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A Review : Identification and Classification of Plants From Perceptible Descriptors of Lead Images

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***Abstract*—Plants are essential for the existence of life on earth. With the advancement of technology research has been carried out in different fields of digital image processing including plant disease detection, plant identification and classification, plant age detection etc. In this review paper plant classification and identification from the leaf image has been discussed using various techniques for visual feature extraction like shape feature, color feature, vein margin etc. This is followed by classification and identification approaches like SVM, KNN, neural network etc. And for the testing of the above discussed methods various evaluation parameters have been described where it has been concluded that maximum efficiency of the system can be attained with combined classifiers.**

Keywords*—*shape features, clor features, texture features, vein margin, vein features, SVM, KNN

I. Introduction

Plants are irrefutably critical for the survival of living creatures on earth being the radix of profuse natural resources. The abundance of plants exist on earth that appears to be similar, which, makes it onerous for humans to classify these by their physical aspects. On contrary, their appropriate identification is vital to circumvent any menace due to venomous or perilous plants. Relevant recognition of plants is not only imperative for botanist for productive research but farmers also. As an elixir to this problem, digital system has been devised which identifies the category of plant from digital image. Since, irrefutably, erroneous rate of digital systems are infinitesimal when compared to manual recognition by humans.

These digital systems can be categorize as pattern recognition systems [1] and image retrieval systems. Pattern recognition system is used to recognize the desired object in the image and classifies it to the class to which it belongs based on the group of features extracted from the image. It serves the objective of classification of the images in the dataset and identification of the class of the query image based on the classification result. The image retrieval systems aims at retrieving the desired images from the database containing images of the multiple classes. The image retrieval system can be further classified as text base image retrieval and content based image retrieval.

Plants can be identified and classified in to their respective classes from leaf image using pattern recognition system.

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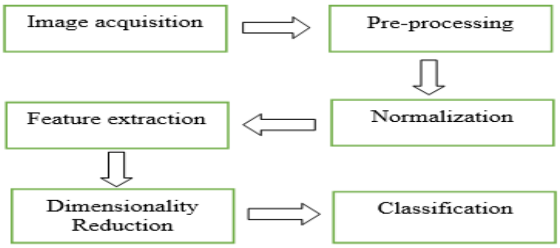
II. PLANT CLASSIFICATION FROM LEAF IMAGE

There are various attributes of plants, such as, fruits, leaves, roots, and flowers which forms the basis of their spotting and categorization. Being seasonal, fruits and flowers of the plants may wither with the season but leaves sustain whole year eventuating as the optimal parameter for identification.

The classification on plants based on leaf image generally consist of five stages – Image acquisition, Preprocessing, feature extraction, feature normalization, dimensionality reduction, and classification.



The acquired image is input to system for preprocessing that includes resizing, segmenting, removing noise from image etc. Features are extracted from pre-processed image using various feature extraction techniques. Extracted features are normalized before feeding to classifier. Feature vector is obtained of the normalized features by performing dimensionality reduction using technique like principle component analysis and result is fed to classifier for classification and identification.

III. FEATURE EXTRACTION

Differentiation of objects in classification process is done on the bases of the various features extracted from the image of the objects. Basically features are described as low level features and high level features [2]. In plant identification system, visual low level features such as shape, color and texture features are extricated from the image using various feature extraction tools.

Features can also be classify into global and local features [2]. Global features are extracted from image as whole not part of it. These generalize the whole image with a single vector. Local features describes the key points in the image i.e. small patches in the image.

The leaf images can be classified into their respective classes using either of shape, color, texture features or combination of these features along with vein features.

A. Shape Features

Shape features gives information about the shape of the object in the image. Leaves of different plants have different shape thus they plays key role in differentiating classes of plants in image. Shape feature extraction methods can be classified into global and local approach. Global approaches such as Curvature Scale Space approach [3], Fourier-based descriptors [4] etc. in general defines the leaf shape and obtain global features such as leaf width, length and area.

Local approaches such as polynomials on contrary attains the local features and describes leaf details such as correlation, homogeneity, texture and contrast. There exist tradeoff between details extracted and noise in both approaches. Global approach is more robust to noise but is incapable of extracting fine details whereas local approach extracts fine details from image but is sensitive to noise.

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Multi-scale approaches on other hand doesn't requires preprocessing of an image and captures both global and local features. Various multi-scale approaches present are multi-scale triangle-area representation (MTAR) [5] uses area of triangle for representing shape of object, multi-scale Fourier [6] performs better than Zernike moments and elliptic Fourier descriptor against noise, multi-scale similarity matching method [7] for shape retrieval is affine-invariant and stable against noise and shape deformations.

Attribute extraction methods based on shape are generally categorized into two [8] contour based methods and region based method. Contour based methods dealt with external attributes like contour of leaf in image. The Contour extraction methods are circularity, eccentricity, orientation, elongation, perimeter, diameter, compactness, extent, narrow factor, Fourier descriptor, wavelet descriptor, geometric representation, chain codes [9], polygonal approximation [10], curvature scale space, shape signatures [11], centroid contour distance curve [12], polar Fourier transform [13]. The Fourier descriptor values are obtained by performing Fourier transform on image in frequency domain. The lower frequency descriptors gives detail about general shape and high frequency descriptors gives information about finer details in image.

On contrary region based techniques dealt with internal features of the image and methods are moment descriptors [14], morphology description, grid descriptors and skeletons. The moment descriptors include geometric moments [15], Zernike moments [16], pseudo- Zernike moments [17], HU invariants [15] and Legendre moments. The basis of the Zernike moments are orthogonal thus they possess the advantage of minimum redundancy in information. The other advantage of Zernike moments are their magnitude is rotation invariant, noise invariant and shape invariant. Polar Fourier transform is better than Zernike moments for image retrieval [13] regardless of these advantages of Zernike moments. There exist drawbacks in contour extraction techniques that these can't capture entire information about object and these don't work for disjoint shapes but these drawbacks are overcome by region based approaches. The compactness and the aspect ratio of the region based methods provide better result than contour based method.

In plant identification schemes from leaf images, diameter, physiological length, physiological width, leaf area and leaf perimeter are consider as five basic features from which twelve digital morphological features are derived. Digital morphological features are smooth factor, aspect ratio, form factor, rectangularity, narrow factor, perimeter ratio of diameter and five vein features [61].

B. *Color Features*

Color features provides information about the image color content. These are scale, translation and rotation invariant. The color feature extraction techniques also are classified into global and local descriptors.

Various color descriptors are color histograms, adaptive color histogram [18], color moments, color co-coccurance matrix, Color Histogram for K-mean (CHKM) [19], color coherence Vector (CCV), color correlograms, chromaticity moments [20] etc. Color histogram is rotation and translation invariant and represents the distribution of the number of pixels of each color in the image. It can be classified as Global color histogram (GCH) and Local color histogram (LCH). The color histogram doesn't consider spatial information in image and this problem has been addressed by color coherence Vector (CCV) [21]. It classifies each color histogram bin of the image into coherent and incoherent. Large colored region represents coherent and another incoherent.

Color moments [22] provides color similarity measurement between images. Its basis lays in an assumption that image color distribution can be consider as probability distribution which is characterized by a number of moments. Generally only three color moments i.e. moment1-mean, moment2-standard deviation, moment3-skewness are considered. The color histogram and color moments gives color information only

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about each pixel in the image but doesn't gives the local relationship between neighbor pixels in the image. This issue has been addressed by color correlogram [23]. It gives spatial correlation of colors of the pixels and global distribution of local spatial correlation of colors.

The MPEG-7 visual standard [24] proposed descriptors such as dominant color, scalable color, color space, color quantization, color structure, group of frames/group of pictures and color layout. The color space descriptors offers selection of color space and color quantization descriptors quantize it into bins. The dominant color values and their statistical properties like variance and distribution are specified by dominant color descriptor. The scalable descriptors make use of novel haar transform. The extension of scalable descriptors to video frames forms group of frames/group of pictures. The representation of color layout descriptor is based on Discrete Cosine Transform (DCT) coefficient. It gives the grid of the dominant colors in an image.

C. *Texture Features*

Texture feature extraction techniques are classified as structural approach, statistical approach, model based approach and transform approach.

The structural approach is classified as first order, second order and higher order. The first order based features includes estimating the properties of individual pixels in an image considering spatial interaction between pixels from the intensity histogram of an image. The properties calculated are four statistical moments mean, variance skewness and kurtosis. The second or higher order moments are responsible for calculating the properties of pair of pixels or more present at specific location with respect to each other. The gray level images textures can be easily discriminated using second order statistics. The Co-occurrence matrixes such as Spatial Gray Level Dependency (SGLD) matrices, Gray Level Co-Occurence Matrix (GLCM) [25] are used for obtaining second order statistics. The discrimination rates attained by second order statistics are higher than transform methods and structure methods [26].

Transform method includes Fourier transform [27], wavelet transform [28] and gabor filter [29]. Fourier transform lacks in spatial localization thus gives poor performance. This issue has been addressed by gabor filter but there is no single filter resolution at which spatial structures can be localized. Wavelet transform outperforms gabor filter and Fourier transform due to its advantages.

The model based method [30] includes fractal models [31] and stochastic models. The fractal model is used for images having self-symmetry and roughness at different scales. The models such as AR model, Gaussian Markov Random field model (GMRF) [32] and Gibbs RMF model [33] are used for segmenting image based on texture features obtained using these models.

The model based methods are used for discrimination and structural analysis but have drawback of not providing orientation selectivity. The other methods for calculating texture features are Gray Level Run Length Matrix useful for representing binary textures, Local Binary Pattern (LBP) calculates local image contrast and autocorrelation features. The GLCM is preferred method for plant classification and identification application.

D. *Leaf Margin*

The leaf margin present along the contour of the leaf contains pattern of tooth and provides set of features. In some plant species leaf margins are present while absent in others and in some species tooth are sharp while blunt in others. These set of features can be obtained using curvature scale space, wavelet local extrema [34], SUSAN algorithm [35], Convex Hull for leaf lobe extraction [36], self-organizing map obtains tooth

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structure from morphological features [37]. The features obtained from leaf margin are teeth number, inclination, and sharpness. Leaf margins provide important parameters but still they aren't prominently use in automatic leaf classification systems as they can't be reliably detect by any computer algorithm [36]. This may be the result of facts that leaf margins are absent in some species, these may get damage on leaves before collection of specimen or difficulty in automatic calculation.

E. *Vein Features*

Leaves of different plants since exhibits different vein network providing vein features. Vein features of leaves can be extracted using various vein feature extraction methods. Independent component analysis (ICA) algorithm [38] obtains set of linear basis function or features.

There are various methods for extracting leaf vein pattern from leaf image based on morphological features. The series of morphological operations are performed on the gray image followed by segmentation to obtain desire vein pattern [39]. Another approach include performing morphological operation on gray image and subtracting the result from gray image [40].

The robust vein extraction on plant leaf image approach provides the tool for extracting side veins of the leaf along with the main taking care of the hierarchy of the vein system present in the leaf [41].

The neural networks can also be used for extracting leaf vein patterns. A two-stage approach for leaf vein extraction is based on the combination of segmentation and ANN [42] and the results and computation time obtained by this method is better than the direct neural network method [43]. The evolved vein classifiers for extracting vein patterns is able to extract tertiary veins along with complete primary and secondary veins [44]. The continuous veins can be extracted using ant colony algorithm [44]. Another method includes training neural network for vein extraction using extracted features like local contrast, edge gradients and statistical features. It works more accurately then conventional thresholding based methods [45].

IV. CLASSIFICATION AND IDENTIFICATION

Classifiers performs the operation of classification. It classifies the input images in one of the class by comparing the input image features with feature vectors dataset prepared as the output of the training. The basis of the measurement is the metric i.e. the distance measured between the input image features and the feature vectors to find the similarity between both. Image is classified in the class of minimum distance. Classifiers works either on supervised or unsupervised learning. In supervised learning output database is provided to train the machine whereas in unsupervised no database is provided and machine trains itself by forming clusters. Classifiers available are Naive Bayes, Ensembles (Bagging, Boosting, Random forest), Perceptron, KNN classifier, Neural networks, SVM classifier, Decision trees, Linear regression, Logistic regression etc.

Identification is the recognition of the object in the input image. Identification can be performed with the use of the classifiers like SVM. In plant leaf identification system the class of the leaf in the image is to be identified.

V. EVALUATION PARAMETERS

The performance of the plant identification and classification system using various feature extraction techniques and classifiers can be evaluated on the basis of the parameters like accuracy, precession, recall, confusion matrix etc.

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VI. SCOPE OF PLANT CLASSIFICATION SYSTEMS

In plant identification and classification systems, combination of multiple features are used with classifiers. The features of the leaves symmetrical on central axis can be obtained from only half leaf image. The system for plant classification based on half leaf image includes extraction of morphological features and classification using PNN [46]. Extracted token features along the half leaf shape can be represented as sinus and cosines angles. The resultant obtained by classifying feed-forward back-propagation network shows that feature reduction is obtained by using half leaf [47].

The texture of the bark of the plant can also be used for plant classification. The classifier is formed for classification from the gabor filter banks that are designed from texture model obtained from the bark texture [48].

The computer-aided plant species identification (CAPSI) system has been also proposed which uses Douglas-Peucker approximation algorithm for shape approximation and modified dynamic programming (MDP) algorithm for shape matching [49]. This robust system identities intact, distorted, partial and overlapped plant leaves.

The system for the detection of plants having only broad leaves has also developed consisting of five steps including segmentation, morphological and unique set of feature extraction, normalization and classification using probabilistic neural network [50]. The angle, sharpness and size of the leaf dent is extracted using wavelet maximum as shape feature along with other features [51]. The new multi-dimensional and multi-resolution curvlet transform developed for feature extraction is rotation invariant [52].

The hyper sphere classifier is applied on geometric features and seven moment invariants can be extracted from leaf [53]. In order to recognize object having N-fold rotation symmetry a new set of rotation moment invariants with respect to scaling, rotation and translation based on complex moments has been developed. These moments has been developed as moments derived early can't be used for symmetry objects since most of them will vanish [54]. The Zernike moments are combined with geometric features, color moments, gray level co-occurrence matrix (GLCM) for feature extraction and two techniques distance measure and PNN [55] are used for classification purpose but the important thing in Zernike moment is the number of moments to be considered for acquiring high performance [56]. The comparative study has been done on Zernike moments (ZM), Legendre moments (LM) and Tchebichef Moment Invariant (TMI) by extracting the global features and classifying using General Regression Neural Network (GRNN) [57].

The L-2 norm has been used for classifying the extracted leaf features edge histogram, area and color histogram [58]. Move median centers (MMC) hyper sphere a new classifier proposed has been applied on digital morphological features [59]. The combination of GLCM and PCA for plant classification provides better result than only GLCM [60].

VII. CONCLUSION

This paper represents feature extraction techniques of plant leaf image. There exist various techniques for extracting different features like leaf shape, color, texture, vein pattern and leaf margin. In plant identification and classification system combination of different methods of various features are used along with different classification techniques. The results are obtained by combination of different techniques which can be evaluated on the basis of evaluation parameters. The results obtained can be improved by modifying the combination of techniques.

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Although different combinations for the improvement of the results are implemented but a particular combination can't be consider as a suitable technique. Furthermore in order to obtain better results different combined classifiers can be implemented for classification purpose.

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