.87891	80.39365	74.45634	78.93736
ailanthus triphysa_6	101.1479	105.8647	87.11604	82.53855	76.34402	81.37407
ailanthus triphysa_7	106.3945	109.7038	91.44901	82.94375	77.12815	81.66163
ailanthus triphysa_8	114.4956	118.3979	99.13675	88.77223	82.00271	87.6627

Table 4: Extracted Texture features.

Plant species	contrast	correlation	inv_diff_mom	entropy
Aegle marmelos_1	19.25238	0.997888	0.345005	10.21062
Aegle marmelos_2	18.5385	0.997878	0.351723	10.20773
Aegle marmelos_3	17.95928	0.998003	0.361608	10.21628
Aegle marmelos_4	20.3257	0.997807	0.352091	10.31386
Aegle marmelos_5	20.16209	0.997862	0.340387	10.46039
Aegle marmelos_6	14.27651	0.998411	0.381784	10.04162
Aegle marmelos_7	17.87958	0.998022	0.364783	10.14947
Aegle marmelos_8	18.15147	0.998019	0.361866	10.28264
ailanthus triphysa_1	49.29486	0.99592	0.319695	10.97412
ailanthus triphysa_2	57.22393	0.995795	0.277053	10.94659
ailanthus triphysa_3	51.31349	0.995347	0.294389	11.00291
ailanthus triphysa_4	45.47765	0.995505	0.3012	11.03666
ailanthus triphysa_5	48.23892	0.995905	0.312661	10.92717
ailanthus triphysa_6	47.23537	0.996195	0.301419	10.94955
ailanthus triphysa_7	47.7067	0.996211	0.3014	10.92384
ailanthus triphysa_8	46.26399	0.99677	0.297792	10.929

VI. CONCLUSION

In this paper we have made an attempt in creation of a dataset based on the native plants available in the Western Ghats region, the data collection process has given us an insight into challenges in procuring the leaf samples from the region and has also given us an understanding of the technique of capturing digital images of leaves in controlled environments . The study emphasizes on the significance of the application of preprocessing techniques like noise reduction, filtering and thresholding that enhances the image quality. The features from these processed images are retrieved using feature extraction techniques, various feature descriptors of shape, color and texture are extracted and their data is presented.

The results from this study can be used for recognition and classification of leaves based on the features specified.

VII. FUTURE SCOPE

In our future work we would be applying various machine learning algorithms on our dataset for recognition and classification purposes and checking for better accuracy. We also plan to implement deep learning algorithm for plant classification purposes [22].

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