ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL SCIENCES

Automatic Plant Species Identification Using Image Processing Techniques

Dejene Tsegaye Ayane

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ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL SCIENCES

Dejene Tsegaye Ayane

Advisor: Yaregal Assabie(PHD)

This is to certify that the thesis prepared by *Dejene Tsegaye Ayane*, titled: *Automatic Plant Species Identification Using Image Processing Techniques* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Computer Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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	Name	Signature	Date
Advisor :	*Yaregal Assabie*(PHD)	______	______
Examiner:	______	______	______
Examiner:	______	______	______

ABSTRACT

Plants are one of the important things that plays a very essential role for all living beings exists on earth. Plants form a fundamental part of life on Earth, providing us with breathable oxygen, food, fuel, medicine and more. Plants also help to regulate the climate, provide habitats and food for insects and other animals. But due to unawareness and environment deterioration, many plants are at the verge of extinction. Understanding of plant behavior and ecology is very important for human being and the entire planet.

Plants possess unique features in their leaf that distinguish them from others. Taxonomists use these unique features to classify and identify plant species. However, there is a shortage of such skilled subject matter experts, as well as a limit on financial resources.

Several leaf image based plant species identification methods have been proposed to address plant identification problem. However, most methods are inaccurate. Invariant moments that are used for leaf shape features extraction are inadequate. Hu moments are inadequate when leaves from different species have very similar shape. The computation of Zernike moments involve discrete approximation of its continuous integral term which result in loss of information. Hence, it is extremely important to look for an improved method of plant species classification and identification using image processing techniques.

In this work a new method based on combined leaf shape and texture features using a class of ensemble method called Random Forest for the classification and identification of plant species has been proposed. Morphological features and Radial Chebyshev moments are extracted from the leaf shape and Gabor filters are extracted from leaf texture. These three features are combined, important features are selected to form a feature set that trained the Random Forest classifier.

The Random Forest was trained with 1907 sample leaves of 32 different plant species that are taken form Flavia dataset. The proposed approach is 97% accurate using Random Forest classifier.

Keywords: Plant Species Identification, Morphological Features, Radial Cheybshev Moments, Gabor Filter, Random Forest

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ACRONYM AND ABBREVIATION

IDE	Integrated Development Environment
Spyder	Scientific PYthon Development EnviRonment
OpenCV	Open Computer Vision
RGB	Red, Green, Blue
JPEG	Joint Photographer Expert Group
k-NN	K-Nearest Neighbor Classifier
PNN	Probabilistic Neural Network
SVM	Support Vector Machine
RCM	Radial Chebyshev moments
MSE	Mean square Error
CSV	Comma Separated Value
SciPy	Scientific Python

CHAPTER 1: INTRODUCTION

1.1 Background

Plants form a fundamental part of life on Earth, providing us with breathable oxygen, food, fuel, medicine and more. Plants also help to regulate the climate, provide habitats and food for insects and other animals and provide a natural way to regulate flooding. A good understanding of plants is necessary to improve agricultural productivity and sustainability, to discover new pharmaceuticals, to plan for and mitigate the worst effects of climate change, and to come to a better understanding of life as a whole. It is therefore becoming increasingly important to identify new or rare plant species [1].

Plant species identification is the finding of the correct name for an unknown plant in order to access all the information so far available about that plant. Plants have many characteristics that can be used to identify particular species: overall size and shape; the color, size and shape of leaves; the texture, color and shape of twigs and buds; and the color and texture of bark, fruit and flowers. Growing range is also useful in identifying plant species. Most people use several of these characteristics to identify a specific plant [2, 3].

There are a number of methods for plant species identification. Use of pictures and illustrations, identification keys in botanical books and floras and asking experts are among others [4].The image-based identification of different species of plants that both botanical scientists and expert users have collected has become a key study among plant biology science [5].

Herbaria are also used for identifying plant species. One such herbarium is the National Herbarium of Ethiopia. This herbarium is the sole Laboratory for researches to identify and study the plant biodiversity of Ethiopia. The herbarium houses over 80,000 plant specimens collected from all over Ethiopia and Eritrea(and also from Somalia, Kenya, Tanzania, Uganda and other countries as well). The Herbarium, in addition to housing well authenticated plant specimens in two rooms has copies of eight volumes (ten books) of the Flora of Ethiopia and Eritrea [6].

Although there are well known methods of plant species identification in plant science, the methods are tedious and exhausting which demand for an automatic species identification method. Hence, this research is to address plant species identification problem using image processing techniques.

1.2 Motivation

Plant species identification is a tedious task. There are huge numbers of specimen in the National Herbarium of Ethiopia which will serve for plant species identification. The books (the Flora of Ethiopia; ten books in eight volumes) are also the key reference for plant species identification. However, Researchers spent considerable time to search and identify specimen they brought from different places at the herbarium and referring to the books to identify the plant is cumbersome and time taking. To greatly speed up the process of plant species identification, there should be a solution that eases the researches plant species identification burden and save their precious time. One such solution is the use of leaf image based plant species identification.

Leaf image based plant species identification method will greatly simplify the identification process by allowing a user to search through the species image data using models that match images of newly collected specimens with images of those previously discovered and described.

1.3 Statement of the Problem

The traditional approach of identifying plant species and their relationships is to train taxonomists who can examine specimens and assign taxonomic labels to them. However, there is a shortage of such skilled subject matter experts, as well as a limit on financial resources. Furthermore, an expert on one species or family may be unfamiliar with another. This has led to an increasing interest in automating the process of plant species identification.

Botanists collect specimens of plants and preserve them in herbarium. Herbarium collections can be seen as major, structured repositories of expert knowledge. For example, there are huge numbers of specimen (over 80,000) collections at the National herbarium of Ethiopia. But, these collections are not easily accessible as there are no visual means of specimen identification.

Other significant sources of knowledge include flora, taxonomic keys and monographs. Identifying the name of a plant using these sources of knowledge is time consuming and requires an experienced taxonomist. Moreover, there are a number of plant species in a given family that complicates identification of species. For example, there are twenty two endemic plants of Ethiopia with the same family name Euphorbiaceae [7].

Therefore, there is a need to develop a robust automated species identification system that would allow people with only limited botanical training and expertise to carry out plant species identification.

1.4 Objective

General objectives

- The general objective of this research is to develop an automatic plant species identification system using image processing techniques.

Specific objectives

The specific objectives of the research are to:

- Review relevant literature and related works to understand the domain;
- Study the physical characteristics that are used for plant species identification;
- Identify tools and technologies that will be used for designing and modeling automatic plant species identification system;
- Design model for automatic plant specifies identification;
- Develop prototype; and
- Evaluate the performance of the developed model.

1.5 Methods

The following methods will be applied to achieve the objectives of this research work.

Literature Review

Different literature on image processing techniques and identification of plant species will be reviewed. Articles, thesis and conference papers that are related to the research topic will also be examined.

Data collection

The publically available Flavia [8] dataset will be used for modeling the automatic plant species identification system. Attributes (local plant species name, scientific name, etc.) of each plant species will also be captured as additional data for easy description of each plant species.

Evaluation

The model designed for identification of plant species will be evaluated for its accuracy, precision, recall, f-score and support [9].

1.6 Scope and limitation

The focus of this work is primarily on the modeling of the characteristics of plant leaf shape for easy identification of plant species using Chebyshev Redial Moments, digital morphological and texture features.

This work does not include:

- Use of color features for the identification of plant species.
- Use of other parts of a plant such as flowers, fruits, stems, roots, etc. for identification plant species.
- Use of the whole image of a plant for identification of the plant species.
- Working with high-noise images, with complex backgrounds or with bad resolution images.

1.7 Application of Results

Results of this method can generally be applied in areas where plant species studies being conducted. The result of this research benefits taxonomists, botanists, agriculturalists, environmentalists etc. Different institutions that can research on plant species are also among the candidate beneficiaries of this study.

The application of such a method has advantage for the plant species identification as it greatly simplifies the process of plant species identification. Some of the advantages are:

- It provides reliable, faster and convenient plant species identification;
- It reduces the time that the researches will have to spend in the field and herbarium to identify and classify plant species; and
- It automatically identify and classify plant species.

1.8 Organization of the Rest of the Thesis

The rest of this thesis report is organized as follows. Chapter two discusses about plant species identification, digital image processing and the related subject areas as literature review. Chapter three is devoted to discuss related works done on plant species identification and other topics related to plant species classification. Chapter four gives a detailed description of the architecture and design issues of our system. The main components of the system, their functional operation and the specific components are discussed in this Chapter. Chapter 5 presents the implementation of the proposed system architecture and experimental results. Chapter 6 concludes the thesis by recommending some feature work. It also shows some research directions that can be used in the future to improve automatic plant species identification.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter is concerned with plant identification, images and image processing techniques. The main goal of this research is to build a plant species identification model that classifies leaves and assigns the names of the plant that they belong to, when supplied only with the leaf image as input. This goal is met through a series of sequential steps, namely, image preprocessing, segmentation, extraction of features, fusion of features, feature selection, classification and identification of plant species. Several researchers have contributed and proposed various algorithms in each of these steps. This chapter presents a review of some important publications made in these steps to understand the current research status.

2.2 Overview of plant species

Plants are living organisms belonging to the kingdom of vegetable that can live on earth. There are about 3,000,000 plant species that has been name and classified [10]. Life on earth depends on plants. Plants are responsible for the presence of oxygen, which is vital for human beings. They are the base of the human food chain and humans directly or indirectly take their food from plants. Plants are used to prevent soil erosion and they are also used for providing building materials. They play a vital role in the field of medicines, where more than one-quarter of all prescribed drugs come directly from derivatives of plants [11].

A typical plant body consists of different parts as illustrated in Figure 2.1

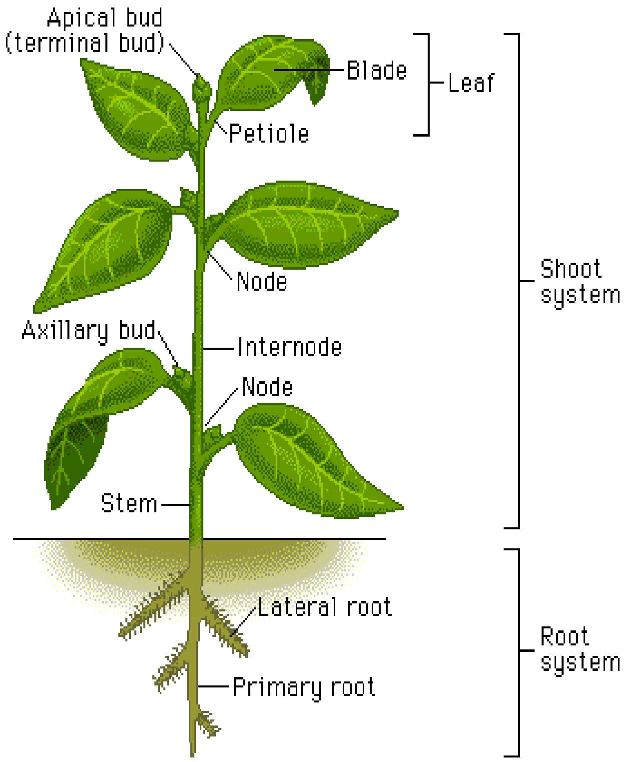

Figure 2.1: Different parts of plant as illustrated in [12]

The plant body consists of two major organ systems, namely, shoot system and root system. The shoot systems exist above the ground and include organs like buds, leaves, fruits, flowers and seeds.

Leaf structure: Leaves of most plants have a flat structure called the lamina or blade, but all leaves are not flat, some are cylindrical. Leaves can be simple, with a single leaf blade, or compound, with several leaflets. Figure 2.2 and Figure 2.3 show simple and compound leaves respectively [13].

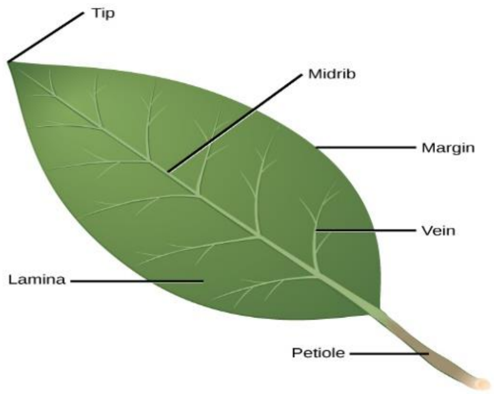

Figure 2.2:Simple leaf parts

Figure 2.3: Compound leaf

Edges (or margin) of leaf is structure of leaf at its boundary. The edges (or margin) of leaves may be smooth, toothed, lobed, incised, or wavy. Figure 2.4 shows the different leaf margins.

Figure 2.4: Leaf margin as illustrated in [13]

Arrangement of a leaf: it refers to how leaf grows on the stem. Some leaves grow opposite, some alternate, some in rosette forms and others in whorls. The different leaf arrangement are illustrated in Figure 2.5.

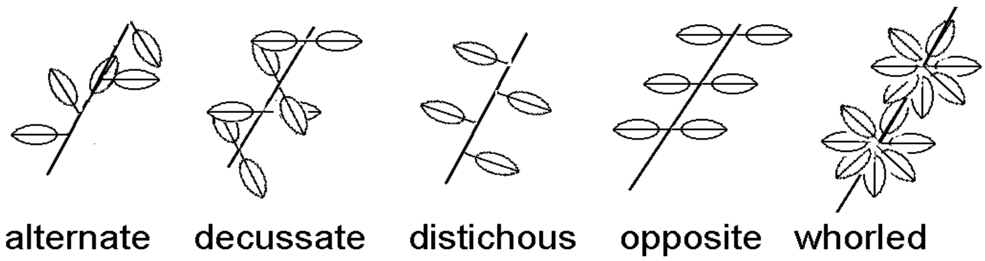

Figure 2.5: Arrangement of leaf as depicted in [13]

Venation is the imprinted veins in the leaf surface. Venation may be parallel, dichotomous (forming a “Y”), palmate (emanating out from a central point), pinnate (where the veins are arrayed from the midrib).

The texture of the leaf is another aspect to consider during plant leaf identification. Leaf texture can be firm and waxy, shiny, thick, stiff, limp, etc. It is easy to identify whether the leaf has sticky glands, prickly thorns, or fine hairs. The different leaf types based on their form, shape venation, margins and arrangement of leaf on the stem are summarized and shown in Figure 2.6 below [16].

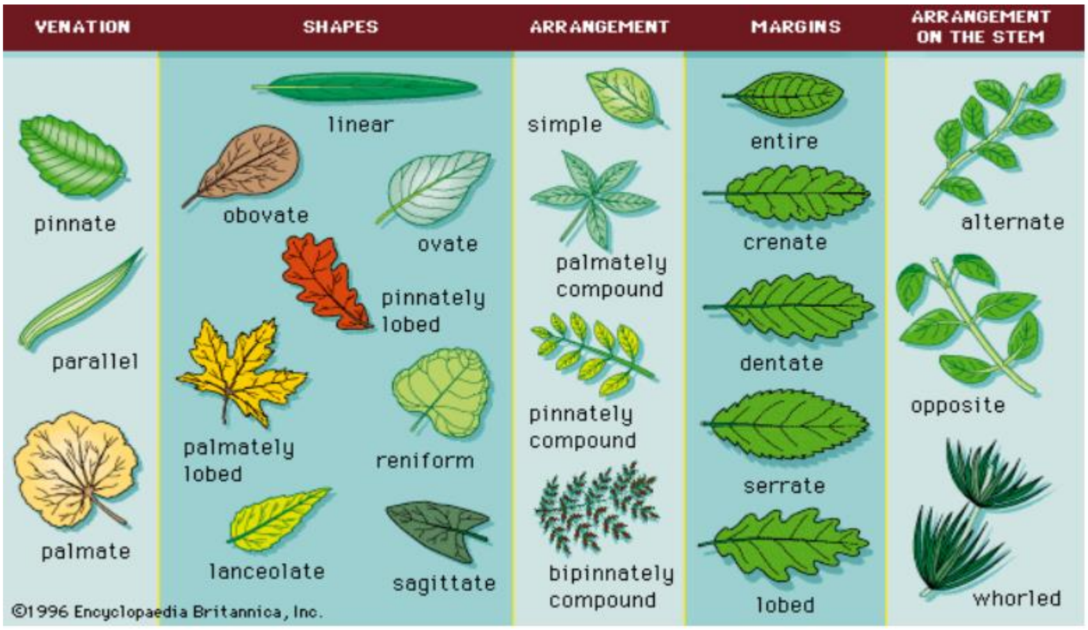

Figure 2.6: Summary of Leaf variation as illustrated in [14]

Plant classification : is the placing of known plants into groups or categories to show some relationship within the category. Scientific classification follows a system of rules that standardizes the results, and groups successive categories into a hierarchy. In this hierarchy, kingdom is the broadest and species is the most specific category. As an example, olive classification is depicted in Table 2.1 [17].

Table 2.1: Classification of olive according to classical taxonomy

Kingdom	Green Plants
Subkingdom	Tracheobionata - vascular plants
Superdivision	Spermatophyta - seed plants
Division	Magnoliophyta - flowering plants
Class	Magnoliopsida - Dicotyledons
SubClass	Asteridae
Order	Scrophulariales or Lamiales
Family	Oleaceae - ash, privet, lilac and olives
Genus	Olea
Species	Europa

2.2.1 Plant Species Identification

Plant species identification is the determination of the identity of an unknown plant using the morphological characteristics of the plant such as structure of stems, roots, leaves and flowers followed by comparison with previously collected specimens or with the aid of books or identification manuals. The identification process connects the specimen with a published name. If a plant specimen is identified, its name and properties will be known [17, 18].

Leaf shape is valuable for plant species identification. Plant organs such as flowers and fruits are seasonal in nature and root and stem characteristics are inconsistent. On the other hand, leaves are present for several months and they also contain taxonomic identity of a plant which is useful for plant classification. Moreover, plant leaves are two dimensional in nature while flowers and fruits are three dimensional and are not suitable for machine processing compared to plant leaves. Hence, a plant's leaf shape is the most discriminative feature and classification of plants based on leaves is the quickest and easiest way to identify a plant [10, 19].

2.2.2 Digital Morphological features

The digital morphological features generally include basic geometric features and morphological features [20]. The features are computed from the contour of leaf. The basic geometrical features of a leaf include longest diameter, physiological length, physiological width, leaf area and leaf perimeter. The basic geometrical features of a leaf are defined below.

- **Longest Diameter**: it is longest distance between any two points on the contours of leaf. It is denoted as D.
- **Physiological length**: It is the distance between two terminals of a leaf. It is denoted as L_P.
- **Physiological Width**: It is the longest distance orthogonal to physiological length. We consider two lines are orthogonal if their degree is 90^0. It is denoted as W_P.
- **Leaf Area**: Smoothed leaf image is considered to find out leaf area. Number of pixels having binary value 1 is termed as leaf area. It is denoted as A.
- **Leaf Perimeter**: Leaf Perimeter is calculated by counting the number of pixels consisting leaf margin. It is denoted as P.

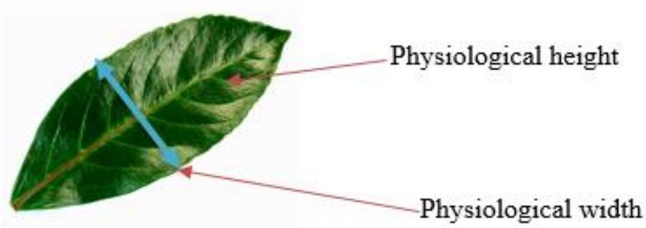

Figure 2.7: Relationship between physiological width and height of plant leaf

Based on above five basic geometric features, it is possible to define the following commonly used morphological features.

1. Smooth factor: It is defined as the ratio between area of leaf image smoothed by 5×5 rectangular averaging filter and area of leaf image smoothed by 2×2 rectangular averaging filters.
2. Rectangularity: It is defined as the ratio between physiological length (PL), physiological width (PW) and leaf area (A). Thus, (PL* PW)/A.
3. Aspect ratio: It is defined as the ratio between physiological length and physiological width. Thus, LP/ WP.
4. Perimeter ratio of diameter: It is defined as the ratio between perimeter (P) and diameter (D). Thus, P/D.
5. Form factor: It is defined as $4\pi A/P$. where A is area of leaf and P is perimeter of the leaf margin.
6. Narrow factor: It is defined as the ratio between diameter and physiological length. Thus, D / LP.
7. Perimeter ratio of physiological length and physiological width: It is defined as the ratio between perimeter and sum of physiological length and physiological width. Thus, P / (PL + PW).

2.3 Digital Image Processing

Digital image processing is an interesting field that provides improved pictorial information for human interpretation and processing of image data for storage, transmission, and representation for machine perception. Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications [21].

A digital image is an array of real numbers represented by a finite number of bits. The basic definition of image processing refers to processing of digital image, i.e. removing the noise and any kind of irregularities present in an image. The noise or irregularity may creep into the image either during its formation or during transformation etc. For mathematical analysis, an image may be defined as a two dimensional function f(x, y) where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. It is very important that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements, image elements, and pixels [22].

There are different types of digital images [23]. These are binary, grayscale and RGB images. Binary image is the simplest type of image and has two values, black and white or ‘0’ and ‘1’. The binary image is referred to as a 1 bit image because it takes only one binary digit to represent each pixel.

Grayscale image is a monochrome image or one-color image. It contains brightness information only and no color information. Then grayscale data matrix values represent intensities. The typical image contains 8 bit allows the image to represent (0-255) different brightness (gray) levels.

RGB Image: RGB image does not use a color map and an image is represented by three color component intensities such as red, green, and blue. RGB image uses 8-bit monochrome standard and has 24 bit where 8 bit for each color (red, green and blue).

2.3.1. Image Acquisition

The leaf images can be acquired using a digital camera which is also embedded in our cell-phone. There is no restriction on resolution and image format. Generally scanned image or digital image which is two dimensional in nature and RGB format is used for image processing. In some cases we can use binary and grayscale images as well. However, the image background needs to be cleaned and single colored using image segmentation [24].

2.3.2. Image Enhancement

Image enhancement is the modification of image by changing the pixel brightness values to improve its visual impact. Images suffer from poor contrast and noise because of the limitations of imaging sub systems and illumination conditions while capturing image. Hence, it is necessary to enhance the contrast and remove the noise to increase image quality. In image processing, image enhancement is the most important stage that improves the quality (clarity) of images by removing blurring and noise, increasing contrast, and revealing image details for human viewing or machine interpretation. While image noise is a random effect that causes variation in image brightness or color information, image contrast is the difference in visual properties making an object in image distinguishable from other objects and the background. In general, image enhancement techniques can be divided into three categories [25, 26].

- Spatial-domain methods that directly manipulate pixels in an image;
- Frequency-domain methods that operate on the Fourier transform or other frequency domains of an image; and
- Combinational methods that process an image in both spatial and frequency domains.

The commonly used image enhancement techniques includes point processing operation, logarithmic transform, histogram equalization and smoothing filters [26].

Point Processing Operation: it is the most basic operations in image processing where each pixel value is replaced with a new value obtained from the old one. Point processing operations take the form shown in equation (2.1)

$$g(x, y) = T[f(x, y)] \tag{2.1}$$

Where, f(x, y): input image, g(x, y): output image and T is the transformation function or point processing operation.

Logarithmic Transforms: it is spatial domain image enhancement technique that maps a narrow range of low gray levels into a wider range of gray levels. i.e., expand values of bright pixels and compress values of dark pixels. More often, it is used to increase the detail (or contrast) of lower intensity values and brighten the intensities of an image. If k is the scaling factor, then logarithmic transformation is achieved using equation (2.2)

$$y = k * \log(1 + |x|) \tag{2.2}$$

Histogram Equalization: it is a common technique for enhancing the appearance of images. Suppose we have an image which is predominantly dark. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail is compressed into the dark end of the histogram. If we could `stretch out' the grey levels at the dark end to produce amore uniformly distributed histogram then the image would become much clearer.

Smoothing filters: smoothing filters are used to reduce noise or prepare the image for further processing such as segmentation. There are different type of smoothing filters [27]. A simple mean smoothing filter or operation intends to replace each pixel value in an input image by the mean (or average) value of its neighbors, including itself. This has an effect of eliminating pixel values that are unrepresentative of their surroundings. This filter is based around a kernel, which represents the shape and size of the neighborhood to be sampled in calculation. Often a 3 x 3 square kernel is used, as shown in Figure 2.8, although larger kernels (e.g., a 5 x 5 square) can be used for more severe smoothing.

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Figure 2.8: An example of applying the 3x3 averaging kernel

Gaussian filter: this method of image smoothing convolves an input image by the Gaussian filter. The Gaussian filter will screen noise with the high spatial frequencies and produce a smoothing effect. In two dimensions, an isotropic (i.e., circularly symmetric) Gaussian filter function is given by equation (2.3).

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (2.3)$$

Median filter: it is another smoothing filter that is used to reduce noise in an image, somehow like a mean filter. However, it performs better than a mean filter in the sense of preserving useful details in the image. It is especially effective for removing impulse noise, which is characterized by bright and or dark high-frequency features appearing randomly over the image. Statistically, impulse noise falls well outside the peak of the distribution of any given pixel neighborhood, so the median is well suited to learn where impulse noise is not present, and hence to remove it by exclusion.

2.3.3. Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments to locate different objects and boundaries in the image content. Its goal is to partition an image into multiple segments that are more meaningful to analyze. First, the digital image is divided into two parts: background and foreground, where the foreground is the interesting objects and the background is the rest of the image. All the pixels in the foreground are similar with respect to a specific characteristic, such as intensity, color, or texture. The result of image segmentation is a set of segments that collectively cover the entire image. Image segmentation methods are classified into threshold based, region based, cluster based and edge based image segmentation [28].

Threshold Based Image Segmentation: This method partition an input image into pixels of two or more values through comparison of pixel values with the predefined threshold value T individually [29]. It transforms an input image to segmented binary image. The three commonly known threshold algorithms includes global thresholding, Local thresholding and Adaptive thresholding [30].

Global thresholding: This threshold algorithm is applicable when the intensity distribution of objects and background pixels are sufficiently distinct. In the global threshold, a single threshold value is used in the whole image. If G(x, y) is a threshold version of f(x, y) at some global threshold T, then the G(x,y) will be given as in equation (2.4)

$$G(x, y) = \begin{cases} 1\,, & if\ f(x,y) \geq T \\ 0, & othewise \end{cases} \tag{2.4}$$

There are a number of global thresholding techniques. Otsu thresholding, optimal thresholding, histogram analysis thresholding, iterative thresholding, maximum correlation thresholding, clustering thresholding, Multispectral and Multithresholding techniques are among the global tresholding techniques.

Local Thresholding: **-** A single threshold will not work well when we have uneven illumination due to shadows or due to the direction of illumination. In local thresholding, the idea is to partition the image into m x n sub images and then choose a threshold.

Adaptive Thresholding:– In this method, different threshold values for different local areas are used and typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.

Region Based Image Segmentation: The region based segmentation is partitioning of an image into similar/homogenous areas of connected pixels through the application of homogeneity/similarity criteria among candidate sets of pixels. Each of the pixels in a region is similar with respect to some characteristics or computed property such as color, intensity and/or texture [29].

Cluster Based Image Segmentation: It is to partition an image data set into a number of disjoint groups or clusters. That is, classifying pixels in an image into different clusters that exhibit similar features. A cluster is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters [31].

Edge Based Image Segmentation: it is a fundamental tool for image segmentation. Edge is the location of pixels in the image that correspond to the boundaries of the objects seen in the image. It is assumed that since it is a boundary of a region or an object then it is closed and that the number of objects of interest is equal to the number of boundaries in an image. There are several edge detection techniques in the literature for image segmentation and the most widely used techniques are Canny edge detection, Sobel edge detection, Laplacian of Gaussian edge detection, Roberts edge detection and Prewitt edge detection [32].

Canny Edge Detection: The Canny edge detection is a multi-step algorithm that can detect edges with noise suppressed at the same time. The algorithm is not very susceptible to noise and it is superior edge detector compared to many of the newer edge detection algorithms.

Sobel Edge Detection: This method finds edges using the Sobel approximation to the derivative. It precedes the edges at those points where the gradient is highest. The Sobel technique performs a 2-D spatial gradient quantity on an image and so highlights regions of high spatial frequency that correspond to edges. In general it is used to find the estimated absolute gradient magnitude at each point in n input grayscale image.

In conjecture at least the operator consists of a pair of 3x3 kernels as given in the tables below. One kernel is simply the other rotated by 90°. This is very alike to the Roberts Cross operator.

-

G_x

-1	-2	-1
0	0	0
1	2	1

G_y

-1	0	1
-2	0	2
-1	0	1

Figure 2.9: Sobel 3 x 3 masks in x and y direction

Laplacian of Gaussian (LoG) edge detection: The LoG of an image f(x, y) is a second order derivative defined by equation (2.5)

$$\nabla^2 = \frac{\partial^2 f}{x^2} + \frac{\partial^2 f}{y^2} \qquad (2.5)$$

It has two effects, it smooth the image and it computes the Laplacian, which yields a double edge image. Locating edges then consists of finding the zero crossings between the double edges. It is generally used to find whether a pixel is on the dark or light side of an edge. The digital implementation of the Laplacian function is usually made through the mask below.

0	-1	0
-1	4	-1
0	-1	0

G_x

-1	-1	-1
-1	8	-1
-1	-1	-1

G_y

Figure 2.10: Laplacian 3 x 3 masks in x and y direction

Roberts Edge Detection: The Roberts edge detection is introduced by Lawrence Roberts (1965). It performs a simple, quick to compute, 2-D spatial gradient measurement on an image. This method emphasizes regions of high spatial frequency which often correspond to edges. The input to the operator is a grayscale image the same as to the output is the most common usage for this technique.

Pixel values in every point in the output represent the estimated complete magnitude of the spatial gradient of the input image at that point.

G_x	- 1	0
	0	+1

G_y	0	- 1
	+1	0

Figure 2.11: Roberts 2 x 2 masks in x and y direction

Prewitt Edge Detection: The Prewitt edge detection is proposed by Prewitt in 1970. To estimate the magnitude and orientation of an edge Prewitt is a correct way. Even though different gradient edge detection wants a quiet time consuming calculation to estimate the direction from the magnitudes in the x and y-directions, the compass edge detection obtains the direction directly from the kernel with the highest response. It is limited to 8 possible directions; however knowledge shows that most direct direction estimates are not much more perfect. This gradient based edge detector is estimated in the 3x3 neighborhood for eight directions. All the eight convolution masks are calculated. One complication mask is then selected, namely with the purpose of the largest module.

	-1	-1	-1
G_x	0	0	0
	1	1	1

	-1	0	1
G_y	-1	0	1
	-1	0	1

Figure 2.12: Prewitt 3 x 3 masks in x and y direction

Prewitt detection is slightly simpler to implement computationally than the Sobel detection, but it tends to produce somewhat noisier results.

2.2. Feature Extraction

When the pre-processing and the desired level of segmentation have been achieved, feature extraction technique is applied to the segments to obtain image features. Image features are those items which uniquely describe an image, such as size, shape, composition, location etc. Quantitative measurements of object features allow classification and description of the image [21].

Feature extraction refers to taking measurements, geometric or otherwise, of possibly segmented, meaningful regions in the image. Features are described by a set of numbers that characterize some property of the plant or the plant's organs captured in the images. Shape is one of the most important image features of recognizing objects by human perception. Humans generally describe objects either by giving examples or by sketching the shape. In computer vision, shape is the most commonly used feature for characterizing objects [33].

An image descriptor is applied globally and extracts a single feature vector. Feature descriptors on the other hand describe local, small regions of an image. It is possible to get multiple feature vectors from an image with feature descriptors. A feature vector is a list of numbers used to abstractly quantify and represent the image. Feature vectors can be used for machine learning, building an image search engine, etc. [34]

There are a number of feature extraction techniques available for the extraction of image features. It is essential to focus on the feature extraction phase as it has an observable impact on the efficiency of the recognition system. The most commonly used feature extraction techniques are discussed below.

2.3.1. Moments

Moments are scalar quantities that are used in a variety of applications to describe shape of an object for recognition of different types of images. Image moments that are invariant with respect to the transformations of scale, translation, and rotation find applications in areas such as pattern recognition, object identification and template matching [35, 36].

There are several moment based descriptors available in the literature and of these the well-known are presented below.

A general definition of moment functions Φpq of order (p+q), of an image intensity function f(x, y) is given as follows [20]:

$$\Phi_{\mathrm{pq}} = \iint_{xy} \Psi_{pq}(x,y) f(x,y) dxdy, \qquad \text{p, q=0, 1, 2, 3....} \quad (2.6)$$

where Ψ_{pq} is a continuous function of (x, y) known as the moment weighting kernel or the basis set.

Geometric moments: Geometrical moment of order (p+ q) for a two-dimensional discrete function like image is computed by using equation (2.7). If the image has nonzero values in the finite part of xy plane; then moments of all orders exist for it [37].

$$m_{pq} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} x^p \, y^q f(x,y) \qquad (2.7)$$

where f(x, y) is image function and M, N are image dimensions. Then, by using (2.8) geometrical central moments of order equal to (p+ q) can be computed as under:

$$m_{pq} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (x - \overline{x})^p \, (y - \overline{y})^q f(x,y) \qquad (2.8)$$

where $\overline{x}$and $\overline{y}$ are center of gravity of image and are calculated using equation (2.9)

Actually by image translation to coordinate origin while computing central moments, they become translation invariant.

$$\overline{x} = \frac{m_{10}}{m_{00}} \quad , \quad \overline{y} = \frac{m_{01}}{m_{00}} \qquad (2.9)$$

For binary image, m00 = μ00 is count of foreground pixels and has direct relation to image scale. Therefore, central moments can become scale normalized using (2.10).

$$\eta_{pq} = \frac{\mu_{pq}}{m_{00}^{a}} \quad , \text{a} = \frac{p+q}{2} + 1 \qquad (2.10)$$

Hu Invariant Moments: Based on normalized central moments, Hu (1962) introduced seven nonlinear functions which are invariant with respect to object's translation, scale, and rotation. Hu defines the following seven functions, computed form central moments through order three, that are invariant with respect to object scale, translation and rotation [38]:

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20}-\eta_{02})^2 + 4\eta_{11}^2$$

$$\phi_3 = (\eta_{30}-3\eta_{12}) + (3\eta_{21}-\eta_{03})^2$$

$$\phi_4 = (\eta_{30}+\eta_{12})^2 + (\eta_{21}+\eta_{03})^2$$

$$\phi_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] \qquad (2.11)$$

$$+(3\eta_{12}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2]$$

$$\phi_6 = (\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2] + 4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})$$

$$\phi_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2]$$

$$+ 3(\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\mu_{12})^2 - (\eta_{21}+\eta_{03})^2]$$

Zernike Moments: Zernike moments are obtained from a transformed unit disk space that allows for the extraction of shape descriptors which are invariant to rotation, translation, and scale as well as skew and stretch, thus preserving more shape information for the feature extraction process [39].

Zernike moment of order n and repetition m is defined as for a continuous image function f(x, y) are as under:

$$V_{nm}(x,y) = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 f(\rho,\theta)R_{nm}(\rho)e^{(-jm\theta)}\rho d\rho d\theta \qquad (2.12)$$

In the xy image plane,

$$V_{nm}(x,y) = \frac{n+1}{\pi}\iint f(x,y)V^*(\rho,\theta)dxdy;\ x^2+y^2 \leq 1$$

The real valued radial polynomial R_{nm} is defined as

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}}(-1^s)\frac{(n-s)!}{s!\left(\frac{n-|m|}{2}-s\right)!\left(\frac{n+|m|}{2}-s\right)!}$$

Using this equation Zernike moments from order 2 to 10 for extracting features can be computed.

Radial Chebyshev moment (RCM): It [40] is a discrete orthogonal moment that has distinctive advantages over other moments for feature extraction. Unlike invariant moments, its orthogonal basis leads to having minimum information redundancy, and its discrete characteristics explore some benefits over Zernike moments (ZM) due to having no numerical errors and no computational complexity owing to normalization. The radial Chebyshev moment of order p and repetition q for an image of size N x N with m = (N/2) + 1 is defined in equation (2.13)

$$\mathrm{Spq} = \frac{1}{2\pi\rho(p,m)} \sum_{r=0}^{m-1} \sum_{\theta=0}^{2\pi} t_p\,(r) e^{-jq\theta} f(r,\theta) \qquad (2.13)$$

where $t_p(r)$ is an orthogonal basis Chebyshev polynomial function for an image of size N x N :

$$t_0(x) = 1$$

$$t_1(x) = \frac{2x-N+1}{N}$$

$$t_p(x) = \frac{(2p-1)t_1(x)t_{p-1}(x)-(p-1)\left\{1-\frac{(p-1)^2}{N^2}\right\}t_{p-2}(x)}{P}$$

$\rho(p,N)$ is the squared – norm:

$$\rho(p,N) = \frac{N\left(1-\frac{1}{N^2}\right)\left(1-\frac{2^2}{N^2}\right)\left(1-\frac{2^p}{N^2}\right)}{2p+1}$$

p= 0, 1, N -1, m = (N/2) + 1

2.3.2.Texture Features

Textures are characteristic intensity variations that typically originate from roughness of object surfaces that are capable of representing the content of many real-world images. In leaf based plant species identification, texture features capture the internal vein structure of leaf image. Texture features can be extracted by using various methods. Gray-level co-occurrence matrices (GLCMs), Gabor Filter, Histogram of Oriented Gradients and Local binary pattern (LBP) are examples of popular methods to extract texture features [41].

Grey-level co-occurrence matrices (GLCM) Texture: Grey-level co-occurrence matrices (GLCM) have been successfully used for deriving texture measures from images. This technique uses a spatial co-occurrence matrix that computes the relationships of pixel values and uses these values to compute the second-order statistics. The GLCM approach assumes that the texture information in an image is constrained in the overall or "average" spatial relationships between pixels of different grey level.

For texture feature extraction, the following four measures are commonly used from the gray level co-occurrence matrix of the gray scaled image: contrast, correlation, energy and homogeneity [42].

Energy: one approach to generating texture features is to use local kernels to detect various types of texture. After the convolution with the specified kernel, the texture energy measure (TEM) is computed by summing the absolute values in a local neighborhood:

$$L_e = \sum_{i=1}^{m} \sum_{j=1}^{n} |C(i,j)| \qquad (2.14)$$

If n kernels are applied, the result is an n-dimensional feature vector at each pixel of the image being analyzed.

Homogeneity: homogeneous image will result in a co-occurrence matrix with a combination of high and low P [i,j]'s.

$$C_h = \sum_{i} \sum_{j} \frac{P_d[i,j]}{1+|i+j|} \qquad (2.15)$$

Where the range of gray levels is small the P[i,j] will tend to be clustered around the main diagonal. A heterogeneous image will result in an even spread of P[i,j]'s.

Contrast: contrast is a measure of the local variations present in an image.

$$C(k,n) = \sum_{i} \sum_{j} (i-j)^k \, P_d[i,j]^n \qquad (2.16)$$

If there is a large amount of variation in an image the P[i,j]'s will be concentrated away from the main diagonal and contrast will be high (typically k=2, n=1).

Correlation: correlation is a measure of image linearity

$$C_c = \frac{\sum_i \sum_j \left[ijP_d[i,j]\right] - \mu_i\mu_j}{\sigma_i\sigma_j} \tag{2.17}$$

Where,

$$\mu_i = \sum_i iP_d[i,j]$$

$$\mu_j = \sum_j jP_d[i,j]$$

$$\sigma_i{}^2 = \sum_i i^2P_d[i,j] - \mu_i{}^2$$

$$\sigma_j{}^2 = \sum_j j^2P_d[i,j] - \mu_j{}^2$$

Gabor Filter: The term Gabor filter has been coined after the name of Dennis Gabor, who in the year 1946 experimented and subsequently proposed the representation of the signals. In image processing tasks, Gabor filters have been extensively been used for feature extraction for the digital leaf images due to their nature of spatial locality, orientation selectivity and frequency characteristic. The frequency and orientation representation as used in Gabor filters, are useful for texture representation and discrimination and the same concept is used in human visual system. The Gabor features are invariant to illumination, rotation, scale and translation. The Gabor filters have several advantages in feature extraction process over other techniques such as Gray Level Co-occurrence Matrix (GLCM). The Gabor feature vectors can be used directly as input to a classifier. A two-dimensional Gabor function g(x, y) consists of a sinusoidal plane wave of some frequency and orientation (carrier), modulated by a two dimensional translated Gaussian envelope [43, 44, 45]. The Gabor filter is defined as in equation (2.18)

$$g\ (x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (2.18)$$

Where, $x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

λ: represents the wavelength of the sinusoidal factor,

θ: represents the orientation of the normal to the parallel stripes of a Gabor function,

ψ : phase offset,

σ: Sigma or standard deviation of the Gaussian envelope ,

γ: spatial aspect ratio

The Gabor transform of an image R(x,y) is defined as the convolution of a Gabor filter g (x, y) with image I(x,y)

$$R(x, y) = g\ (x, y) * I(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} g(m, n).I(x-m, y-n) \quad (2.19)$$

where * denotes two-dimensional linear convolution and M and N are the size of the Gabor filter mask.

The following six texture features are extracted using Gabor filter:

a) **Mean** : it is defined as given in equation (2.20) below :

$$\mu_{(s,\theta)} = \frac{1}{NM} \sum_{X=1}^{N} \sum_{y=1}^{M} G_{(s,\theta)(x,y)} \quad (2.20)$$

b) **Energy:** The local energy of the filtered image E(x, y) is obtained by computing the absolute average deviation of the transformed values of the filtered images from the mean μ within a window W of size MxMy. The texture energy E(x, y) is given by the equation (2.21):

$$E(x, y) = \frac{1}{M} \sum_{(a,b\ \in W)} |R(a, b) - \mu| \quad (2.21)$$

c) **Standard Deviation:** The standard deviation is computed as given in Equation (2.22).

$$\boldsymbol{\sigma}_{(s,\theta)} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{NM}} \left(\sum_{x=1}^{N} \sum_{y}^{M} \boldsymbol{G}_{(s,\theta)(x,y)} - \mu_{(s,\theta)}\right)^{2}} \quad (2.22)$$

d) **Skewness :** It is the measure of asymmetry and is denoted by γ , it can be positive which means that the distribution tends towards right and if it is negative when the distribution tends towards left and is represented by Equation (2.23)

$$\gamma_{(s,\theta)} = \frac{\mu^3_{(s,\theta)}}{\sigma^3_{(s,\theta)}} \tag{2.23}$$

e) Kurtosis : It defines the degree of peakiness in the dataset and it is provided in Equation (2.24)

$$k_{(s,\theta)} = \frac{\mu^4_{(s,\theta)}}{\sigma^4_{(s,\theta)}} \tag{2.24}$$

f) Contrast : It is given by Equation (2.25)

$$\psi_{(s,\theta)} = \frac{\mu_{(s,\theta)}}{k^{0.25}_{(s,\theta)}} \tag{2.25}$$

Histogram of Oriented Gradients (HOG): Histogram of oriented gradients, divides an image into squares, cells and blocks. Then, the gradient and its directions of pixels in cells are computed. Later, a histogram is created. Each bin of this histogram contains the number of pixels in equal direction. The histogram of each block is formed by accumulating the histograms of its cells. Finally, all histograms are concatenated to form a HOG descriptor [41].

For example, if we consider grayscale image f(x,y) of size 512x512 with horizontal kernel DX= [-1 0 1] and vertical kernel DY =$[-1\ 0\ 1]^T$, Thus, the horizontal and vertical gradients are given by Equation (2.26) and (2.27) respectively.

$$\nabla f_X(x,y) = f(x,y)*D_X \tag{2.26}$$

$$\nabla f_Y(x,y) = f(x,y)*D_Y \tag{2.27}$$

Where * denotes the convolution operator, ∇fX(x,y) and ∇fY(x,y) are horizontal and vertical gradients. The magnitude and orientation of the gradients are given by Equation (2.28) and (2.29) respectively.

$$G = \sqrt{\nabla fX(x,y)^2 + \nabla fY(x,y)^2} \tag{2.28}$$

$$\theta = \tan^{-1}\left(\frac{\nabla fX(x,y)}{\nabla fX(x,y)}\right) \tag{2.29}$$

2.3. Feature Fusion

The aim of the feature fusion technique is to combine many independent (or approximately independent) features to give a more representative features for leaf images that increase the accuracy of identification. The features are combined by concatenating into one feature set.

Feature fusion technique has two problems. The first problem is the compatibility of different features; i.e. the features may be in different ranges of numbers. Thus, the features must be normalized to same range of numbers. There are different normalization methods such as Z_{Score}, Min-Max, and Decimal Scaling. Z_{score} normalization method is the most common and simplest method and it is used to map the input scores to distribution with mean of zero and standard deviation of one as follows, $x_i = \frac{f_i - \mu_i}{\sigma_i}$, where f_i represents the i^{th} feature vector, μ_i and σ_i are the mean and standard deviation of the i^{th} vector, respectively, x_i is the i^{th} normalized feature vector . The second problem of the feature fusion technique is a high dimensionality, which may lead to high computation time and needing more storage space. Thus, feature selection technique such as Linear Discriminant Analysis or Principal Component Analysis are used to reduce the dimensionality of the combined feature set [46].

2.4. Dimensionality Reduction

Usage of combined feature set increases the accuracy of identification, but on the other hand it suffers from the curse of high dimensionality. Feature selection, a process of removing irrelevant and redundant features overcome this problem. Principal Component Analysis (PCA) and linear discriminant analysis (LDA) are two popular methods which have been widely used in many classification applications for reducing the dimensionality of feature set. PCA is unsupervised while LDA is supervised and can achieve better classification results due to the utilization of label information. PCA preserving as much of the variance in the high dimensional space as possible while LDA preserving as much of the class discriminatory information as possible [47].

LDA takes full consideration of the class labels for patterns. It is generally believed that the label information can make the recognition algorithm more discriminative. LDA projects the original data into an optimal subspace by a linear transformation. The transformation matrix consists of the eigenvectors whose corresponding eigenvalues can maximize the ratio of the trace of the between-class scatter to the trace of the within-class scatter [48].

Let S_B and S_W denote the between-class and the within-class scatter matrices, which are defined in Equation (2.30) and (2.31) respectively.

$$S_B = \sum_{i=1}^{c} n_i(m_i - m)((m_i - m)^T) \tag{2.30}$$

$$S_W = \sum_{i=1}^{C}(\sum_{j=1}^{n_i}(X_i^j - m_i)(X_i^j - m_i)^T) \tag{2.31}$$

Where, m_i denotes the class mean and m is the global mean of the entire sample. The number of vectors in class X_i^j is denoted by n_i.

LDA looks for a linear subspace W (C - 1components) within which the projections of the different classes are best separated by maximizing discriminant criteria defined by Equation (2.32)

$$J(W) = \max \frac{tr\{W^T S_B W\}}{tr\{W^T S_W W\}} \tag{2.32}$$

Along with the orthogonal constraint of W, this can be solved as a generalized eigenvector and eigenvalue problem stated in Equation (2.33)

$$S_B W_i = \lambda_i S_w W_i \tag{2.33}$$

Where, where W_i and λ_i are the i -th generalized eigenvector and eigenvalue of S_B with regard to S_w . The LDA solution, i.e., W, contains all the C-1 eigenvectors with non-zero eigenvalues (S_B has a maximal rank of C-1).

2.5. Image Classification

The primary objective of image classification is to detect, identify and classify the features occurring in an image in terms of the type of class these features represent on the field. Image Classification can be broadly divided into supervised and unsupervised. The most common classification methods used recently in plant recognition systems are revised below [49, 50].

2.3.1. Supervised Image Classification

A supervised classification problem falls under the category of learning from instances where each instance or pattern or example is associated with a label or class. Conventionally an individual classifier like Neural Network, Decision Tree, or a Support Vector Machine is trained on a labeled data set. Depending on the distribution of the patterns, it is possible that not all the patterns are learned well by an individual classifier. The most common classification methods used recently in plant recognition systems are presented below:

K-Nearest Neighbor Classifier: This classifier calculates the minimum distance of a given point with other points to determine its class. Suppose we have some training objects whose attribute vectors are given and some unknown object w is to be categorized. Now we should decide to which class object w belongs. Let us take an example. According to the k-NN rule suppose we first select k = 5 neighbors of w. Because three of these five neighbors belong to class 2 and two of them to class 3, the object w should belong to class 2, according to the k-NN rule. It is intuitive that the k-NN rule doesn't take the fact that different neighbors may give different evidences into consideration. Actually, it is reasonable to assume that objects which are close together (according to some appropriate metric) will belong to the same category. According to the k-NN rule suppose we first select k = 5 neighbors of w. Because three of these five neighbors belong to class 2 and two of them to class 3, the object w should belong to class 2, according to the k-NN rule.

For plant leaf classification, we first find out feature vector of test sample and then calculate Euclidean distance between test sample and training sample. This way it finds out similarity measures and accordingly finds out class for test sample. The k-nearest neighbor’s algorithm is amongst the simplest of all machine learning algorithms. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors. k is a positive integer, typically small. If $k = 1$, then the object is simply assigned to the class of its nearest neighbor. In binary (two class) classification problems, it is helpful to choose k to be an odd number as this avoids tied votes. It is intuitive that the k-NN rule doesn't take the fact that different neighbors may give different evidences into consideration. Actually, it is reasonable to assume that objects which are close together (according to some appropriate metric) will belong to the same category.

Probabilistic Neural Network: Probabilistic neural networks can be used for classification problems. It has parallel distributed processor that has a natural tendency for storing experiential knowledge. PNN is derived from Radial Basis Function (RBF) Network. PNN basically works with 3 layers. First layer is input layer. The input layer accepts an input vector. When an input is presented, first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. The last layer i.e. competitive layer in PNN structure produces a classification decision, in which a class with maximum probabilities will be assigned by 1 and other classes will be assigned by 0.A key benefit of neural networks is that a model of the system can be built from the available data.

Support Vector Machine: It is a discriminative classifier which formally defined by a separating hyperplane. In other words, given labeled supervised learning (training data), the algorithm outputs of an optimal hyperplane which categorizes a new examples. A Support Vector Machine training algorithm creates a model which assigns new examples into one category or the other. The idea behind the method is to non-linearly map the input data to some high dimensional space, where the data can be linearly separated, thus providing great classification performance. For plant leaf classification it will transform feature vector extracted from leaf's shape. SVM finds the optimal separating hyperplane by maximizing the margin between the classes. Data vectors nearest to the constructed line in the transformed space are called the support vectors. The SVM estimates a function for classifying data into two classes. Using a nonlinear transformation that depends on a regularization parameter, the input vectors are placed into a high-dimensional feature space, where a linear separation is employed. Inner product (x,y) is supplanted to construct a non-linear product by kernel function K (x,y) which can be described by Equation (2.34):

$$f(x) = Sgn\left(\sum_{i=1}^{n} \alpha_i \gamma_i k\,(x_i x) + b\right) \tag{2.34}$$

Where f indicates the member of x. From given kernel set, the basis $k(x_i,x)$ where i=1,2,....N is selected using the first layer of the SVM and linear function in the space is created by second layer. SVM is independent of dimensionality of the input space. It has simple geometric construction and it generates spare solution. Classification is performed by support vectors n large number which is obtained by training set.

Deep Neural Network: In Deep Neural Network [60] classification initially random weights are used for training set. Main advantage of Deep Neural Network is that it is capable to reduce classification error while performing for huge datasets. Conventional neural network requires more time for training whereas deep neural network considers input for training based on their weights. It is feed-forward neural network which contains more hidden layer. Hidden layers are used to map the input features. A conventional mapping function is used in this work.

$$O = \frac{1}{1+e^{-(b+fw)}} \tag{2.35}$$

Input features denoted by f, weights denoted by w, b denotes biasing and output is denoted as O. Complex relation between input and output are modeled with the help of this mapping function. This network can be trained by using back-propagation derivatives which gives similarity between input and output for each training set.

Deep Neural Network pre-training can be performed by using discriminative method and supervised pre-training approach.

2.3.2. **Unsupervised Classification**

In unsupervised classification, we have only input data (X) and no corresponding output variables. The goal for unsupervised classification is to model the underlying structure or distribution in the data in order to learn more about the data. These are called unsupervised learning because unlike supervised learning or classification above there is no correct answers and there is no teacher. Algorithms are left to their own devises to discover and present the interesting structure in the data. Unsupervised learning problems can be further grouped into clustering and association problems [51].

2.4 Plant species identification model and techniques

Plant species identification model and techniques follow a known sequence of steps. That is, image acquisition, image preprocessing, feature extraction, classification, and labeling output as depicted in Figure 2.13

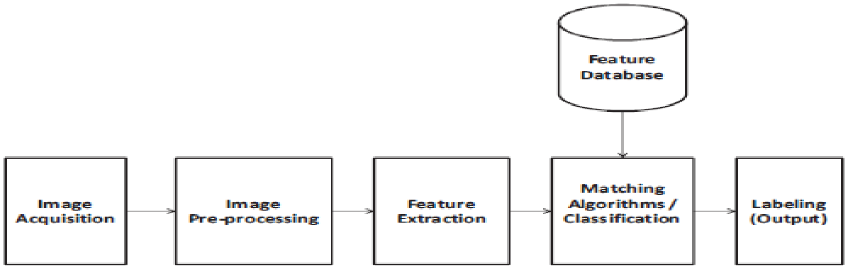

Figure 2.13: Block diagram of classification system as illustrated in [10]

CHAPTER 3: RELATED WORK

3.1 Introduction

In this Chapter, related works of different researchers in the area of plant species identification using image processing techniques are reviewed. In recent years, the techniques of plant species identification based on leaf features have achieved great progress. Morphological features, leaf shape moments, morphological features combined with other leaf shape feature descriptors and other miscellaneous plant leaf shape feature descriptors have been used along with different classification models for plant species identification. In order to describe each research clearly we divided the chapter in to three sections based on the features used for classification and recognition in each area of related works.

3.2 Classification based on morphological feature

Qingmao Zeng et al. [52] used Periodic Wavelet Descriptor (PWD) as shape descriptor for plant leaf shape. This shape descriptor is a global morphological feature of a leaf shape which is invariant to translation, scaling, rotation and used to retrieve shape under multiresolution. The authors select the leaves of six kinds of different apocynaceae plants as experimental objects and Back Propagation Neural Network (BPNN) classifier is trained to fulfill the experiment of plant species identification. Accuracy of the method is evaluated and correct identification rate of about 90% is reported.

Adil Salman et al. [53] preprocessed leaf shape image, traced the boundary of the leaf using Canny Edge Operator and extracted fifteen features (Area, Convex Area, Filled Area, Perimeter, Eccentricity, Solidity, Orientation etc.) from the binary image and used Support Vector Machine Classifier to classify 22 plant species of the Flavia dataset. Overall classification accuracy of 85%-87% is reported.

3.3 Classification base on moments

Marko Lukic et al. [54] used invariant Hu moments as leaf discriminative features but it is indicated that Hu moments are inadequate for some cases when leaves from different species have very similar shape. In order to overcome this, the authors used uniform local binary pattern histogram parameters (mean, standard deviation, energy and entropy) as discriminative features descriptor. Support vector machine is used as a classifier and it is tuned using hierarchical grid search for leaf recognition which issued for plant classification. The algorithm is tested using Flavia dataset and accuracy of 94.13 % is reported.

Zalikha et al. [55] compared the effectiveness of Zernike Moment Invariant (ZMI), Legendre Moment Invariant (LMI), and Tchebichef Moment Invariant (TMI) as features descriptor of leaf images. A Generalized Regression Neural Network (GRNN) is used for classification of 130 pre-processed leaf images of four plant family. A 100% classification accuracy is reported but the authors recommended the need for further study as the number of leaf images used for the study are small and the result may be due to over fitting of the GRNN. However, it is ascertained that TMI is better feature descriptor with classification results showing features from the TMI are the most effective.

Celebi and Aslandogan [56] also studied and compared three moment-based descriptors: Invariant moments such as Hu moments, Zernike moments, and radial Chebyshev (a.k.a.Tchefichef) moments. Invariant moments suffer from a high degree of information redundancy, sensitivity to noise and numerical instability. The authors experimentally proved that radial Chebyshev moments have the highest retrieval performance compared to the other two shape descriptors.

Isnanto et al. [57] developed herbal plants identification system based on the shape of the herbal plants' leaves. Hu's seven moments invariant feature extraction method is used. Euclidean and Canberra distance similarity measures are used as a recognition method and the results of both methods are analyzed. The highest and lowest accuracy result achieved using Euclidean distance similarity measure is 86.67% and 40% respectively while it is 72% and 20% using Canberra similarity measure.

3.4 Classification base on texture feature

Gunjan et al.[58] used the gray level co-occurrence matrix (GLCM) for extraction of texture features(Absolute Value, Contrast, Contrast-Inertia, Correlation, Energy, Entropy, Haralick Correlation, Homogeneity, Sum average, Sum entropy ,etc) of two popular Indian medicinal plants leave, namely, Neem and Tulsi. Back propagation multi-layer perceptron (BP-MLP) neural network classifier is used for classification 30 Neem and 30 Tulsi leaves image. Classification accuracy of 80% is reported using preprocessed combined GLCM texture features. It is indicated that use of preprocessed combined GLCM features can provide higher classification rate compared to raw single GLCM features.

Patil and Bhagat [59] used combination of Gabor and Gray-Level Co-Occurrence Matrix (GLCM) texture features to recognize leaf shape and Decision tree as a classifier. The authors also used Principal component analysis (PCA) to reduce the dimensionality of the extracted features to increase the discriminative power of the Decision tree classifier. The highest classification accuracy reported is 96% on Swidish Leaf Dataset of 10 plant species.

3.5 Classification base on fused feature

Rao and Kulkarni [60] used hybrid approach for feature extraction by combining morphological, shape and SIFT feature. The authors also used auto-regressive model to enhance image quality prior to feature extraction and applied Deep Neural Network for classification performance evaluation. The proposed hybrid model of leaf based plant classification is tested using publically available dataset of 1800 common plant leaves of china that are collected by Wu et.al [61] and classification accuracy of 95.38% is reported that shows the robustness of their approach compared to other methods.

Leaf growth, image translation, rotation and scaling independent morphological features along with Zernike moments are used by Harish et.al [10] to identify and classify plant leaves. The features are then fed as an input to four classifiers (Naive Bayes, k-NN, SVM, and PNN). It is reported that Naive Bayes and k-NN are lazy learners and less accurate compared to SVM and PNN.

AlaaTharwat et al. [62] used feature fusion technique to combine color, shape, and texture features of colored images of leaf. Color moments, invariant moments, and Scale Invariant Feature Transform (SIFT) are used to extract the color, shape, and texture features, respectively. Linear Discriminant Analysis (LDA) is used to reduce the number of features and Bagging ensemble is used as a classifier. The proposed approach was tested using Flavia dataset which consists of 1907 colored images of leaves. The feature fusion method achieved accuracy (70%) better than all single feature extraction methods.

Du and Zhai [63] proposed plant species identification based on multi feature radial basis probabilistic neural networks ensemble classifier (RBPNNE). The RBPNNE consists of several different independent neural networks trained by different feature domains extracted using texture extraction techniques such as autocorrelation, edge frequency, wavelet transform and discrete cosine transform of the original plant leaf images. In addition, Hu invariant moments is also used for feature extraction. The final classification results represent a combined response of the individual networks. For testing purpose, the authors used their own dataset of 1100 images of 50 species of different plants leaf. The experimental results show that the RBPNNC achieves higher recognition accuracy (79.24 %.) and better classification efficiency than single feature domain.

3.6 Summary

Several leaf based plant classification methods have been proposed to address plant identification problem. Plant leaf shape descriptors such as Hu, Zernike, and Chebyshev moments are extensively used with different learning algorithm for plant species identification. Digital morphological features combined with other feature descriptors are also used for plant species identification. However, most methods are inaccurate and the dataset size used for experiment is limited. In some cases, the classification results achieved are high but the sample size is too small [54, 55, 59]. The computation of Zernike moments involve discrete approximation of its continuous integral term which result in loss of information. Hu moments are inadequate for some cases when leaves from different species have very similar shape [59]. Radial Chebyshev moment has distinctive advantages due to its discrete characteristics over other moments for feature extraction. Unlike invariant moments, its orthogonal basis leads to having minimum information redundancy. It has also no numerical errors and computational complexity owing to normalization [40]. Therefore, in this work, an improved method based on fusion of morphological features and Radial Chebyshev moments of leaf shape and Gabor filter of leaf texture with a class of ensemble method called Radom Forest is proposed for plant species classification and identification.

CHAPTER 4: DESIGN OF PLANT SPECIES IDENTIFICATION

4.1 Introduction

In recent years there has been an increased interest in applying image processing techniques to the problem of automatic plant species identification. There are ample opportunities to improve plant species identification through the designing of a convenient automatic plant species identification system. Many different approaches are used to classify plant species to its predefined classes using the features of plants leaf. In this work, we will explain the design and system architecture of the proposed work. The different processes such as plant leaf preprocessing, segmentation, feature extraction, model training and classification that are used in the system architecture are also explained in detail.

4.2 System Architecture

The architecture of the proposed work is depicted in the figure 4.1. Its major components includes plant preprocessing, leaf image segmentation, feature extraction, learning and plant species classification.

The proposed approach consists of two phases, namely, training phase and identification phase. In the training phase, leaf image of plant species (i.e. training images) are preprocessed, features are extracted from each leaf image and fused to feature set. Lastly, important features are selected from the feature set and provided as input to the learning model. In the identification phase, same procedure will be followed as the training phase except that at later stage, instead of using the plant leaf image features for training, it will use for classification. In the identification phase, the extracted features will be used for identification of the plant leaf using the knowledge base.

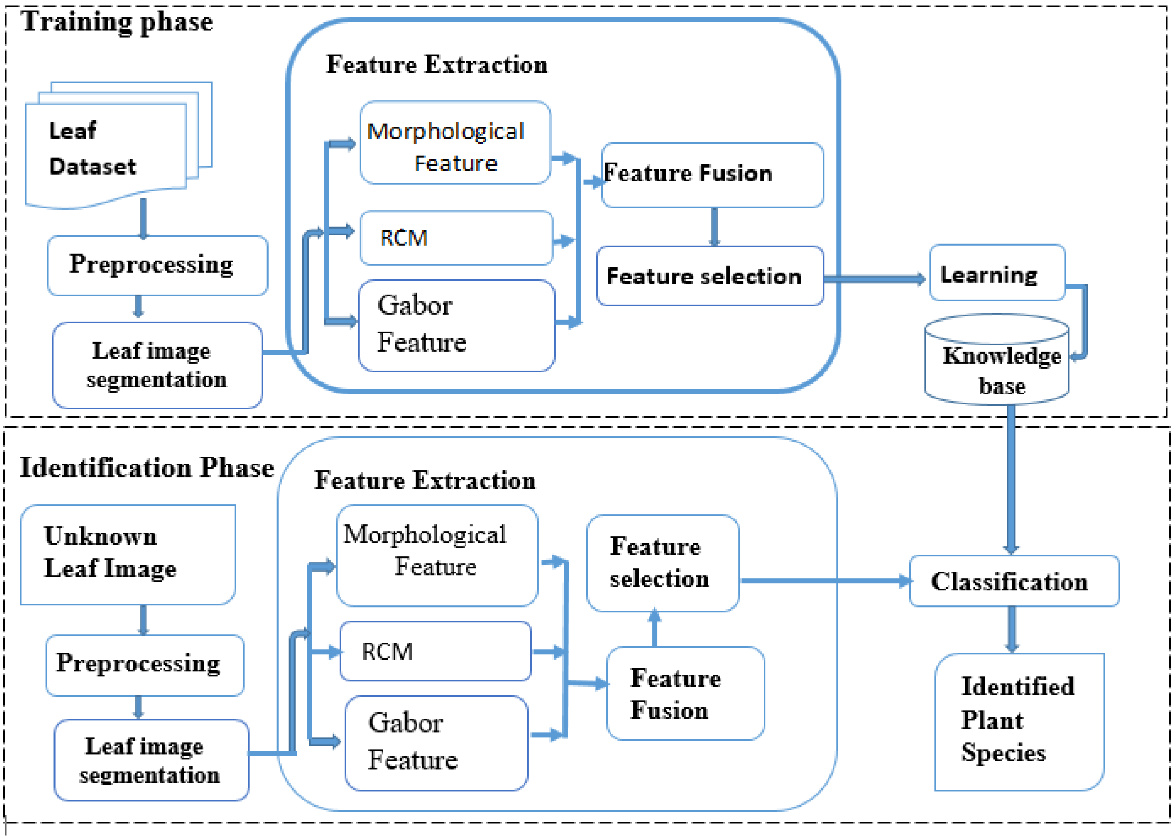

Figure 4.1: Architecture of Automatic Plant Species Identification

4.3 Leaf image preprocessing

The main goal of preprocessing is to identify the leaf in an image and discard all other information other than the leaf shape and texture. As part of image processing, we resized the input image size, converted RGB image to gray scale and gray scale to binary. We also extracted the boundary of the leaf image. These operations are described below.

Image resizing: it is computationally expensive to process large images. Hence, the size of leaf images in the database is resized to reduce image processing time.

Conversion of RGB image to Grayscale Format

Leaf texture is extracted from grayscale image and in this work we applied Gabor filter on grayscale leaf images to extract Gabor features. Hence, the RGB image is converted to grayscale image. To convert RGB leaf image to grayscale, weighted averaging method is used. Assuming R, G and B represent the respective intensities for red, green and blue channel of a pixel, the grayscale value is computed using weighted averaging method as given in equation (4.1)

$$\text{Grayscale} = 0.2989*R + 0.5870*G + 0.1140*B \tag{4.1}$$

Figure 4.2: Original RGB leaf image

Figure 4.3: Grayscale leaf image after applying weighted averaging method

Conversion of Grayscale Format to Binary

Extraction of features is faster with binary images because all the pixel values in a binary image can either be zero or one, hence, computations become faster. Thus, the images are preprocessed and converted into smaller size files in binary format without the loss of any morphological (shape related) information. In this work, Morphological features and Radial Chebyshev moments are extracted from binary images.

To convert a grayscale image into a binary image, Otsu's [64] method of automatic thresholding which is explained in section 4.4 is applied. During the thresholding process, if pixel value is greater than a threshold value, it is assigned one value (may be white), else it is assigned another value (may be black). The shape of the histogram is used for automatic thresholding and the threshold is chosen so as to minimize the interclass variance of the black and white pixels.

Figure 4.4: Grayscale leaf image

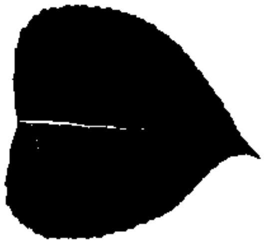

Figure 4.5: Binary leaf image obtained after applying Otsu thresholding method

Boundary extraction: Identifying the contour of leaf plays paramount role for the computation of morphological features of leaf image. Convolving leaf image with a canny edge detection produces an image where higher grey level values indicate the presence of an edge in the leaf image.

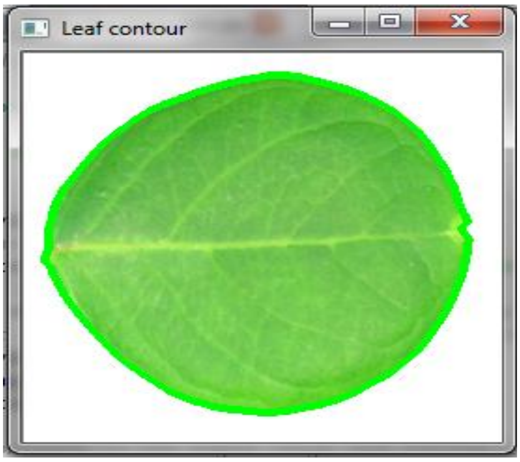

Figure 4.6: Plant leaf image contour

4.4 Leaf image segmentation

Among all the segmentation methods, Otsu method is one of the most successful region based segmentation methods for automatic image thresholding because of its simple calculation. In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes [65].

$$\sigma_w^2(t) = w_0(t)\sigma_0^2(t) + w_1(t)\sigma_1^2(t)$$

Weights w_0 and w_1 are the probabilities of the two classes separated by a threshold t, and σ_0^2 and σ_1^2 are variances of these two classes.

The class probability $w_{0,1}(t)$ is computed from the L bins of the histogram:

$$w_0(t) = \sum_{i=0}^{t-1} p(i)$$

$$w_1(t) = \sum_{i=t}^{L-1} p(i)$$

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = w_0(\mu_0 - \mu_T)^2 + w_1(\mu_1 - \mu_T)^2$$
$$= w_0(t)w_1(t)[\,\mu_0(t) - \mu_1(t)]^2$$

which is expressed in terms of class probabilities ω and class means μ.

While the class mean $\mu_{0,1,T}$(t) is:

$$\mu_0(t) = \sum_{i=0}^{t-1} i\frac{p(i)}{w_0} \quad , \quad \mu_1(\mathrm{t}) = \sum_{i=t}^{L-1} i\frac{p(i)}{w_1}$$

$$\mu_T(t) = \sum_{i=0}^{L-1} ip(i)$$

The class probabilities and class means can be computed iteratively. This idea yields an effective Ostu algorithm.

```
1. Compute histogram and probabilities of
   each intensity level
2. Set up initial w_i(0) and μ_i(0)
3. Step through all possible
   thresholds t=1,... to maximum intensity
    3.1. Update w_i and μ_i
    3.2. Compute σ_b^2(t)
4. Desired threshold corresponds to the
   maximum σ_b^2(t)
```

Algorithm 4.1: Ostu Algorithm

4.5 Features Extraction

A leaf image can be characterized by its color, texture, and shape. Since the color of a leaf varies with the seasons and climatic conditions and also most plants have similar leaf color, this feature may not be useful as discriminating feature for the plant species identification [40]. Hence, we used only shape and texture features as discriminating features for plant species identification.

There are a number of shape and texture features that can be extracted from plant leaves for the identification of plant species using image processing techniques. In this work, Radial Chebyshev moments and morphological features are used as shape descriptors and Gabor features are used as texture descriptors. The shape descriptor captures the global shape of leaf image. The internal vein structure is captured by the texture descriptors. Both the shape and texture are combined by concatenation before fed as in input to the ensemble of classifiers. Finally, from the combined shape and texture features, important features are selected and fed as input to the ensemble of classifiers. Feature extraction from shape and texture of plant leaves involves major steps and each of these steps consists of many methods that contribute to improved results. The three shape features are presented below along with their corresponding algorithm.

4.5.1 Radial Chebyshev Moments

Radial Chebyshev moment of order p and repetition q for an image of size N x N is defined in equation (2.13) of Chapter 3, section 4 as [40]:

$$Mpq = \frac{1}{2\pi\rho(p,m)}\sum_{r=0}^{m-1}\ \sum_{\theta=0}^{2\pi} t_p\,(r)e^{-jq\theta}f(r,\theta) \qquad (4.2)$$

Where, $t_0(x) = 1$

$$t_1(x) = \frac{2x-N+1}{N}$$

$$t_p(x) = \frac{(2p-1)t_1(x)t_{p-1}(x)-(p-1)\left\{1-\frac{(p-1)^2}{N^2}\right\}t_{p-2}(x)}{P} \qquad (4.3)$$

$\rho(p,N)$ is the squared – norm:

$$\rho(p,N) = \frac{N\left(1-\frac{1}{N^2}\right)\left(1-\frac{2^2}{N^2}\right)\left(1-\frac{2^p}{N^2}\right)}{2p+1} \qquad (4.4)$$

p= 0, 1, N -1, m = (N/2) + 1, and i = $\sqrt{-1}$

```
1. Input:
        Image f(x, y), 0 ≤ x, y ≤ N – 1, m = N/2, n = 3N, 0<=tetha<=2π, N, p,q
2. Compute Chebyshev polynomials using Equation (4.3)
        if p == 0:
            return 1.0
          elif p == 1:
            return (2.0*x+1-N)/N
          else:
            return    ((2.0*p    -1)*ChebyshevPoly(1,x,N)*ChebyshevPoly(p-1,x,N)-(p-
   1)*ChebyshevPoly(p-2,x,N)*(1-(p-1)**2/N**2))/p
3. Compute norm using Equation (4.4)
  prod=1
    for (i =1 i< p, i++){
      prod=float(N/(2*p+1)*(1-power(1,2)/power(N,2)))
      prod=prod*(1-power(p,2)/power(N,2))
  }
   return prod
4.   Compute Radial Chebyshev moments using Equation  (4.2)
  set norm=2*pi*normalize(p,m) //using step 4 above.
  for(r=0; r<m; r++){
     for (te=0; te< len(tetha); te++) {
            set x= (r*N*cos(te))/(2*m-1) +N/2
            set y= (r*N*sin(te))/(2*m-1) +N/2
            set f(r,te) = f(x,y)
            sum=sum+ChebyshevPoly(p,r,N)*exp(-1j*q*te)*f(r,te)
            }
   }
   return sum/norm

5.Compute invariant moments using step 5 above.
      for (p=0; p<pmax;p++){
          for(q=0;q<qmax;q++}
            Compute m_pq
```

Algorithm 4.2: Radial Chebyshev Moments

4.5.2 Morphological Feature

In this work, morphological feature have been considered which provide significant information about leaf image. Leaf images from same class follow same properties such as area, aspect ratio, convex, extent etc. These properties can be extracted significantly with the help of morphological features [49]. Leaf image contour plays significant role in extraction of the different morphological features. Contour is a curve that join all the continuous points having same color or intensity along the boundary of leaf shape. For better accuracy, the leaf images are converted to binary images using threshold method before the selected features are extracted. A contour stores the (x, y) coordinates of the boundary of a shape in a 2-dimensional array. The following morphological features are extracted from leaf image [66].

1. Aspect Ratio := width/height
2. Extent := Object area/Bounding rectangle area
3. Solidity:= Contour area/Convex hull area
4. Equivalent diameter := sqrt(4* contour area/π)
5. Form Factor:= (4*π* Leaf Area)/square(Leaf contour area)
6. Area := $\sum_x \sum_y (\textit{region of interest in leaf image})$
7. Computed Major Axis Length as the distance between tip and base of the leaf image
8. Computed Minor Axis Length as maximum width which perpendicular point to major axis

Algorithm 4.3: morphological features

4.5.3 Gabor Filter

In this work, Gabor filters have been used for texture feature extraction from the digital leaf images due to their nature of spatial locality, orientation selectivity and frequency characteristic as explained chapter 2,section 2.2.2

Scheme of the algorithm

In this study the texture features were obtained as follows using Gabor filter.

1. Use a bank of Gabor filters at multiple scales and orientations to obtain filtered images R(x,y).
2. The texture feature which is Local Energy of each filtered images is computed using equation 2.21 of chapter 2, section 2.2.2

Gabor filter with 8 orientations and 4 frequency values is used for texture features extraction from leaf image. This filter is illustrated in Table 4.1 for the 8 orientations($0,\pi/8$, $2\pi/8$, $3\pi/8,4\pi/8,5\pi/8,6\pi/8,7\pi/8$) and 4 frequencies(0.2, 0.4, 0.6,0.8) values which are experimentally determined. Hence, a total of 8*4=32 filter for each leaf image are used for extraction of the texture features.

Table 4.1: Parameters Used for Gabor feature extraction

#	Parameter	Description	Value
1	ksize	Size of the filter returned	9
2	sigma	Standard deviation of the Gaussian envelope	1.0
3	theta	Orientation of the normal to the parallel stripes of a Gabor function.	($0,\pi/8,2\pi/8,3\pi/8,4\pi/8,5\pi/8,6\pi/8,7\pi/8$)
4	lambd	Wavelength of the sinusoidal factor	{0.2,0.4,0.6,0.8}
5	gamma	Spatial aspect ratio	0.5
6	psi	Phase offset	0
7	ktype	Type of filter coefficients.	CV_32F

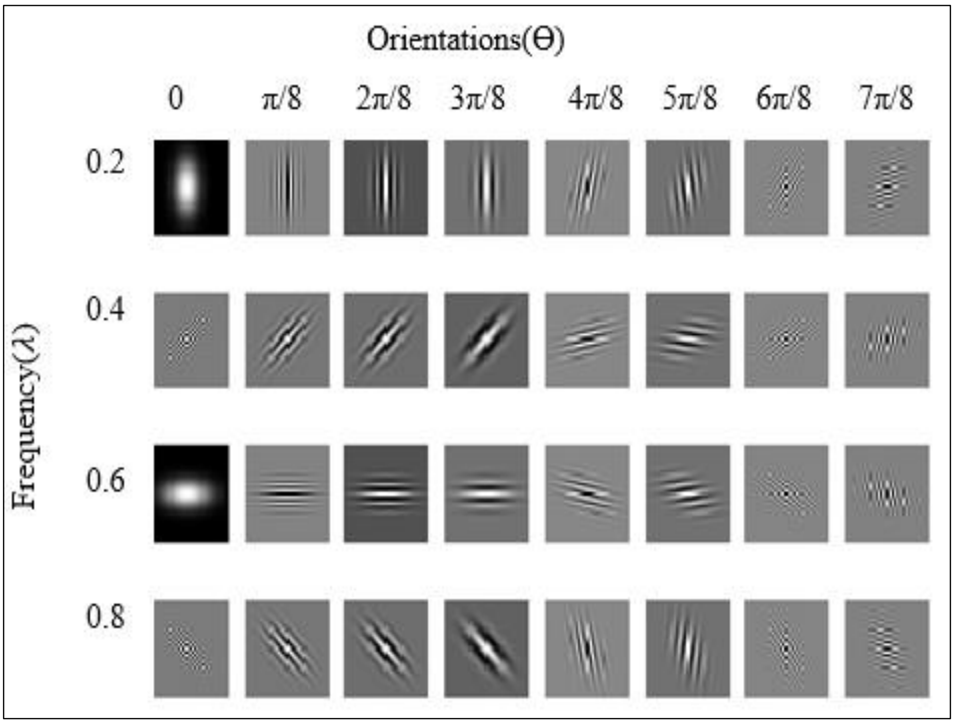

Figure 4.7: Gabor filter output for different orientations and frequency values

The following leaf image is used to illustrate Gabor filter.

Figure 4.8: Sample Leaf image before Gabor filter is applied

When we convolve Gabor filters on the sample leaf image in figure 4.8, it produces 32 different filtered leaf images. The 32 filtered leaf images are depicted in figure 4.9

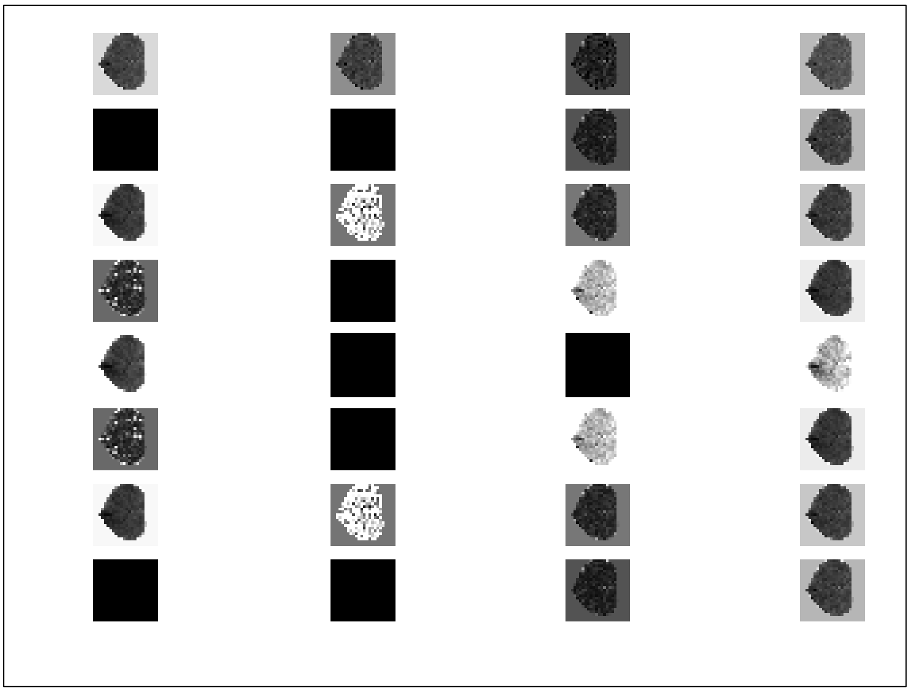

Figure 4.9: Leaf images after application of Gabor filter

4.5.4 Features Fusion

The aim of the feature fusion technique is to combine many independent (or approximately independent) features to give a more representative features for the objects or patterns. The features are combined by concatenating it into one feature vector. Usage of combined feature set increases the accuracy of recognition of plant species. Hence, we combined morphological features, Radial Chebyshev moments and Gabor local energy features in to one feature vector.

```
For each image:
    1. MF := morphological features
    2. GM := Chebyshve Moments
    3. GF := Gabor Local energy
    4. Fused feature := CONCATENATE(MF,GM,GF)
```

Algorithm 4.4: Feature Fusion

4.5.5 Feature selection

In this work, the number of features are high and selecting important features that contribute significantly for the predication of model is essential for improved performance and accuracy. Random forest plays paramount role in feature selection as it uses Gini importance or mean decrease in impurity (MDI) to calculate the importance of each feature. Gini importance is also known as the total decrease in node impurity. This is how much the model fit or accuracy decreases when we drop a variable. The larger the decrease, the more significant the variable is. Here, the mean decrease is a significant parameter for variable selection. The Gini index can describe the overall explanatory power of features [67].

To compute Gini impurity for a set of features with K classes, let $i \in \{1, 2, 3 \ldots K\}$, and let pi be the fraction of features labeled with class in the set. Then, the Gini index is provided by equation 4.5. [66]

$$\text{Gini} = 1 - \sum_{i=1}^{k}(P_i^2) \tag{4.10}$$

4.6 Learning

The results obtained from the different scientific researches [67, 68, 69] showed high efficiency of ensemble methods for image classification. Random Forest is a class of ensemble method that builds an ensemble of multiple decision trees and merges them together to get a more accurate and stable prediction [72].

In random forests, each tree in the ensemble is built from a sample drawn with replacement from the training set. In addition, instead of using all the features, a random subset of features is selected, further randomizing the tree. As a result, the bias of the forest increases slightly, but due to the averaging of less correlated trees, its variance decreases, resulting in an overall better model [67, 72].

Random forest method is highly accurate and robust because of the number of decision trees participating in the process. This method does not suffer from the over fitting problem as it takes the average of all the predictions, which cancels out the biases. The method also plays paramount role in feature selection which is a key advantage over alternate machine learning algorithms. Hence, we decide to use Random Forest method for automatic plant species identification.

1. For b = 1 to B:
   a. Draw a bootstrap sample Z* of size N from the training data.
   b. Grow a random-forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.
      i. Select m variables at random from the p variables.
      ii. Pick the best variable/split-point among the m.
      iii. Split the node into two daughter nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$.
3. To make a prediction at a new point x:

Classification: Let $\widehat{C_b}$ (x) be the class prediction of the b^{th} random-forest tree.

Then $\hat{C}_{rf}^{B}(x)$ = majority vote $\{\hat{C}_b(x)\}_1^B$

Algorithm 4.5: Algorithm of Random Forest [73]

Random Forest works in four steps:

1. Select random samples from a given dataset.
2. Construct a decision tree for each sample and get a prediction result from each decision tree.
3. Perform a vote for each predicted result.
4. Select the prediction result with the most votes as the final prediction.

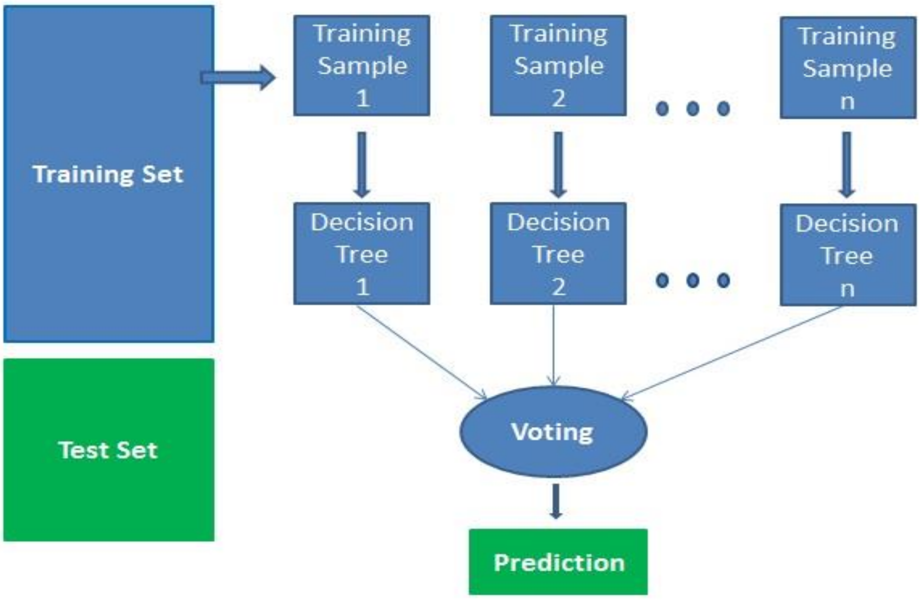

Figure 4.10: How Random Forest works as illustrated in [67]

4.7 Leaf Identification

The identification component of the automatic plant species identification architecture takes extracted, combined and selected features from plant leaf morphology, radial Chebyshev moments and Gabor filters and input to the knowledge base. The knowledge base will identify the input plant leaf image using the trained random forest classifier.

CHAPTER 5: EXPERIMENTATION

5.1. Introduction

Developing a prototype is one of the objective of this work. The prototype serve to demonstrate the validity and usability of the proposed automatic plant species identification system. Prototype is developed for plant leaf preprocessing, segmentation, feature extraction, feature fusion, future selection in order to demonstrate as well as evaluate the developed automatic plant species identification model. We also presented the tools and development environments used to realize this work.

5.2.Data collection

There are several leaf dataset that are commonly used for experimentation. The Flavia data set [8] and the “Leaf” dataset [74] are the dataset with high number of leaf. For this work, we primarily used Flavia data set for testing of our proposed work. The Flavia data set contains 1907 leaf images from 32 different species. In Flavia dataset, all images have resolution of 1600x1200. Sample leafs from this dataset are shown in Figure 5.1

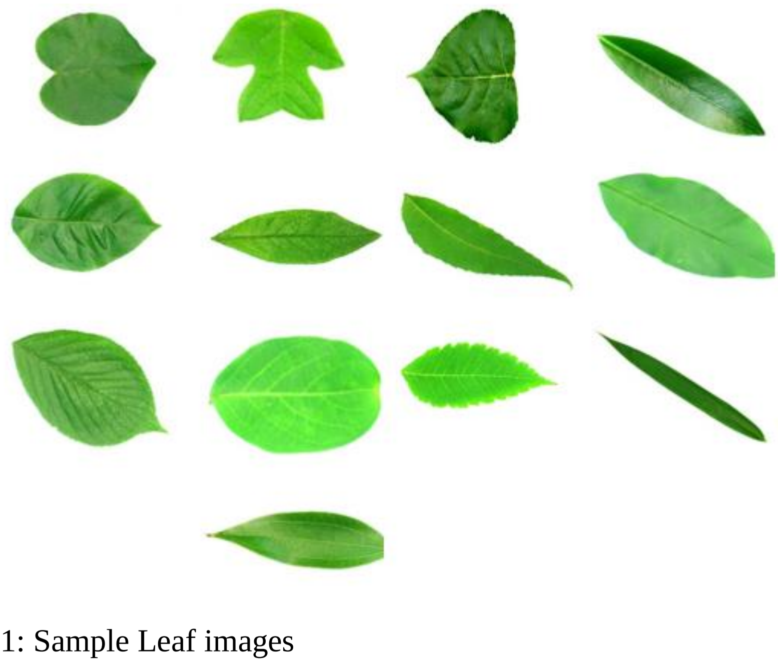

Figure 5.1: Sample Leaf images

5.3.Implementation

In order to implement the Plant species identification model, we made use of several open source libraries. The following libraries are used on Windows 10 Pro with Processor Intel(R) Core(TM) i7, CPU 2.70 GHz and RAM 12.0 GB [75, 76, 77, 78].

- Python: We choose Python as the programming language to develop the algorithms. The main reason for its selection is mainly because of its simplicity and code readability.
- The IDE used is Anaconda 3, Spyder 3.2.8.
- OpenCV-Python which is a library of Python bindings designed to solve computer vision problems.
- NumPy: is the fundamental package for scientific computing with Python that contains a powerful N-dimensional array object. This library is needed in order to treat images as matrices. NumPy is the key library for image manipulation. It is very fast, which allows our algorithms to run with high computational efficiency, which is part of the desired features of the proposed work. OpenCV-Python makes use of Numpy, which is a highly optimized library for numerical operations.
- We also used pandas which is an open source library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language purpose of writing extracted features to CSV file.
- Scikit-learn is a free machine learning library for the Python. It features various classification, regression and clustering algorithms including support vector machines, random forests, etc. and is designed to interoperate with NumPy and SciPy.

5.3.1. Leaf preprocessing and segmentation

As part of leaf image preprocessing, we resized each leaf image, converted RGB image to Grayscale and Grayscale Format to Binary. Leaf image boundary extraction for the purpose of morphological features extraction is also performed. The pseudo code for these processes is presented below.

OpenCV Python pseudo to resize image size

```
image = cv2.imread(imagePath)
resizedImage = cv2.resize(image,(256, 256), interpolation =
cv2.INTER_AREA)
```

where, cv2.INTER_AREA is interpolation method used for image resizing purpose

OpenCV Python pseudo code of RGB to Grayscale conversion using weighted averaging method

```
image = cv2.imread(imagePath)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
```

OpenCV Python pseudo code of Grayscale to binary conversion using Otsu's thresholding method

```
image = cv2.imread(imagePath)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
binary = cv.threshold(gray,0,255,cv.THRESH_BINARY
+cv.THRESH_OTSU)
```

OpenCV Python pseudo code of Canny edge detection and Contours identification

```
image = cv2.imread(imagePath)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
edges = cv2.Canny(gray, gray, threshold1, threshold2)
# find contours in the edged image
im2,cnts,hierarcy      =      cv2.findContours(edges,
cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
```

where,

i) image – input image of RGB color.
ii) gray – grayscale image.
iii) edges – output edge map; it has the same size and type as image .
iv) threshold1 – first threshold
v) threshold2 – second threshold
vi) im2 – is modified image
vii) cnts – contour
viii) hierarchy – contains information about image topology
ix) RETR_EXTERNAL – contour retrieval mode
x) CHAIN_APPROX_SIMPLE – contour approximation method

5.3.2. Feature extraction

We extracted 25 Radial Chebyshev moment features(m00,m01,m02,m03,m04 ,m10, m11,…m44), 8 morphological features (area, aspect ratio, extent, solidity, equivalent diameter, form factor, major axis and minor axis) and 32 Gabor texture features(mse1, mse2,…mse31) for each leaf image.

5.3.3. Training model

For the proposed solution, we decided to use Random Forest algorithms as it has already been explained in Section 4.6. Random Forest is a class of ensemble classifier with robust and accurate classification capabilities. This classifier is first trained with the combined features. The result is evaluated and trained again with selected features which are 48 in number. We excluded 17 features as their importance is very low for training the model. The feature selection is done using the Gini index where it is readily available with the implementation of Random Forest in the Sciket Learn. The threshold for deciding the importance of the features is decided empirically by conducting experiments several times.

Scikit Learn Pseudo code for Random Forest implementation

```
# Load data
filename ='path to data'
data=readData(filename)
X = data.iloc[:,0:n]# assign features set
y = data.iloc[:, n] # assign class labels
X_train, X_test, y_train, y_test = train_test_split(X,
y, test_size = 0.20)
rfc = RandomForestClassifier(n_estimators=1000)
    rfc.fit(X_train, y_train)
# Use the random forest's predict method on the test data
p = rfc.predict(X_test)
displayAccuracy(p)
```

Pseudo code to view a list of features with their importance scores

```
featureImportance=list(zip(X_train,rfc.feature_
importances_))
    for item in featureImportance:
       print(item[0], item[1])
```

5.4. Evaluation

5.4.1. Evaluation Techniques

To test the accuracy of the model, 20% of the leaves in the database are used as query images. The widely used measurement metrics such as precision, recall, f1 score and support are used to compute the accuracy of the system which are defined as follow [9,].

Precision is defined as the ratio of tp / (tp + fp), where tp is the number of true positives and fp is number of false positives. The precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

The recall is the ratio tp / (tp + fn) where tp is the number of true positives and fn the number of false negatives. The recall is intuitively the ability of the classifier to find all the positive samples.

The f1score can be interpreted as a weighted harmonic mean of the precision and recall and is defined as f1 Score = 2*(Recall * Precision) / (Recall + Precision).

Support is defined as the number samples of the true response that lie in that class.

Accuracy is defined as a ratio of correctly predicted observation to the total observations. That is, accuracy = (tp+tn)/(tp+fp+fn+tn), where tn is true negative which is defined as the ration of tn/(tn+fp).

Scikit-learn provide a convenience report when working on classification problems to give us a quick idea of the accuracy of a model using a number of measures. The ***classification_report()*** function displays the precision, recall, f1-score and support for each class.

5.4.2. Test Result

In section 5.3.2 and 5.3.3, we have explained about the features extracted and how the selected algorithm is used for training the model using the extracted feature set. We presented here the experimental results first by training the algorithm for each feature set (Morphological features, Radial Chebyshev moment features and Gabor texture features) and then for the combined feature set with feature selection and without feature selection. That is, using morphological features, Radial Chebysheve moments and Gabor texture features together before feature selection and after feature selection.

Table 5.1: Test Result using various features

Feature	Accuracy	Remark
Morphological features	93.0%	
Radial Chebyshev moments	91.0%	
Gabor texture features	85.0%	
Combined features	96.0%	before feature selection
Combined features	97%	after feature selection

The classification accuracy of Random Forest model using morphological, Radial Chebyshev moment and Gabor texture features is 93.0%, 91.0% an 85.0% respectively. However, when we fused the three feature set and train the model, we achieved 96.0% accuracy. We further proceed with feature selection and re-trained the model. The accuracy of the model on selected feature is 97.0%.

Individually, the test results are presented in Table 5.2, 5.3, 5.4, 5.5 and 5.6 for test result using morphological features, Radial Chebyshev moments, Gabor texture features, fused features and selected features respectively.

Table 5.2: Test result for training model using morphological features

Scientific Name	class	precision	recall	f1-score	support
Phyllostachys edulis (Carr.) Houz.	1	1	1	1	13
Aesculus chinensis	2	1	1	1	15
Berberis anhweiensis Ahrendt	3	1	1	1	13
Cercis chinensis	4	1	1	1	8
Indigofera tinctoria L.	5	0.95	0.95	0.95	19
Acer Palmatum	6	0.82	1	0.9	9
Phoebe nanmu (Oliv.) Gamble	7	1	1	1	11
Kalopanax septemlobus	8	1	0.86	0.92	14
Cinnamomum japonicum Sieb.	9	1	1	1	13
Koelreuteria paniculata Laxm.	10	0.82	1	0.9	9
Ilex macrocarpa Oliv.	11	1	0.92	0.96	12
Pittosporum tobira (Thunb.) Ait.	12	0.94	0.89	0.92	19
Chimonanthus praecox L.	14	0.67	0.75	0.71	8
Cinnamomum camphora (L.) J.	15	0.87	0.81	0.84	16
Viburnum awabuki K.Koch	16	0.91	0.77	0.83	13
Osmanthus fragrans Lour.	17	1	1	1	11
Cedrus deodara (Roxb.) G. Don	18	0.93	1	0.96	13
Ginkgo biloba L.	19	1	0.88	0.93	16
Lagerstroemia indica (L.) Pers.	20	0.75	1	0.86	12
Nerium oleander L.	21	1	0.92	0.96	12
Podocarpus macrophyllus	22	0.92	1	0.96	11
Prunus serrulata Lindl. var.	23	0.83	0.83	0.83	12
Ligustrum lucidum Ait. f.	24	1	1	1	11
Tonna sinensis M. Roem.	25	1	1	1	15
Prunus persica (L.) Batsch	26	1	0.88	0.93	8
Manglietia fordiana Oliv.	27	1	0.86	0.92	7
Acer buergerianum Miq.	28	0.78	0.88	0.82	8
Mahonia bealei (Fortune) Carr.	29	0.75	0.86	0.8	7
Magnolia grandiflora L.	30	1	1	1	6
Populus ×canadensis Moench	31	1	0.94	0.97	17
Liriodendron chinense (Hemsl.)	32	0.94	0.94	0.94	17
Citrus reticulata Blanco	33	1	1	1	7
	avg / tot	0.94	0.93	0.94	382
	Accuracy: 93.0 %				

Table 5.3: Test result for training model using Chebyshev moments

Scientific Name	class	precision	recall	f1-score	support
Phyllostachys edulis (Carr.) Houz.	1	1	1	1	7
Aesculus chinensis	2	1	0.93	0.96	14
Berberis anhweiensis Ahrendt	3	1	1	1	13
Cercis chinensis	4	0.93	1	0.97	14
Indigofera tinctoria L.	5	1	0.95	0.97	20
Acer Palmatum	6	1	1	1	9
Phoebe nanmu (Oliv.) Gamble	7	0.93	0.87	0.9	15
Kalopanax septemlobus	8	0.88	1	0.93	7
Cinnamomum japonicum Sieb.	9	0.58	0.78	0.67	9
Koelreuteria paniculata Laxm.	10	0.9	1	0.95	18
Ilex macrocarpa Oliv.	11	1	0.8	0.89	10
Pittosporum tobira (Thunb.) Ait. f.	12	1	0.88	0.93	8
Chimonanthus praecox L.	14	0.87	0.87	0.87	15
Cinnamomum camphora (L.) J. Presl	15	0.71	0.77	0.74	13
Viburnum awabuki K.Koch	16	0.82	0.82	0.82	11
Osmanthus fragrans Lour.	17	0.88	0.78	0.82	9
Cedrus deodara (Roxb.) G. Don	18	1	1	1	17
Ginkgo biloba L.	19	0.67	0.91	0.77	11
Lagerstroemia indica (L.) Pers.	20	0.92	1	0.96	12
Nerium oleander L.	21	0.88	0.94	0.91	16
Podocarpus macrophyllus (Thunb.)	22	0.92	1	0.96	11
Prunus serrulata Lindl. var.	23	0.86	0.67	0.75	9
Ligustrum lucidum Ait. f.	24	0.88	1	0.93	7
Tonna sinensis M. Roem.	25	1	0.75	0.86	12
Prunus persica (L.) Batsch	26	0.85	0.79	0.81	14
Manglietia fordiana Oliv.	27	1	0.88	0.93	8
Acer buergerianum Miq.	28	1	0.77	0.87	13
Mahonia bealei (Fortune) Carr.	29	0.86	0.86	0.86	7
Magnolia grandiflora L.	30	1	0.9	0.95	21
Populus ×canadensis Moench	31	1	1	1	15
Liriodendron chinense (Hemsl.)	32	0.83	1	0.91	5
Citrus reticulata Blanco	33	0.86	1	0.92	12
	avg / tota	0.91	0.91	0.91	382
	Accuracy: 91.0 %				

Table 5.4: Test result for training model using Gabor texture features

Scientific Name	class	precision	recall	f1-score	support
Phyllostachys edulis (Carr.) Houz.	1	1	0.93	0.96	14
Aesculus chinensis	2	0.91	1	0.95	10
Berberis anhweiensis Ahrendt	3	1	0.91	0.95	11
Cercis chinensis	4	1	1	1	19
Indigofera tinctoria L.	5	0.91	1	0.95	10
Acer Palmatum	6	1	0.73	0.85	15
Phoebe nanmu (Oliv.) Gamble	7	0.83	0.77	0.8	13
Kalopanax septemlobus	8	0.64	1	0.78	7
Cinnamomum japonicum Sieb.	9	0.85	0.65	0.73	17
Koelreuteria paniculata Laxm.	10	0.62	0.93	0.74	14
Ilex macrocarpa Oliv.	11	0.8	0.8	0.8	5
Pittosporum tobira (Thunb.) Ait. f.	12	1	0.82	0.9	11
Chimonanthus praecox L.	14	0.75	0.69	0.72	13
Cinnamomum camphora (L.) J.	15	0.82	0.5	0.62	18
Viburnum awabuki K.Koch	16	0.83	0.91	0.87	11
Osmanthus fragrans Lour.	17	0.54	0.64	0.58	11
Cedrus deodara (Roxb.) G. Don	18	1	1	1	16
Ginkgo biloba L.	19	0.73	0.8	0.76	10
Lagerstroemia indica (L.) Pers.	20	1	0.75	0.86	12
Nerium oleander L.	21	0.7	0.78	0.74	9
Podocarpus macrophyllus	22	0.93	1	0.97	14
Prunus serrulata Lindl. var.	23	0.55	0.67	0.6	9
Ligustrum lucidum Ait. f.	24	0.86	0.86	0.86	7
Tonna sinensis M. Roem.	25	0.89	1	0.94	8
Prunus persica (L.) Batsch	26	0.83	1	0.91	10
Manglietia fordiana Oliv.	27	0.92	0.92	0.92	12
Acer buergerianum Miq.	28	1	0.93	0.96	14
Mahonia bealei (Fortune) Carr.	29	0.71	0.91	0.8	11
Magnolia grandiflora L.	30	0.85	0.79	0.81	14
Populus ×canadensis Moench	31	0.75	0.75	0.75	8
Liriodendron chinense (Hemsl.)	32	0.9	0.82	0.86	11
Citrus reticulata Blanco	33	0.94	0.94	0.94	18
	avg / tota	0.86	0.85	0.85	382
	Accuracy: 85.0 %				

Table 5.5: Test result for training model using fused features

Scientific Name	class	precision	recall	f1-score	support
Phyllostachys edulis (Carr.) Houz.	1	1	1	1	12
Aesculus chinensis	2	1	1	1	11
Berberis anhweiensis Ahrendt	3	1	1	1	7
Cercis chinensis	4	1	1	1	16
Indigofera tinctoria L.	5	1	1	1	11
Acer Palmatum	6	1	1	1	8
Phoebe nanmu (Oliv.) Gamble	7	1	0.89	0.94	9
Kalopanax septemlobus	8	0.92	1	0.96	11
Cinnamomum japonicum Sieb.	9	0.91	0.91	0.91	11
Koelreuteria paniculata Laxm.	10	0.86	1	0.92	6
Ilex macrocarpa Oliv.	11	0.82	0.93	0.87	15
Pittosporum tobira (Thunb.) Ait. f.	12	1	1	1	12
Chimonanthus praecox L.	14	0.83	1	0.91	10
Cinnamomum camphora (L.) J.	15	0.93	0.88	0.9	16
Viburnum awabuki K.Koch	16	0.89	1	0.94	8
Osmanthus fragrans Lour.	17	1	0.85	0.92	13
Cedrus deodara (Roxb.) G. Don	18	1	1	1	16
Ginkgo biloba L.	19	1	0.75	0.86	8
Lagerstroemia indica (L.) Pers.	20	1	0.95	0.97	20
Nerium oleander L.	21	1	0.93	0.96	14
Podocarpus macrophyllus (Thunb.)	22	0.94	1	0.97	15
Prunus serrulata Lindl. var.	23	0.8	0.89	0.84	9
Ligustrum lucidum Ait. f.	24	1	1	1	15
Tonna sinensis M. Roem.	25	0.92	1	0.96	11
Prunus persica (L.) Batsch	26	1	1	1	12
Manglietia fordiana Oliv.	27	1	0.9	0.95	10
Acer buergerianum Miq.	28	1	0.9	0.95	10
Mahonia bealei (Fortune) Carr.	29	1	0.94	0.97	16
Magnolia grandiflora L.	30	0.87	1	0.93	13
Populus ×canadensis Moench	31	1	0.91	0.95	11
Liriodendron chinense (Hemsl.)	32	0.92	1	0.96	11
Citrus reticulata Blanco	33	1	0.93	0.97	15
	avg / total	0.96	0.96	0.96	382
	Accuracy: 96.0 %				

Feature selection: We closely examined the importance of each feature for the training of the Random Forest classifier. After repeated experimentation, we decided that features with feature importance value less than 0.009 do not contribute much for the training of the classifier. Hence, Radial Chebyshev moment m01,m11,m20,m21,m23,m41,m43 and Gabor texture features mse3,mse7,mse9,mse12,mse13,mse17,mse20,mse21,mse25,mse31 are removed from the fused feature set as their feature importance value is less than the threshold value we set. After removing these features, the algorithm is re-trained using the remaining selected features.

Table 5.6: Test result of training model using selected features

Scientific Name	class	precision	recall	f1-score	support
Phyllostachys edulis (Carr.) Houz.	1	1	1	1	14
Aesculus chinensis	2	1	1	1	14
Berberis anhweiensis Ahrendt	3	1	1	1	7
Cercis chinensis	4	1	1	1	15
Indigofera tinctoria L.	5	1	1	1	17
Acer Palmatum	6	1	1	1	12
Phoebe nanmu (Oliv.) Gamble	7	1	1	1	11
Kalopanax septemlobus	8	1	1	1	10
Cinnamomum japonicum Sieb.	9	0.9	0.9	0.9	10
Koelreuteria paniculata Laxm.	10	1	1	1	14
Ilex macrocarpa Oliv.	11	0.83	0.83	0.83	12
Pittosporum tobira (Thunb.) Ait. f.	12	1	1	1	13
Chimonanthus praecox L.	14	0.86	1	0.92	12
Cinnamomum camphora (L.) J.	15	0.92	0.85	0.88	13
Viburnum awabuki K.Koch	16	0.86	1	0.92	12
Osmanthus fragrans Lour.	17	1	0.85	0.92	13
Cedrus deodara (Roxb.) G. Don	18	1	1	1	15
Ginkgo biloba L.	19	1	0.94	0.97	16
Lagerstroemia indica (L.) Pers.	20	1	1	1	10
Nerium oleander L.	21	1	1	1	12
Podocarpus macrophyllus	22	1	1	1	8
Prunus serrulata Lindl. var.	23	1	0.93	0.96	14
Ligustrum lucidum Ait. f.	24	1	1	1	7
Tonna sinensis M. Roem.	25	0.93	1	0.96	13
Prunus persica (L.) Batsch	26	0.9	0.9	0.9	10
Manglietia fordiana Oliv.	27	1	0.75	0.86	8
Acer buergerianum Miq.	28	1	0.93	0.96	14
Mahonia bealei (Fortune) Carr.	29	0.9	1	0.95	9
Magnolia grandiflora L.	30	0.94	1	0.97	15
Populus ×canadensis Moench	31	0.92	1	0.96	11
Liriodendron chinense (Hemsl.)	32	1	1	1	9
Citrus reticulata Blanco	33	1	1	1	12
	avg / tota	0.97	0.97	0.97	382
	Accuracy: 97.0 %				

5.5. Discussion

The result show that the classification accuracy of the Random Forest model using morphological features, Radial Chebyshev moments and Gabor texture features is 93.0%,91.0%, and 85.0% respectively. When the classifier is trained on fused and selected features, the accuracy achieved is 97.0% which is higher than the result obtained by training the classifier on individual features.

Morphological features are generally good as shape descriptor but has difficulty at representing some plant species with irregular shape. For example for plant species in class 30, its precision, recall, fscore and support values are 0.75,0.86,0.80 respectively which are slightly low compared to the result for other classes. This is because of the irregularity of the shape of the leaf examples in this class.

Radial Chebyshev moment generation for the higher order and repetition is time taking to compute. We take maximum order 5 and repetition 5. Radial Chebyshev moment is better at representing irregular leaf shape compared to morphological technique. If we see the result for same class, class 30, its precision, recall, fscore and support values are 0.86, 0.86, 0.86 respectively.

Setting Gabor filter parameters such as orientation, frequency, kernel size, standard deviation of the Gaussian envelope, spatial aspect ratio, phase offset and type of filter coefficient require careful selection supported by experiment. Poorly set parameter or parameters impact the result of feature extraction. The Gabor filter parameters used in this work which are provided in Table 4.1 are determined after several rounds of experimentation. However, using the feature selection techniques we employed, we found less important 10 of the Gabor texture features (mse3, mse7, mse9, mse12, mse13, mse17, mse20, mse21, mse25 and mse31). This might be due to the requirement to some extent for further refinement of the Gabor filters parameters setting. The more we have features that represent the leaf image, the more accurate our classification result will be.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this work we described an algorithm for automatic plant species identification. We used Random Forest as a classifier and tuned it using feature selection techniques. The classifier is separately trained using Morphological features, Radial Chebyshev moment features and Gabor texture features and we obtained 93%, 91% and 85% respectively. We also fused these feature set and trained the classifier on the whole feature set and obtained 96% accuracy and finally, we applied feature selection techniques on the fused feature set and trained the Random Forest classifier again and achieved accuracy of 97% which is higher than other approaches in the literature.

From the result achieved, we can conclude that use of feature fusion and a class of ensemble classifier such as Random Forest is an excellent choice for automatic plant species identification.

6.2 Contribution of the thesis work

The main contributions of this thesis work are outlined as follows:

a. The morphological features, Radial Cheybeshev moments and Gabor texture features are fused together and 48 features are selected. These features effectively identify plant species. Thus, our method is more suitable for real-world applications.
b. The study has implemented automatic plant species identification using fused features and Random Forest classifier.
c. The study showed how a fused feature could enhance the automatic plant species identification.
d. This work can be used as a reference for identification of object from images as the basic underlying principle is same concerning object detection and recognition.

6.3 Recommendation

The proposed work can be further extended to identify complex images with petiole and clustered leafs. It can also be extended to identify plant species in real time from their leaf image.

We used leaf shape morphology, moments and texture as leaf shape features. Even though, use of leaf color has its own limitation as described in section 2.2.1, still it is good to consider use of leaf color with the features used in this work as it might improve the result.

The work can also be extended to identify plant species from 3 dimensional (3D) flower as flows are 3D in nature.

Use of Radial Chebyshev moment for feature extraction is proved to provide good result. However, its implementation involves recursive function call and generally it is slow process for higher order and repletion of the moment values. Alternative but efficient algorithm development is area of future work.

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Declaration

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university, and that all source of materials used for the thesis have been duly acknowledged.

Declared by:

Name: _____________________________________

Signature: __________________________________

Date: ______________________________________

Confirmed by advisor:

Name: _____________________________________

Signature: __________________________________

Date: ______________________________________

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