

# A survey of computer-based vision systems for automatic identification of plant species

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## ABSTRACT

Plants are unavoidable for the existence of most living things on this planet. There are many needs of both humans and animals that are satisfied by materials from plants. These needs include food, shelter, and medicine. The ability to identify plants is highly important in several applications, including conservation of endangered plant species, rehabilitation of lands after mining activities and differentiating crop plants from weeds. This paper reviews several applications and works that have been made towards computer-based vision systems for automatic identification of plant species. It shows the various techniques alongside their descriptions. It portrays how future researchers in this field (especially precision agriculture or agricultural informatics) may move the knowledge domain forward.

## 1. Introduction

Traditional recognition of plant species is carried out by manual matching of the plant's features, relating to components of the plant, such as leaves, flowers, and bark, against an atlas (Meeta, 2012). Attempts to automate this process have been made, using features of plants extracted from images as input parameters to various classifier systems (Cope, 2011). Since plant leaves are often more available than the fruits and flowers, and because leaves are also mostly two-dimensional (2D) in shape, most of the existing work on computer-based plant recognition are based on the leaves of plants. This work examines existing systems of computer-based automated system for identification of plant species and various techniques used therein.

## 2. Leaf Characteristics in Manual Identification

The shape of a leaf is an important feature of plant development that depends on genetic, hormonal and environmental factors Weight (2008). The shape and structure of leaves often vary from species to species of plant depending on the adaptability to climatic conditions and as well as availability of light. A normal leaf of an angiosperm consists of a petiole (leaf stalk), a lamina (leaf blade), and stipules (small structures located to either side of the base of the petiole). According to Pat (2000), leaves can be categorized in many ways. For instance, a leaf can be classified as either broad or narrow. A broad leaf has a wide blade, having a visible vein alignment, as in the Northern Catalpa, shown in Figure 1(a). Slender leaves on the other hand have narrow, needle-like leaves, as with the Norway spruce, shown in Figure 1b. The full range of leaf categories documented by Pat (2000), is reproduced in Table1. Information about plants' nomenclature can be obtained from

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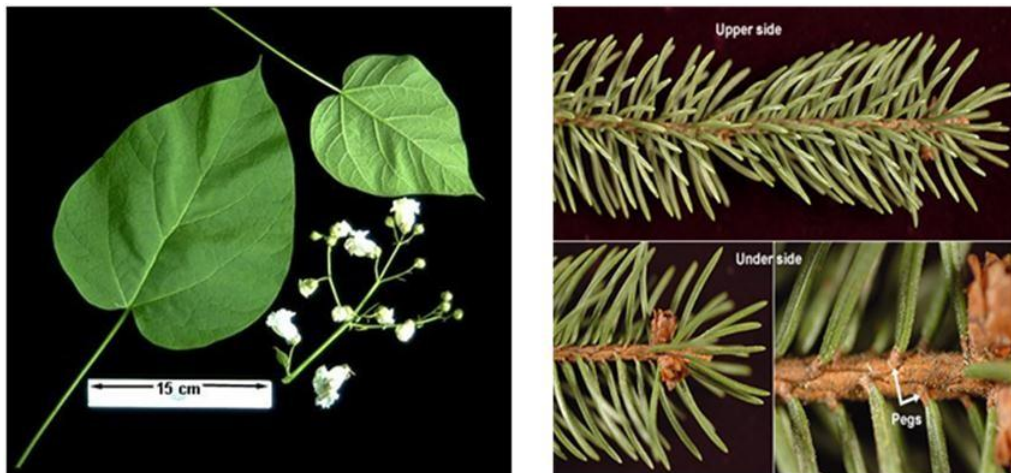
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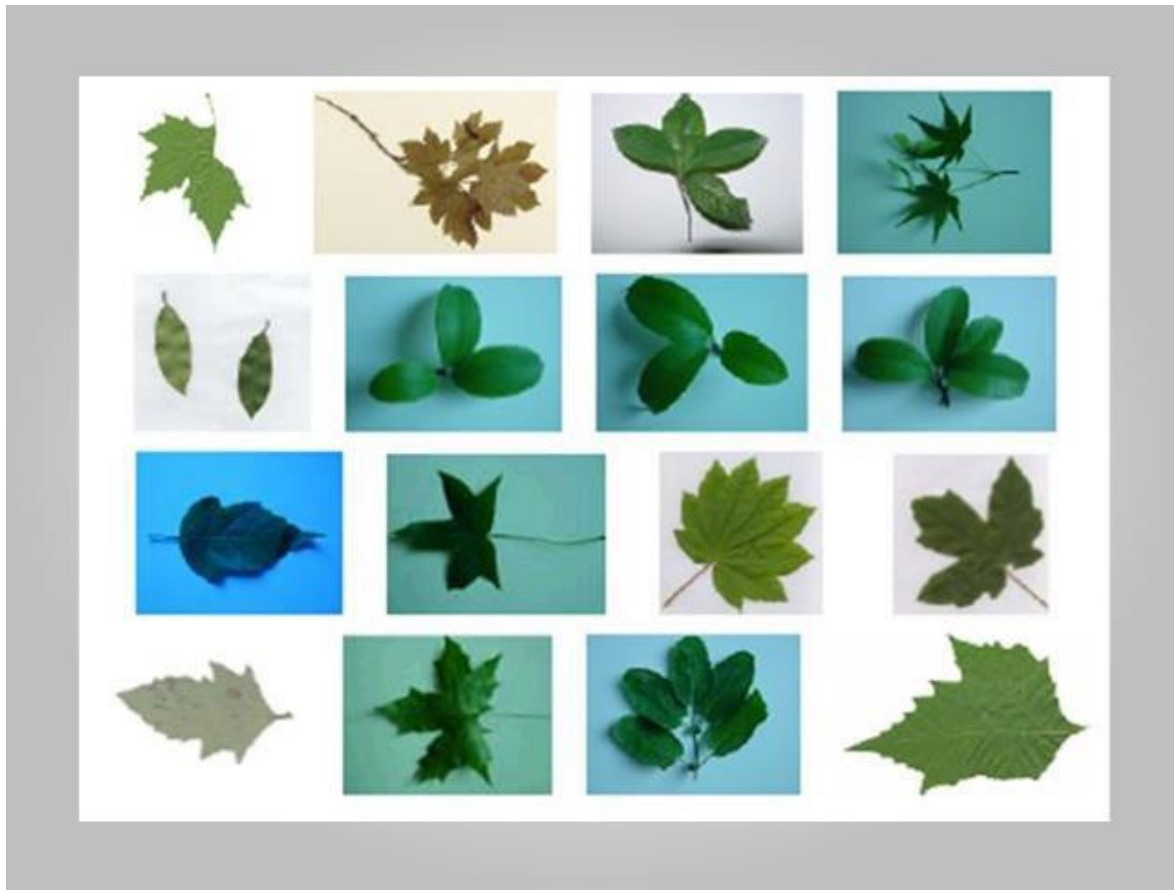
<http://oregonstate.edu/dept/ldplants/Plant%20ID-Leaves.htm>. Cope (2011) asserts that the most discriminative feature of a plant's leaf is its shape.



**Figure 1.** (a) Broad Leaf Image of Northern Catalpa (b) Narrow Leaf Image of Norway spruce (Pat,2000)

**Table 1.** Categorizing Leaves by their shape and structure (Pat, 2000)

LeafType	Definition	Example
Broad	Leaf with wide blade, often with visible network of Veins.	Northern Catalpa
Alternate	Slender leaf without a wide blade. Often called needle or scale-like	Norway Spruce
Opposite	Two leaves on the same stem but in opposite direction	Common Boxwood
Whorled	More than two leaves from the same location on a twig	Red vein Enkianthus
Simple	Have only one blade divided into parts	White Alder
Compound	More than one blade and may have a complex leaf stalk structure.	Paper-bark Maple
Palmate	Have three or more leaflets attached at the end of Stalk (petiole).	Horse chest nut
Pinnate	Have a number of leaflets attached along a central stalk.	American Yellowwood
Lobed	Have a curved or rounded projection.	Hedge Maple
Unlobed	Doesn't have any curved or rounded projection.	Western Catalpa
Entire	Have smooth edges or small notches or teeth along the Margin.	White Forsythia
Toothed	Have teeth at the base, at the tip, or along margin	Paper-bark Maple
Clusters	At least 5 leaves together	Deoder Cedar

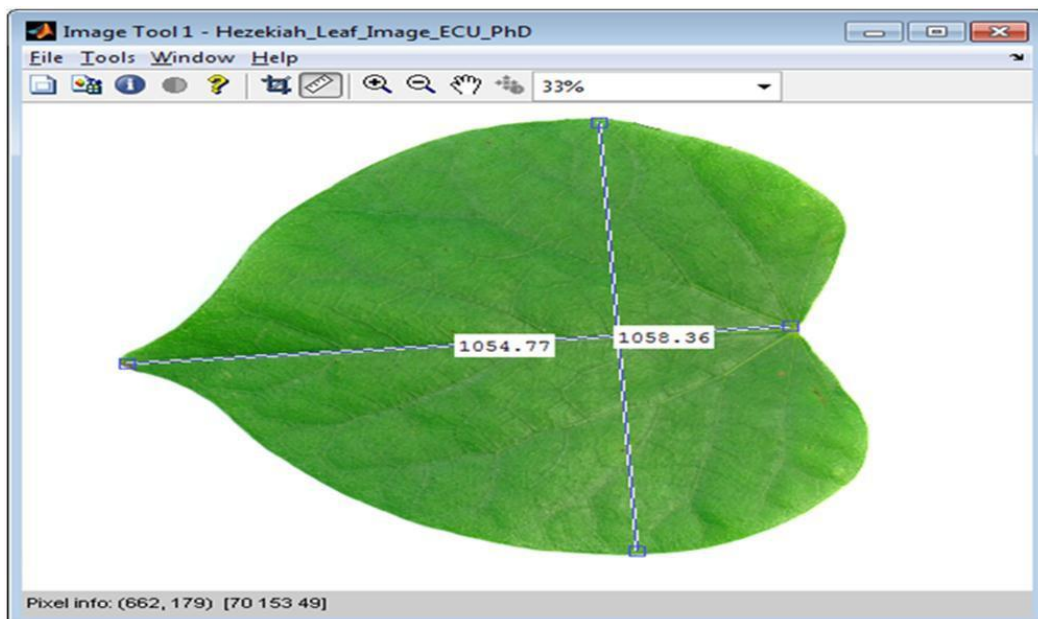


**Figure 2.** Some leaves with different shapes taken from (Ji-Xiang,2005)

**Table 2.** Geometric and Morphological Features of Leaves

S/N	Feature (Name)	Definition (Explanation)	Formula (Symbol)
1	Diameter	This is the longest distance between any two coordinates on the margin of a leaf. (Wu et al., 2007).	$d$
2	Physiological Length	This is the distance between the two terminals (apex and stalk point) (Russ, 2011; also see Figure 3)	$l$
3	Physiological Width	This is the perpendicular distance across the physiological length of a leaf (Wu et al., 2007; also see Figure 3)	$w$
4	Leaf Area	This is the total number of pixels that constitute an image.	$a = \int_x \int_y I(x, y) dx dy$
5	Aspect Ratio(A.R)	This is also called eccentricity and is defined as ratio between length of the leaf minor axis and the length of the leaf major axis (Abdul, Lukito, Adhi, & Santosa, 2012).	$\frac{w}{l}$
6	Circularity	This is a measure of similarity between a 2D shape is and a circle. It is the ratio between area of the leaf and the square of its perimeter (Russ, 2011)	$\frac{a}{p^2}$
7	Irregularity	This is the ratio between the radius of the maximum circle encompassing the region and the minimum circle that can be contained in the region (Kadir, 2011 and	$\frac{\max(\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2})}{\min(\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2})}$

		Nixon, 2002)	
8	Solidity	This is defined as the ratio between the area of the leaf and the area of its convex hull (Russ, 2011)	$\frac{a}{ConvexHullArea}$
9	Convexity	This is the ratio between the convex hull perimeter of the leaf and the perimeter of the leaf (Russ, 2011)	$\frac{ConvexPerimeter}{p}$
10	Form Factor	This feature describes the difference between a leaf and a circle (Wu, 2007)	$\frac{4\pi a}{p}$
11	Rectangularity	This describes the similarity between a leaf and a rectangle. (Russ, 2011).	$\frac{lw}{a}$
12	Narrow factor	This is the ratio of the diameter and length of the leaf. (Wu, 2007)	$\frac{d}{l}$
13	Perimeter ratio of diameter	This is the ratio of perimeter to diameter of the leaf (Russ, 2011)	$\frac{p}{d}$
14	Hydraulic radius	This is derived by dividing the leaf area by the leaf perimeter (Russ, 2011).	$\frac{a}{d}$
15	Perimeter ratio of physiological length and width	This feature is the ratio between the perimeter of a leaf and the sum of its physiological length and physiological width (Russ, 2011)	$\frac{p}{l + w}$



**Figure 3.** Image showing the length and width of a leaf's image

### 3. State of the art on computer-based plants leaves recognition systems

Several plant species recognition systems have been developed based on various features and classifiers. This section provides a summary of work reported in the literature, along with classification accuracy (where reported).

Zalikhya et al. (2011) compared the effectiveness of Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI), and Tchebichef Moment Invariant (TMI) as descriptor features of leaves. The data set consisted of images of 10 different plant species, with different sized leaves. Using grayscale conversion followed by thresholding, the images were converted into binary images, from which the descriptors could be derived. Scaling and rotation of the images was used to produce many variants of the images at different sizes and orientation. The incorporation of variant images allowed the system to be tested for rotation and scale invariance. A Generalized Regression Neural Network (GRNN) was used for the classification, with classification results showing that features from the TMI were the most effective.

Another similar work involving the use of moments as features was reported by Abdul (2012), where Zernike moments were combined with geometric features, color moments and gray-level co-occurrence matrices (GLCM). The classifier used was Probabilistic Neural Networks (PNN) while the Euclidean distance was used to measure the similarity index of the leaf of query (vector 1) to every leaf in the database (vector 2). The investigation showed that Zernike moment performs better when they are combined with other features in leaf classification systems. An optimum accuracy of 94.69% was reported by using Zernike moments of order 8.

Wu et al. (2007) also applied the PNN for plant leaf classification, attempting to differentiate between 32 different plants in Yangtze, China. Twelve features (geometrical and morphological) were used. These features were: diameter, length, width, area, perimeter, smooth factor, aspect ratio, form factor, rectangularity, narrow factor, perimeter to diameter ratio, and length to width ratio. Principal Component Analysis (PCA) was used to reduce the feature vector to 5 principal components. In this project, called the Flavia project, the classifier (PNN) was trained using 1800 leaves. Ten leaves sample were taken from each plant, implying that the test data set contained 320 leaves. The average accuracy was recorded to be 90.312%.

In a study carried out by Sandeep (2012), leaf color, area and edge features were used for identification of Indian medicinal plants (Hibiscus, Betle, Ocimum, Murraya, Leucas, Vinca, Ruta, Centella, Mentha). The method in this work involves reading the test image and comparing with the database images. The images were segmented through grayscale conversion followed by binarization via thresholding and comparison of edge histogram, colour histogram, and difference in area of test and database image were carried out between a candidate image and those in the database. The candidate image was classified based on the class of images stored in a database using Euclidean distance. Results showed all the plants were correctly classified except Tulsi menthe species which was wrongly identified as mint ocimum and vice-versa due to similarities in leaves venation.

Jyotismita and Ranjan (2011) combined a thresholding method with H-Maxima transformation Gonzalez (2007) to extract veins of 180 leaves taken from a website source Jyotismita (2011). The data set was divided into three classes, Pittosporum Tobira, Betula Pendula and Cercis Siliquastrum, each consisting of 60 images. Moment-Invariants (Geometric Moments) and centroid-radii approaches were then used to extract features needed for classification. The first four normalized central moments  $M_1$ ,  $M_2$ ,  $M_3$ ,  $M_4$  of each image of the trained and test datasets were computed and individual features from (any of  $M_1$ ,  $M_2$ ,

M3, M4) and (combinations of features from M1, M2, M3, M4) were fed into multilayer perceptron (MLP) to find the best combinations. The 180 dataset was divided into two parts where 90 images were used as training dataset (T) and the remaining 90 images as the test dataset (S). For the computation of recognition rates, comparisons between training and test datasets were done using a MLP with feed-forward back-propagation architecture which gave Mean Squared Error (MSE) of 0.005 and reached convergence in 38280 epochs. The results showed that individual moment values M1 provided the best results of 88.9%. The feature combinations M1-M3 and M1-M3-M4 provided classification results of 95.5% and 93.3% respectively.

Chomtip, Supolgaj, Piyawan, and Chutpong (2011) developed the Thai Herb Leaf Image Recognition System (THLIRS) using k-Nearest Neighbor (k-NN) as the classifier. A digital camera was first used to take the pictures of leaves, together with a one-baht coin as a size gage, against a white background. The second phase in THLIRS involved image pre-processing and segmentation (resizing, black-and-white conversion (grayscale conversion followed by thresholding), image enhancement, juxtaposition of photographed images of leaf and one-baht coin for the purpose of comparison, cropping of leaf image, and boundary tracking). The discriminative measure in the leaf-coin images on the background is that the leaf's image was assumed to be the largest object in the image, while the coin is the second largest object in the same image. In the third stage, 13 features (leaf and coin ratio, aspect ratio, roundness, ripples counting, ripples pixels counting, half-leaf area ratio, upper leaf area ratio, lower leaf area ratio, colour features, vein features (at threshold of 0.05, 0.03, and 0.01 respectively) were extracted. The dataset in THLIRS was divided into training and testing data. With a value  $k = 6$  in the k-NN classifier, THLIRS achieved classification accuracy of 93.29%, 5.18%, and 1.53% for match, mismatch, and unknown, respectively for the training dataset, while that of test dataset was 0%, 23.33%, and 76.67% for match, mismatch, and unknown, respectively.

The work of Kadir (2011) involved the use of the Polar Fourier Transform (PFT) and three geometric features to represent shapes of leaves. Color moments consisting of the mean, standard deviation, and skewness were computed to represent color features. Texture features were also extracted from Grey-Level Co-occurrence Matrix (GLCM) by counting the co-occurrence pixels with grey value  $i$  and  $j$  at the given Euclidean distance. The classifier scheme used was Probabilistic Neural Networks (PNN). In testing this system, two dataset (Foliage and Flavia, were used in comparing the proposed method with the work of Wu (2007). The overall classification result was stated by the author to be 94.687%. A hybrid approach involving a combination of Wavelet Transform (WT) and Gaussian Interpolation was proposed together with k-NN and Radial Basis Probabilistic Neural Network (RBPNN) for leaves recognition by Xiao (2005). Following image acquisition, the image was converted to greyscale and decomposed by the WT. The essence of decomposition by WT and Gaussian Interpolation was to produce low-resolution images and a series of detailed images. The wavelet features extracted by WT and Gaussian Interpolation were then used to train the k-NN and RBPNN for classification. The reported accuracy in this work was 95%.

A fuzzy selection technique based on morphological features was used in Panagiotis (2005). After the image capture and image preprocessing, a parameterized thresholding depending on the lighting conditions was performed, followed by calculation of the centre of gravity of the leaf's image. Next, the image of the leaf is rotated to have vertical orientation. Morphological and geometrical features such as diameter, length, width, perimeter, area, aspect ratio, smooth factor, form factor, rectangularity, narrow factor, perimeter to diameter ratio, length to width ratio, and vein features were then computed. A fuzzy surface model was

finally used to select images from feature database before they were fed into the RBPNN for classification. It was found that the proposed system was able to correctly classifying even deformed leaves. This paper did not state the actual quantified classification results.

Rashad (2011) used a combined classifier consisting of learning vector Quantization (LVQ) and Radial Basis Function (RBF) for plant classification based on the characterization of texture properties. A digital camera was used to capture plant's images at  $128 \times 128$  resolution. The acquired RGB images were then converted into grayscale images. Texture features were extracted from the grayscale images and using random sample of 30 blocks of each texture as a training set, and another 30 blocks as a test dataset, it was shown that the combined classifier method outperformed other methods (PCA, k-NN, RBPNN), with the least MSE and accuracy of 98.7%.

Belhumeur (2008) developed a working computer vision system for identification of plant species. The e-botany (database of leaves) was made from (a) the flora of Plummers Island containing 5,013 leaves of 157 species, (b) Woody Plants of Baltimore-Washington DC containing 7,481 leaves of 245 species, and (c) Trees of Central Park containing 4,320 leaves of 144 species. From this collection all the images were cropped and later converted to binary images through grayscale conversion followed by thresholding. Shape distances were computed from the binary images using chi-square, while shape matching (classification) was done via Inner Distance Shape Context (IDSC). The purpose of IDSC was to retrieve coordinates of the boundaries of a shape, and establish a 2D histogram at each point. This histogram is a function of the distance and the angle from each point to all other points along restricted path lying entirely inside the leaf shape. The classification accuracy reported by the authors was 85.1%.

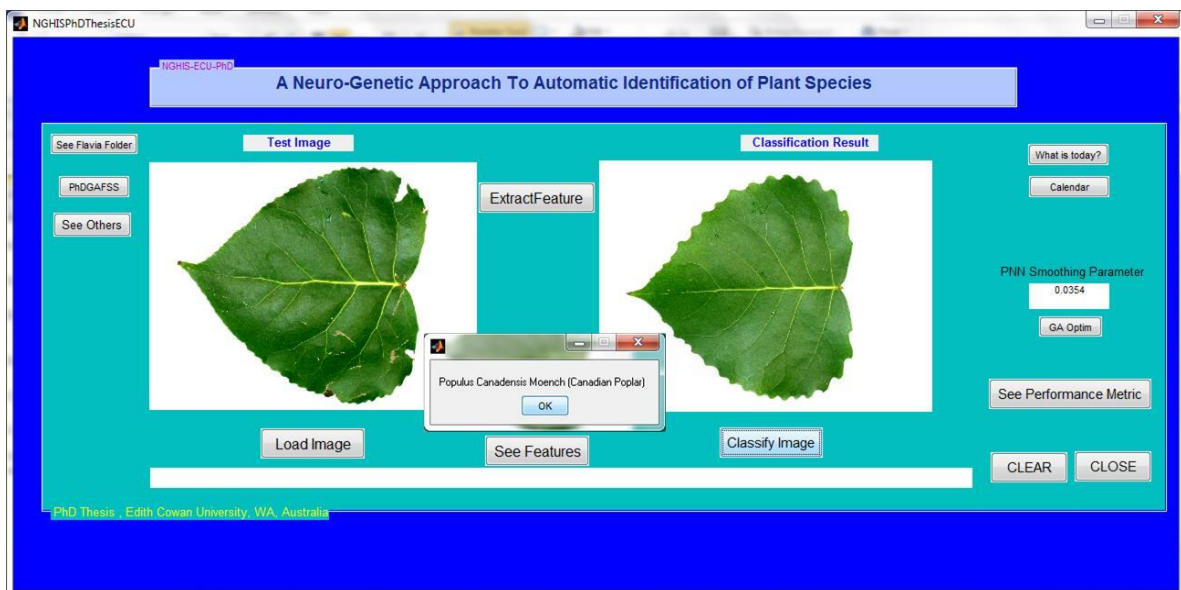
A system called the LeafSnap was developed by Kumar et al. (2011) for identifying tree species using the photographed images of their leaves (see Figure 4). The image database consists of 5972 images taken from 184 trees in the North eastern United States. There were no needs for any color-to-grayscale conversion in this work since color segmentation was used by estimating foreground and background color distributions. The segmentation problem was solved using Expectation-Maximization (EM). The images were then resized into  $300 \times 400$  and rotated by 90 degrees. After this, the histograms of curvatures along the contour of the leaves at multiple scales were extracted from the images of the leaves and finally, species matching was performed through 1-nearest neighbor classification. The classification accuracy as reported in this paper was 96.8%. Being a web-based application, the backend server is a 2quadcore processors Intel Xeon machine with configuration of 2:33 Ghz speed and 16 GB of RAM. The recognition engine of the LeafSnap consists of a backend server which accepts input images from various front-end clients. There is currently, a front-end application of LeafSnap for the iPhone and iPad devices.

Andreas (2010) developed LEAFPROCESSOR- a software package which provides a semi-automatic and landmark-free method for the analysis of a range of leaf-shape parameters, combining both single metrics and PCA. Bending energy was employed as a tool for the analysis of global and local leaf perimeter deformation. The bending energy is a descriptor that provides a global measure of the curvature of the leaf perimeter and it's obtained via integration of the square of the contour's curvature along the perimeter.

Gebhardt (2006) developed a digital image processing system for Identification of broad-leaved dock (*Rumex obtusifolius* L.) on grassland. The authors of this study focussed on the identification of one of the most invasive and persistent weed species on European grassland. The total image samples used were 108 digital photographs obtained through a field experiment under constrained environment (i.e constant recording geometry and illumination conditions). Image segmentation in this work was done through transformation of the {R,G,B} components of the colored images to grayscale images. Binary

images were then derived from the grayscale images by applying local homogeneity threshold of value 0.97. Following this, morphological opening was performed. The features extracted were shape, color and texture-based. The learning system was based on maximum-likelihood estimation (MLE). Furthermore, rank analysis was used for feature analysis to obtain optimal classification accuracy. The accuracy  $x$  reported with the given training set was in the range  $71 \leq x \leq 95$ .

Babatunde (2014) developed a computer-based vision system based on genetic probabilistic neural networks (PNN) and cellular neural networks (CNN). The approach in this work was **Image acquisition** → **Image pre-processing** → **Image segmentation** → **Feature extraction** → **Feature selection**. The parameter of the underlying machine model (PNN) was optimized using genetic algorithm (GA) for performance improvement. The overall results shows that the combination of GA, PNN and CNN is good for building computer-based vision systems. The screen shot for this work is given in Figure 4.



**Figure 4.** Plant Species classification system using Probabilistic Neural Networks and Genetic Algorithm (Babatunde, 2014)



**Figure 5.** An iPhone version of the Leafsnap project (Kumar,et al., 2011)



**Table 3.** Some existing and recent works on plant recognition systems

Author(s)	Techniques	Features
Jyotismita and Ranjan (2011)	Moment Invariants, Centroid-Radii, Neural Network, Image Pre-Processing	Leaf image moments
Zalikhah, Puteh, Itaza, and Mohtar (2011)	Image Pre-Processing, Moment Invariants, General Regression Neural Network.	Leaf image moments
David, James, and Mathew (2012).	Aspect Ratio, Rectangularity, Convex Area Ratio, Convex Parameter Ratio, Sphericity, Circularity, Eccentricity, FormFactor, Regional Moments Inertia, Angle Code Histogram.	Geometric features
Wu(2007)	Probabilistic Neural Network (PNN), Image Pre-Processing, Principal Component Analysis (PCA).	Geometric features
Chomtip, Supolgaj, Piyawan, and Chutpong (2011)	K-nearest neighbor (k-NN), Image pre-Processing, Aspect ratio, Roundness, Ripples features, Half-leaf Area Ratio, Upper Leaf Area Ratio, Lower Leaf Area Ratio, Colour Features, Vein Features, Threshold.	Geometric features
Panagiotis (2005)	Fuzzy Logic Selection, Neural Networks, Image pre-processing, Principal Component Analysis	Geometric features
Valliammal and Geetha-Lakshmi (2011)	Fuzzy Segmentation, Image Pre-Processing, Wavelet Transformation	Leaf image moments
Jyotismita and Ranjan (2011)	Thresholding method, H-Maxima transformation, Moment-Invariants, Centroid-Radii and Neural Networks classifiers.	Leaf image moments
Xiao et al. (2005)	Image Segmentation, Wavelet Transform, Gaussian Interpolation, K-Nearest Neighbor (K-NN), Radial Basis Probabilistic Neural Networks.	Geometric Features, Leaf image moments.
Ji-Xian et al. (2005)	Douglas-Peucker Algorithm (Shape Polygonal Approximation, Invariant Attributes), Genetic Algorithm, kNN.	Leaf image moments
Wang, Chi, and Feng (2003)	Centroid-Contour Distance (CCD) curve, Eccentricity and Angle Code histogram (ACH).	Geometric Features
Sandeep and Parveen (2012)	Color metrics, edge histogram computation, Image Pre-Processing	Colour moments
Yi-Tou et al. (2009)	Rotational Invariant Methods, Grey Level Co-occurrence Matrices (GLCM).	Image Features, Leaf image moments
Marzuki, Yusof, Anis, and Mohd (2011)	Basic Grey Level Aura Matrix (BGLAM) technique and Statistical Properties of pores distribution (SPPD) for wood features.	Colour moments
Arora, Gupta, Bagmar, Mishra, and Bhattacharya (2012)	Image pre-processing (shadow, background correction, binarization), petiole removal, Ellipse-based Blob Ranking, GrabCut leaf segmentation, Random Forest Classifier	Tooth Features and Morphological features as found in (Wu et al., 2007)
Belhumeur & David (2008)	Inner Distance Shape Context (IDSC), KNN, Color image segmentation.	Shape features

#### 4. Discussion and conclusion

Various techniques used by researchers developing computer-based vision systems have been examined. In all the works examined, most authors considered the images of plant leaves for building their systems. The rationale for this is due to the availability of leaves in most part

of the year and images of leaves are also easy to handle being mostly 2D images. However, in all the works mentioned in this paper and in Table 3, some limitations such as low discriminating power between some crop plants and weeds, rejection of variability within the same species and acceptance of variability between different species of plants, extraction of complex features such as a leaf having different colour at the back and at the front, coupled with the need for improved classification speed and accuracy, are still the major challenges facing them. There is no hard and fast rule on how to choose the best of these existing works but nevertheless, the works identified by Figures 3 and 4 are very good choice as the classifier involved in one of these work was genetically optimized. Future works lies in the application of hybrid techniques and amalgamation of various parts of plants to narrow down error in classification as some plants from different species are similar and some from the same species are different. With the inclusion of several parts of the plants in one system and the use of more discriminating classifiers, the knowledge in this domain may move forward.

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