CHAPTER 3

METHODOLOGY

The field of leaf recognition for plant classification has experienced an increased need for fast and efficient classification algorithms to aid in keeping track of important plants. Plant identification through leaf recognition is a research field that has captured the attention of many botanist for several years. Only during the last few years, the advantages of using computers to perform plant identification using leaf have been envisaged. Most of the current researches use neural networks, wavelets and fuzzy network for automating the classification process. These systems are applicable only to specific species and often require human (botanist) intervention to define terms for feature extraction and pre-processing. The efficiency of these systems thus depends on the expertise of knowledgeable experts.

As a solution to this scenario, the identification systems should prove efficient in designing the pre-processing, feature extraction and identification stages. Further, the limited literature available describes the fact that the field is still raw and need to follow a line of investigation to increase the accuracy and speed of identification. This research work proposes techniques that enhance the operation of each stage of plant identification systems that use their leaf images and propose a Computer-Aided Plant Identification through Leaf Recognition (CAP-LR) system. This chapter presents the proposed research methodology and introduces the various techniques and methods used to develop CAP-LR.

3.1. RESEARCH DESIGN

The identification of plant category from leaf image consists of four important steps, namely, acquisition, preprocessing, feature selection and recognition. All the steps involved are considered very important for the accuracy and efficiency of the identifier. The study proposes techniques to enhance each of these steps, so that the resulting system produces maximum advantage to plant identification through leaf recognition in terms of accuracy. Each of these steps is designed as a separate phase and the techniques and methods used are described in this section. The research methodology used for this purpose is shown in Figure 3.1.

3.1.1. Phase I : Preprocessing

Preprocessing is the process of enhancing the quality of an input leaf image and is an important step in CAP-LR because for an incorrect image, preprocessing has a direct impact on the end result of plant identification. The preprocessing stage performs two tasks, namely, denoising and segmentation.

A. Denoising

The proposed desnoising algorithm is termed as 'Enhanced Wavelet based Denoising with inbuilt Edge Enhancement and Automatic Contrast Adjustment Algorithm (WEC Method)'. This method enhances the wavelet transformation based denoising (Kai *et al.*, 2005,Sendur *et al.*, 2002) and enhances an input leaf image in three steps, namely, denoising, contrast adjustment and edge enhancement. Most of the denoising solutions mainly focuses on noise removal and ignore the edge and contrast details. Some methods apply separate algorithms for each of these three steps. This study proposes a single procedure that simultaneously performs these three operations using an amalgamation of image processing techniques.

The algorithm begins by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) to adjust the contrast of the leaf image. CLAHE (Wanga *et al.*, 2004) is a special case of the histogram equalization technique, which seeks to reduce the noise and edge-shadowing effect produced in homogeneous areas. The contrast adjusted image is then decomposed using 2D Haar wavelet transformation. The edge enhancement procedure utilizes texture features like mean, variance and correlation, to categorize the edges of the image as strong and weak edges.

COMPUTER-AIDED PLANT IDENTIFICATION THROUGH LEAF RECOGNITION

PHASE I - PREPROCESSING

(A) DENOISING

Enhanced Wavelet based Denoising with inbuilt Edge Enhancement and Automatic Contrast Adjustment Algorithm (WEC Method)

(B) SEGMENTATION

Enhanced Wavelet based Segmentation using Clustering and Texture based Color Features (WCF Method)

PHASE II - FEATURE EXTRACTION AND SELECTION

FEATURE EXTRACTION

- Geometric Features
- Color Features
- Texture Features
- Fractal Features
- Leaf Specialized Features

Feature Fusion

FEATURE SELECTION

- Genetic Algorithm (GA)
- Kernel Principal Component Analysis (KPCA)
- Combined GA and KPCA

PHASE III - PLANT IDENTIFICATION THROUGH LEAF RECOGNITION

TWO LEVEL CLASSIFICATION ALGORITHM

BPNN-Based		SVM-Based		WNN-Based	
I Level	**II Level**	**I Level**	**II Level**	**I Level**	**II Level**
BPNN	SVM	SVM	SVM	WNN	SVM
	BPNN		BPNN		BPNN
	WNN		WNN		WNN

PERFORMANCE EVALUATION

Datasets : Real and Standard Datasets	
Phase	**Performance Metrics**
Preprocessing	Peak Signal to Noise Ratio (PSNR), Figure of Merit (FoM), Mean Structural Similarity Index (MSSI) and Speed
Feature Extraction and Selection	Number of Features Selected, Speed
Recognition	Recognition Rate, Error Rate, Speed

Figure 3.1 : Research Methodology

The weak edges were then enhanced using a sigmoid function. The next step removes noise in detailed coefficients using a relaxed median filter (Hamsa *et al.*, 1999). After enhancement of edges and detailed regions, an inverse wavelet transformation was performed to obtain an enhanced leaf image.

B. Segmentation

Efficient and effective image segmentation is important for accurate plant identification through leaf recognition. The technique proposed in this phase focus on separating the Region Of Interest (ROI), that is the leaf, from its background. Among the various methods used, wavelet based approaches was more suitable for segmenting images from its background (Jameel and Manza, 2012). But due to the varied color and texture property of leaf images, wavelets have the shortcoming of grouping regions that result in inaccurate segmentation. Therefore to solve this problem, texture, color or a fusion of these features were used for grouping regions (Sengur and Guo, 2011, Ozden and Polat, 2007; Liapis *et al*., 2004). In this study, an approach called 'Enhanced Wavelet based Segmentation using Clustering and Texture based Color Features (WCF Method)' is proposed. The algorithm exploits color and texture features in wavelet domain and uses K means clustering algorithm during segmentation.

The procedure of WCF consists of four steps. The **first step** focuses on extracting texture information. Texture features are obtained using wavelet decomposition, which decomposes the leaf image into four subbands. As maximum texture information is contained in LH (Low High) and HL (High Low) subbands, only these two coefficients are used to obtain texture features. Each of the pixels in these two subbands is grouped into four texture classes, namely, dominant energy in vertical direction, dominant energy in horizontal direction, smooth (insufficient energy in any orientation) and complex (no dominant orientation). A K-means clustering algorithm is used for this purpose and the categorization is based on the mean energy of the subbands.

In the **second step**, a color transformation is performed to convert the RGB (Red Green Blue) color space to L*u*v color space and separate the L, u and v color components. The three color components together with the four texture classes and spatial coefficients (x,y) form the feature vector.

In the **third step**, an enhanced mean shift filtering algorithm, that integrates both color and texture features, is then applied. This step increases the discrimination between regions where the colors are similar but textures are different and improves the segmentation process. Finally, in the **fourth step**, again a K-means clustering algorithm is used to segment the ROI region.

3.1.2. Phase II: Feature Extraction and Selection

The main aim of the second phase is to convert the image data into a format that simplifies the process of matching between leaf images. This phase consists of two steps, namely, Feature Extraction and Feature Selection. The feature extraction step functions to discover various features that best represent a leaf image. As the number of features selected is normally very high, a feature selection algorithm is used in the second stage, to select the most prominent features.

A. Feature Extraction

During feature extraction, five categories of features were extracted. They are geometric features, color features, texture features, fractal features and leaf related features. Most of the studies related to leaf recognition use only leaf, color and texture features. In this study, the geometric and fractal characteristics were also considered. The list of the various features extracted under each category is presented in Table 3.1.

TABLE 3.1

FEATURES EXTRACTED FROM LEAF IMAGE

Feature Category	Feature Details
Geometric Features	Eccentricity, Extent, Orientation
Texture Features	Energy, Entropy, Homogeneity, Variance
Color Features	Mean, Standard Deviation, Skew, Kurtosis
Fractal Features	Average Fractal Dimension, Standard Deviation Fractal Dimension, Lacunarity
Leaf Features	Diameter, Physiological Length and Width, Area, Perimeter, Smooth Factor, Aspect Ratio, Form Factor, Rectangularity, Narrow factor, Perimeter ratio of diameter, Perimeter ratio of PL and PW,Vein features, Ripple

The five feature sets were first analyzed for their efficiency in plant identification through leaf recognition. The experiments revealed that the leaf feature set improved identification accuracy when compared with other four feature categories. Motivated by this fact and in search for further improvement possibilities towards accuracy, the leaf features were fused with the other four categories to obtain combined feature sets, namely, GLFS (Leaf+ Geometric), CLFS (Leaf+ Color), TLFS (Leaf+Texture) and FLFS (Leaf+ Fractal).

B. Feature Selection

Usage of combined feature set increases the accuracy of recognition, but on the other hand it suffers from the curse of high dimensionality. Feature selection, a process of removing irrelevant and redundant features, is used to overcome this problem. For this purpose, two algorithms, Genetic Algorithm (GA) and Kernel Principle Component Analysis (KPCA), were combined in the proposed model. The application of GA (Zhou *et al.*, 2008) and KPCA (Chen *et al.*, 2010) produce two dimensionality reduced feature sets, which are combined using two boolean operators, namly union ($\cup$) and intersection ($\cap$).

An aggregate feature fusion technique is used for KPCA algorithm. The genetic algorithm performs both feature fusion and selection in a single framework. The algorithm uses an entropy based feature selection algorithm to create multiple fused feature subsets, to form a feature pool. Application of GA on feature pool produces the desired dimensionality reduced feature subset.

3.1.3. Phase III: Classification

The last phase of the study is the task of identifying the plant to which the input leaf belongs and is very important for botanical field. This is the most time consuming part of CAP-LR system, as the algorithm mainly revolves round an iterative recognition procedure that matches the features extracted from the input image with feature vectors representing the leaf images of the pre-built dataset. Classification, a task of machine learning algorithms, was used for this purpose. Recently, publications that combine different machine learning algorithms to form hybrid models have also been proposed. Most of these hybrid models combine two or more of predictive or descriptive algorithms in order to improve the performance of identification and recognition. Examples include SVM + WNN (Zhang and Liu, 2010) and Artificial Neural Network & Statistical Analysis (Sarhan and Helalat, 2007).

In this study, another unique way of combining machine learning algorithms is proposed, that is a two-level procedure that combines two predictive algorithms is designed. This 2-step classifier is termed as CL-CL (Classifier-Classifier) method in this study. Three unsupervised classifiers are used in this phase. They are, Back Propagation Neural Network (BPNN), Support Vector Machine (SVM) and WNN (Wavelet Neural Network).

3.2. PERFORMANCE EVALUATION

Performance evaluation of the enhancement methods that are used to develop the final identification system is the most important step in any research. Different researchers use different parameters for analysis. This section presents the various parameters used to evaluate the methods proposed in each phase of the study.

3.2.1. Phase I : Denoising

The parameters used to evaluate the denoising algorithm analyzes the the efficiency of the algorithm in terms of quality of denoised image, efficiency in preserving their edge and structure details, and speed of producing the enhanced image. Four parameters used for this purpose are Peak Signal to Noise Ratio (PSNR), Figure of Merit (FoM), Mean Structural Similarity Index (MSSI) and Speed (seconds). This section presents the method of estimating these metrics.

- **Peak Signal to Noise Ratio (PSNR)**

PSNR is a quality measurement between the original and a compressed image. The higher the PSNR is the better the quality of the compressed or reconstructed image. To compute the PSNR, the block first calculates the mean-squared error using the following equation:

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \tag{3.1}$$

In the above equation, M and N are the number of rows and columns in the input images, respectively. Then the block computes the PSNR for gray scale images using the following equation:

$$PSNR = 10 \log_{10}\left[\frac{R^2}{MSE}\right] \tag{3.2}$$

For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE, which will be the sum over all squared value differences divided by image size and by three. Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. The PSNR for color images with color components, R, G and B is given as below:

$$\mathrm{PSNR} = 10\log_{10}\left[\frac{255^2}{\frac{\mathrm{MSE(R)}+\mathrm{MSE(G)}+\mathrm{MSE(B)}}{3}}\right] \tag{3.3}$$

the previous equation, *R* (=255) is the maximum fluctuation in the input image data type.

- **Pratt's Figure Of Merit (FOM)**

To determine the efficiency of the edge preservation capacity of the proposed denoising method, the Pratt's Figure Of Merit (Yu and Acton, 2002) is adopted and is defined by Equation (3.4).

$$\mathrm{FOM} = \frac{1}{\max\{\hat{N}, N_{ideal}\}}\sum_{i=1}^{\hat{N}}\frac{1}{1+d_i^2\alpha} \tag{3.4}$$

where $\hat{N}$ and N_{ideal} are the number of detected and ideal edge pixels, respectively, d_i is the Euclidean distance between the i^{th} detected edge pixel and the nearest ideal edge pixel, and α is a constant which is typically set to 1/9. FOM ranges between 0 and 1, with unity for ideal edge detection.

- **Mean Structural Similarity Index (MSSI)**

The Mean Structural Similarity Index is a quality measure that is used to evaluate the overall image quality between the original (X) and the enhanced image (Y) in terms of their structure preservation capacity. Equation (3.5) is used to calculate this measure.

$$\mathrm{MSSI}(x,y) = \frac{1}{M}\sum_{j=1}^{M}\frac{(2\mu_x\mu_y + c_1)(2\,\mathrm{cov}_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{3.5}$$

where M is the number of local windows, μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, and cov_{xy} the covariance of x and y. c_1 and c_2 are two small values included to stabilize the division with weak denominator (Wanga *et al.*, 2004). In this research, 8 x 8 window size is used for experimentation.

- **Speed of Enhancement Algorithms**

Enhancement time is a basic measurement used to evaluate the time requirement of an image enhancement algorithm. It is the execution time taken by any defined algorithm to complete the enhancement operation. Enhancement speed depends on the following characteristics.

- The complexity of the algorithm
- The implementation efficiency of the algorithm
- The speed of the processor hardware

Generally, the desired behaviour is to have increased speed which in turn speeds up user interaction during plant identification and leaf recogntiion operations.

3.2.2. Phase I : Segmentation

The second part of preprocessing operation is segmentation, which extracts or segments the leaf image from other regions of the input image. This process avoids unnecessary computations involved by examining irrelevant regions and thus improves the overall performance of CAP-LR system. Two methods are used to evaluate the performance of the proposed segmentation algorithm. The first method analyzes the visual results obtained to analyze the efficiency of the algorithm and second is the speed (measured in seconds) in which the algorithm returns the segmented leaf image.

3.2.3. Phase II : Feature Extraction and Selection

The study analyzes the applicability of five different types of features, namely, geometric features, color features, texture features, fractal features and leaf specialized features.The study further proposes a feature fusion algorithm which combines the selected features for obtaining an added advantage during plant identification and leaf recognition. The performance of the feature selection algorithms were analyzed in two manners. The first was to compare the number of features extracted before and after applying the three feature selection algorithms and second was studying their effect on the identification and recognition process. Additionally, the speed of extracting and selecting the features was also considered.

3.2.4. Phase III : Plant Identification through Leaf Recognition

The last part of CAP-LR was analyzed using three parameters namely, recognition rate, error rate and speed of identification and recognition. The recogntiion rate and error rate are calculated using Equations (3.6) and (3.7).

$$\text{Recognition Rate} = \frac{\text{No. of correct recognition}}{\text{Total Number of Images}} \text{x}100 \tag{3.6}$$

$$\text{Error Rate} = \frac{\text{No. of incorrect recognition}}{\text{Total Number of Images}} \text{x}100 \tag{3.7}$$

Training and testing time refers to the time taken by the algorithm to train and test the proposed classifier. The sum of training and testing was used to analyze the speed of the proposed identifiers.

3.3. DATASETS

All the experiments were conducted using two leaf template datasets, namely, Standard and Real Dataset. The standard dataset was obtained from flavia leaf recognizer (http://flavia.sf.net). It consisted of 32 plant categories comprising of 1908 leaf images. The real dataset is a dataset created by the researcher consisting of 500 leaf images belonging to 20 different plant categories.

	
Leaf 1 Japanese Maple (*Acer dalmatum*)	**Leaf 2** Goldenrain Tree (*Koelreuteria aniculata*)
	
Leaf 3 Ginkgo, Maidenhair Tree (*Ginkgo biloba*)	**Leaf 4** Chinese Horse Chestnut (*Aesculus chinensis*)

Figure 3.2 : Standard Dataset Test Images

	
Leaf 5 Adathoda *(Adathoda vasica)*	**Leaf 6** Cholam *(Sorghum bicolor)*
	
Leaf 7 Vetrilai *(Betel Leaf)*	**Leaf 8** Karpuravalli *(Coleus aromaticus)*

Figure 3.3 : Real Dataset Test Images

The leaf images were acquired using digital cameras and were stored in JPEG image format. All the images were captured in RGB format. Samples of all leaves (20 in the real dataset and 32 in the standard dataset) along with their general and scientific names are presented in Appendices A and B respectively. Test images used for documentation purpose are presented in Figures 3.2 and 3.3. Test Images are Labelled as Leaf 1,Leaf 2,Leaf 3,Leaf 4, Leaf 5, Leaf 6, Leaf 7, Leaf 8 and referred for further process.

3.4. CONTRIBUTIONS

The work was motivated by Wu *et al.* (2007) who proposed a leaf recognition for plant identification system using leaf features and probablistic neural network. The study in search for improving the performance made several enhancements to this system, from preprocessing to the classifier for plant identification. The research work, focusing on the design and development of plant identification through leaf recognition, proposes enhanced techniques at each phase of the study and the specific contributions are presented in this section.

The denoising algorithm proposes a single model that can enhance both the image details, edge details and contrast simultaneously. For this purpose, techniques like wavelets, CLAHE, sigmoid functions and relaxed median filters were used.

Segmentation was carried out by using a technique that combines Wavelet transformation and Mean Shift algorithms and was designed in a manner that integrates the texture, color and spatial features. K-means clustering algorithm was finally used to separate the leaf image from its background.

The study proposes the use of various features like texture, color, geometric, fractal and leaf specialized features. The study also proposes an enhanced vien feature. The five categories of features were combined using a fusion based feature selection algorithm that combines Genetic Algorithm (GA) with KPCA using Boolean operator.

In the plant identification through leaf recognition stage, a two-stage classification system that combines the advantages of more than one classifier to improve the training process is proposed. For this purpose, three proven classifiers, namely, BPNN, SVM and WNN were used and a total of nine classification models were proposed.

The proposed algorithm in each stage is selected to build the CAP-LR system to take advantage of the enhancement operations implemented in preprocessing, feature extraction and classification.

3.5. CHAPTER SUMMARY

This chapter presents the research methodology designed to meet the objectives framed in Chapter 1, Introduction. The proposed CAP-LR consists of four steps (noise removal, segmentation, feature extraction and recognition) that are used for accurate plant identification through leaf recognition. The details of the proposed noise removal algorithm used to enhance the input leaf image are presented in the next chapter, Chapter 4, **Design of Noise Removal Technique.**