PLANT IDENTIFICATION FROM LEAF IMAGE USING IMAGE DESCRIPTORS

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By

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CERTIFICATE

This is to certify that the Dissertation-II entitled **‘‘Plant Identification from Leaf Image using Image Descriptors”** which is being submitted by ***Parul Mittal,*** is in partial fulfillment of the requirements for the award of degree Masters of Technology in Electronics and Communication Engineering to Lovely Professional University, Jalandhar, Punjab is a record of the candidates own work carried out by her under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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DECLARATION

I, Parul Mittal, student of M. Tech under Department of School of Electronics and Electrical Engineering of Lovely Professional University, Punjab, hereby declare that all the information furnished in this Dissertation-II report is based on my own intensive research and is genuine.

This Dissertation-II does not, to the best of my knowledge, contain part of my wok which has been submitted for the award of my degree either of this university or any other university without proper citation.

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ABSTRACT

This work includes the formulation of the automated system for plant classification and identification based on leaf image using visual descriptors. There are large number of plants available in this world. Humans are dependent on the plants for their daily basis needs in one or another way. Animals also dependents on plants for their food and shelter. Humans needs plants for research purposes, food and medicine. The use of correct plants in these fields is very crucial since use of wrong or virulent plant may risk human life. The presence of enormous plants in this world makes it nearly impossible to remember all of their names. Plants of same species may look similar also thus, manual recognition of plants by humans may give wrong results. These leads to the need of the development of the digital system for automatic identification of plant type from leaf images.

The system proposed classifies the leaf image into their respective plant categories and identifies the plant class of the input leaf image. In the developed digital system various visual descriptors such as shape features, color features and texture features are extracted from the leaf images using digital image processing. The leaves of the different plants since exhibit different vein pattern and provides useful information thus vein features are also considered. The extracted features are fed to the classifiers for classification and identification purposes. This automatic identification system finds its main application in the field of botany and agriculture.

The comparative analysis is done of the performance of the system using different classifiers. The concept of the combined classifier is also used and is observed that the performance of the combined classifier is better than the individual classifiers.

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AAS	Adaptive Array System
BER	Bit Error Rate
RGB	Red Blue Green
HSI	Hue Saturation Intensity
HSV	Hue Saturation Value
CYM	Cyan Magenta Yellow
CYMK	Cyan Magenta Yellow Black
GLCM	Gray Level Co-occurrence Matrix
SVM	Support Vector Machine
KNN	K-nearest neighbor
PNN	Probabilistic neural network
MMC	Move median centers
BDT	Binary decision tree
IDM	Inverse different moment
PFT	Polar Fourier transform
PCA	Principal Component analysis

CHAPTER 1

INTRODUCTION

Plants are present in abundance on earth [1]. These are essential for human beings in one or another way. Human beings are dependent on plants from for their survival to research purposes. Plants are proved useful to human beings in many aspects like food, medicines, for respiration, industry and so on. The most beneficial use of plants for human welfare is in Ayurveda. Their plants are used for the preparation of Ayurveda medicines and herbal products. There are enormous categories of plants and some plants look very similar. It is very difficult for a layman, farmers and sometimes even for researchers to identify or distinguish the category of plants by examining manually their parameters. Thus the use of lethal or erroneous plant in medicine or any herbal product can risk human life thus correct identification of the plant is important. Plants are important not only for humans, but also for animals. These are sources of food and shelter for them. Many plants have been extinct and many are on the verge of extinction. It is necessary to protect endangered plants for the welfare of humans, wildlife and maintaining balance in the ecosystem. For stated purpose, it is important to prepare the record of endangered plants for the awareness among people for protecting them from human wild activities. Thus the preparation of the record requires correct identification of known and unknown plants since many plants re identical in looks. There are many parameters for distinguishing plants like their fruits, flowers, leaves and so on. Flowers and fruits of the plants are seasonal and may dry up but leaves remain whole year thus leaves are the best parameter for their identification. Since manual identification by humans as stated is not reliable, always thus there is need of another measure for identification of plants. To overcome all the problem of correct manual identification of plants for all reasons stated above key solution is development of automated plant classification system based on digital image processing.

Digital image of the leaf of the plant is input to the system. Image is than processed for the extraction of various features. The extracted features are fed to the classifier for the purpose of classification of plants in their respective categories. Classification is done based on various features like shape, texture, color and vein. These features can be used separately or in combination.

1.1 Recognizing Digital Systems

Recognition digital systems are automated systems, designed to serve the purpose of image retrieval, classification and interpretation. In classification these systems classifies the input images into their respective classes. In identification, the output of the input image is the class to which it belongs. In image retrieval, all the images present in the image database that are associated to the input text/image are retrieved from it. These systems can be categorize as pattern recognition systems and image retrieval systems.

1.1.1 Image Retrieval System

The image retrieval systems aims at retrieving the desired images from the database containing images of the multiple classes [2]. In the image retrieval systems the particular image or text is given as input to the system and the system searches the database for all those images related to the input and represent them as output. On the basis of the input given the image retrieval system can be classified as text base image retrieval and content based image retrieval. The text based image retrieval system take text as input for the search of particular image, example in google search engine text is input to search particular image. Content based image retrieval system on contrary take image as input for the search of particular images in database [3].

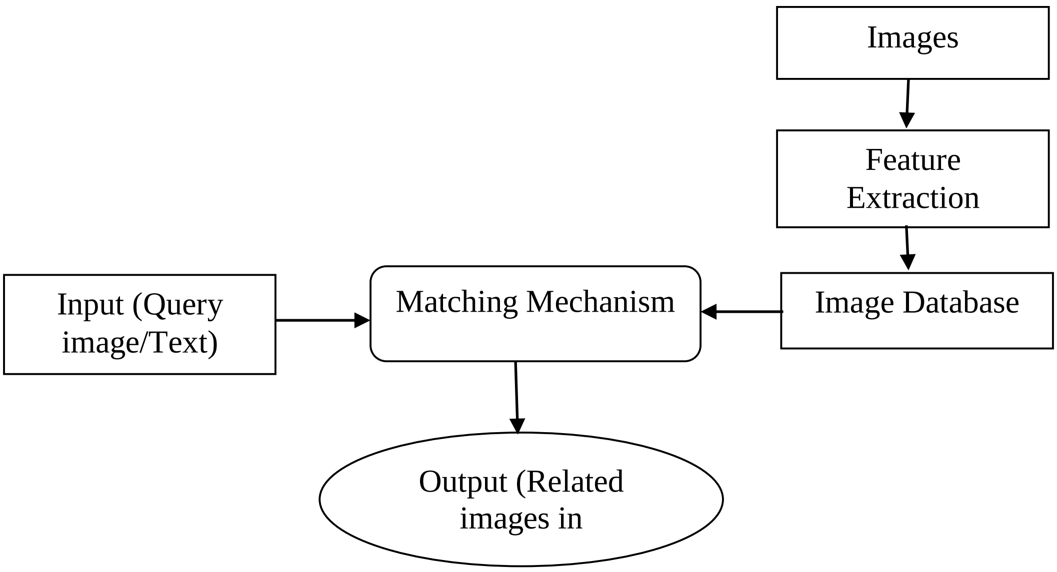


Fig: 1.1: Image Retrieval System

1.1.2 Pattern Recognition System

Pattern recognition system [4] is basically used to recognize the desired object in the image and classifies it to the class to which it belongs based on the group of features extracted from the image. It serves the objective of the classification of the images in the dataset and identification of the class of the query image based on the classification. Input to the system is one or group of images and output is either the images classified in their specific classes or class of the query image.

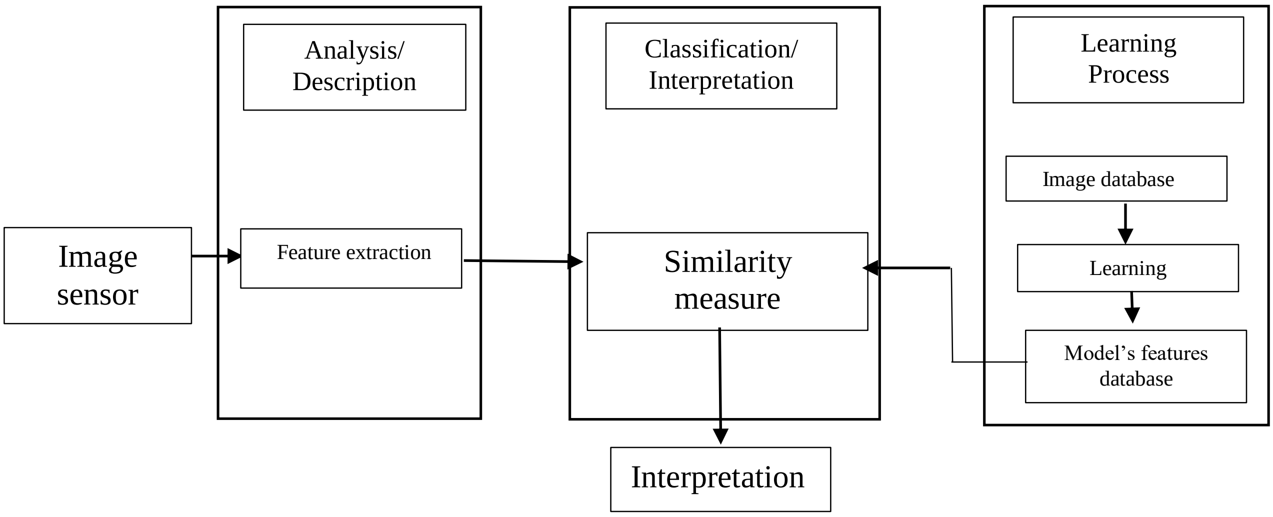


Fig: 1.2: Pattern Recognition System

Pattern recognition process can be broadly carried out in two steps analysis/description and classification/recognition. The various processes involved in pattern recognition system are mentioned below.

- **Image acquisition**: It includes capturing of the image. Image can be captured with devices like scanner, camera etc. The captured image in digital form is fed to the system and system acquires it using image sensors.
- **Image analysis and description:** It includes the analysis of the acquired image using various techniques and the various processes involved are:
    - **Image pre-processing:** This includes various prep-processing processes to be executed on the image. The various images input to the system are generally of different sizes thus by resizing images are resize to one size. It also includes conversion of the image from three dimensional space to two dimensional space i.e. colored image to grayscale image.

- **Image filtering and enhancement**: Captured image may contain undesirable noise, filtering is done for the removal of undesirable noise and for blurring the image. Image enhancement includes manipulating the image for the better visual representation. It includes changing brightness, contrast of the image.
- **Segmentation:** It is the separation of desired object or foreground from background and various other objects present in the image. It subdivides the image into its constituent objects. Various techniques of segmentation techniques are: line, edge, point detectors for monochrome images, thresholding for color images for separating object from background, regional segmentation techniques for separating a particular region from rest of the image.
- **Representation:** It includes representation of the data for further processing. Its input is the output of the segmentation which can include either boundary of the object/region or all pixels in the boundary/region. Boundary representation is required when there is a need to process external shape characteristics like corners and regional representation for internal features like texture and objects shape.
- **Feature Extraction:** It includes extracting the various desired low level features like color, shape and texture from the image for differentiating one class from another. The extracted feature of the particular type are known as descriptors e.g. shape descriptor, color descriptors, texture descriptors.

- **Learning Process:** In the learning process, classifiers trains themselves using the extracted features of the images in the training dataset and at the output of the learning process classifier have trained dataset i.e. dataset of optimal features on the basis of which classification will be performed.
- **Classification:** Classification and interpretation process is done using classifiers. There are various classifiers present, selection of classifier depends on the requirement. In classification/interpretation process, query image is the input to the system, similarity matching is done between input and trained patterns using metric that measures the distance between the both to find the similarity. Depending on the percentage of the similarity matching, query image is classified in one of the classes.

1.2 Feature Extraction

The assorted low level features such as color, texture and shape features are extracted from the image to serve the purpose of classification and identification. These extracted features forms the input to the classifier and on the bases of these features classifier executes classification. There exist enormous feature extraction techniques and these techniques are categorized on the basis of different parameters.

1.2.1 Criterion of Feature Extraction

The features that can be extracted from the images are categorized in to different categories and there exist various feature extraction methods to obtain these features. Every method has its own advantages and drawbacks but there are some desirable properties that efficient features must possess and these are mentioned below.

- **Identifiable**: extracted shapes must have same features as these are perceived by human eye, making the objects identical to human perpetuation.
- **Noise resistance:** features must be robust against noise as possible. These must remain unaffected by the noise despite its strength and even in the range of the noise in which these may get affected.
- **Translation, rotation and scale invariance**: extracted features should remain unaffected by any change in location, the rotation and scaling. Features extracted from technique must be translation, scaling and rotation invariant. Rotation invariant considers image extracted features be independent of the rotation of the image in any direction at any angle. Scale invariant assumes scale change in image during scaling is equal in all direction.
- **Affine invariance:** extracted features must be **a**ffine Invariant i.e. these may remain unaffected to effect of location, rotation and scaling when image is mapped from one coordinate system to other.
- **Locality:** robust to occlusion, clutter and illumination change. Features should be occultation invariance i.e. on occulting the some part of the object in image with another, than the features of the remaining part of the object or the image must remain unaffected.
- **Statistically independent**: for the compactness of the image extracted features must be statistically independent.

- **Reliability**: extracted features of the particular part of the image must remain same till the time dealing with it.

1.2.2 Feature Extraction Techniques

Classification is differentiating objects from each other and assigning them label of the class to which these belong. Differentiation is done on the bases of the various features obtained from the images. Features carry valuable information about the image in numerical form forming set of feature vectors thus in a compact form as compared to the image.

Basically features are described as low level and high level features [5] as mentioned below.

- **Low level features:** shape features, color features, texture features that are obtained by the automated system from the images.
- **High level features:** features like visual, keywords, text descriptors by which humans perceives or interprets images and try to find similarity or classify images.

Features can be broadly classify into global and local features.

- **Global features:** features extracted from the image as whole not the part of the image. These generalize the whole image with a single vector. These are generally used applications such as image retrieval, object detection and classification.
- **Local features:** these describes the key points in the image i.e. small patches in the image. These are computed various points in the image and resultant in more robust to occlusion and clutter. These are used in applications like object identification/recognition, image matching, image stitching.

For the purpose of classification and object identification in the image there is a need to have efficient and effective visual features, thus to serve this purpose various low level visual features are extracted from the images. These low level visual features are shape, color and texture features. There exist various feature extraction techniques to extract these features. The feature extraction technique is selected based on the need whether the features are to be acquired of the one object in the image or particular region in the image or whole of the image.

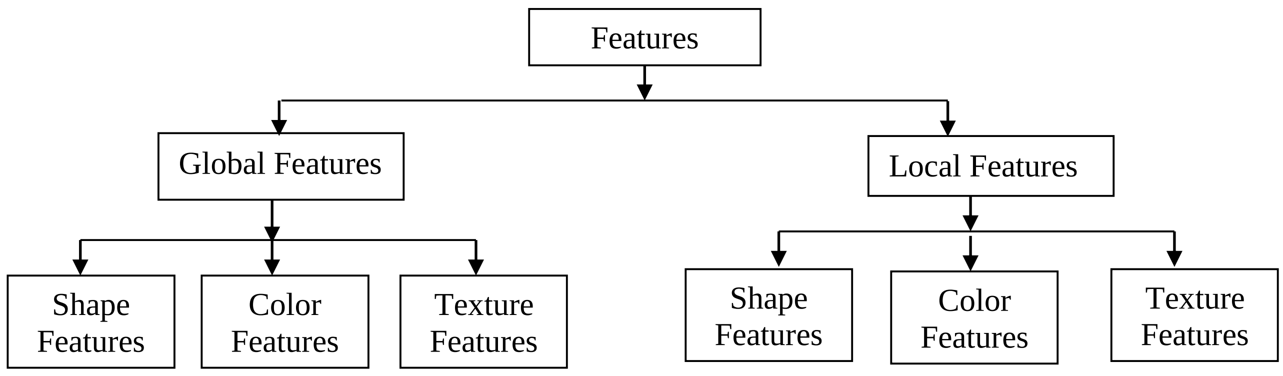


Fig: 1.3: Features Classification

1.2.2.1 Shape features

Humans can easily identify object by its shape. Shape features of the object serves as the basic of object identification system. These are low-level features and represents valuable information about the shape of the object in the image. Shape feature extraction techniques of two dimensional images can be broadly classified into contour based and region based methods [5]. Contour based methods dealt with external features like objects boundary and its features. Shape features in these method are calculated only from the boundary of the object, these are detection of lines and edges of the object in the image. Region based methods dealt with internal features and the extracted features are related to the entire region occupied by the object in the image like area. Regional and contour shape features can be further classified as global and local features.

In plant leaf identification and classification system diameter, area, perimeter, length and width of the leaf in the image are considered as basic geometric features and based on these features other digital morphological features are calculated such as major axis length, convex perimeter, minor axis length, diameter, convex area etc. The other shape descriptors used are PFT, Zernike moments.

1.2.2.2 Color features

Color is another basic visual feature perceived by humans for object identification. Color feature provide information regarding the color content of the image. Color information acquired in the image is scale, rotation and translation invariant. After the shape feature it is another visual feature mostly used. Therefore serves as the powerful tool in object classification and identification applications, thus based on the color features images can be distinguished. Image is present one of the various color spaces [6] like HSI, RGB, CMY, CMYK, and HSV.

These color spaces are different from each other and are developed to serve different purposes. Color space actually serves the purpose of facilitating the colors specifications. Once the color space is specified various color features can be extracted from the image using color feature extraction techniques. The various color feature extraction methods are color histograms, color coherence vectors, color correlograms and color moments [7].

1.2.2.3 Texture features

Texture is the visual patterns of an image having homogeneity property resulting from the group of pixels. It is a repeated pattern of pixels called as texture elements or texels over spatial domain. Texture of object can be smooth or rough. Smoothness indicates proper equalized distribution of pixels; randomness and unstructured is due to noise addition to the pattern and noise frequencies repetition. Texture features are another visual features that human eye can perceive and utilizes for the purpose of identification and classification of objects. Texture perception by human eye is far more complicated than other features due to the brightness, intensities of the image that give rise to a blend of the different human perception of texture.

Texture feature extraction techniques are generally classified as structural approach, statistical approach, model based approach and transform approach. On the bases of the domain in which features are extracted textures features extraction methods are categorized into spatial texture feature and spectral texture feature. In spatial texture feature extraction methods, texture features are obtained by dealing with the pixel in original image domain, whereas in the spectral texture feature extraction methods features are calculated after transforming the image into frequency domain.

The second or higher order statistics gray level co-occurence matrix proposed by Haralick [8] is most popular method and is preferred method for plant classification and identification systems.

1.3 Classification and Identification

Classifiers performs the operation of classification and identification. The classifiers classifies the input images in one of the class by comparing the features of the input image with the feature vector dataset prepared as the output of the training operation. Comparison is done on the basis of the metric that measures the distance between the features of the input image and feature vectors to find the similarity between the both. Image is classified in the class having minimum distance.

Classifiers works either on supervised or unsupervised learning.

- **Supervised learning:** In this output database is provided to train the machine.
- **Unsupervised learning:** In this no database is provided and machine trains itself by forming clusters.

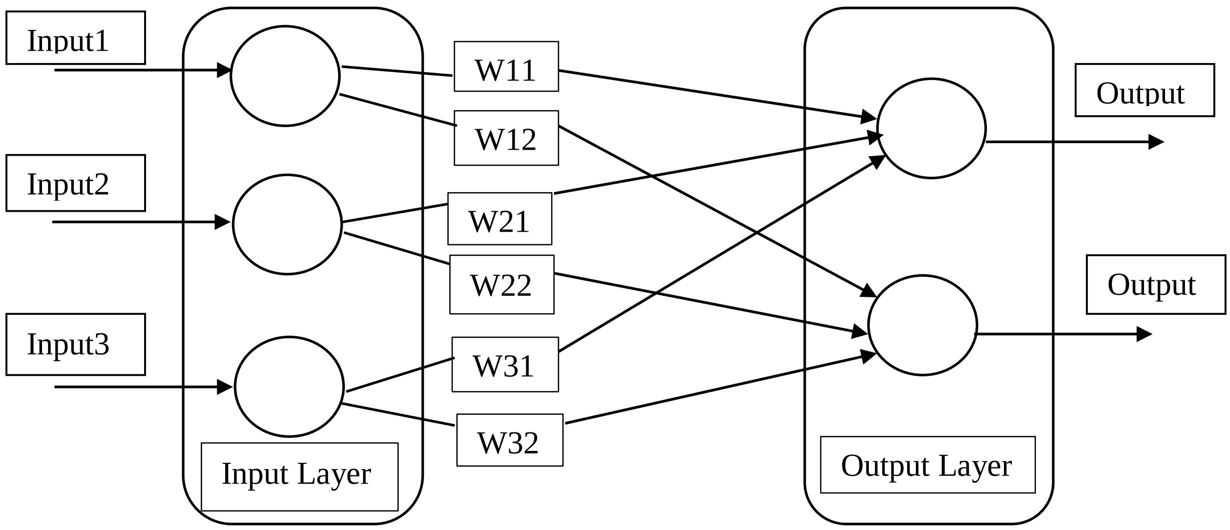
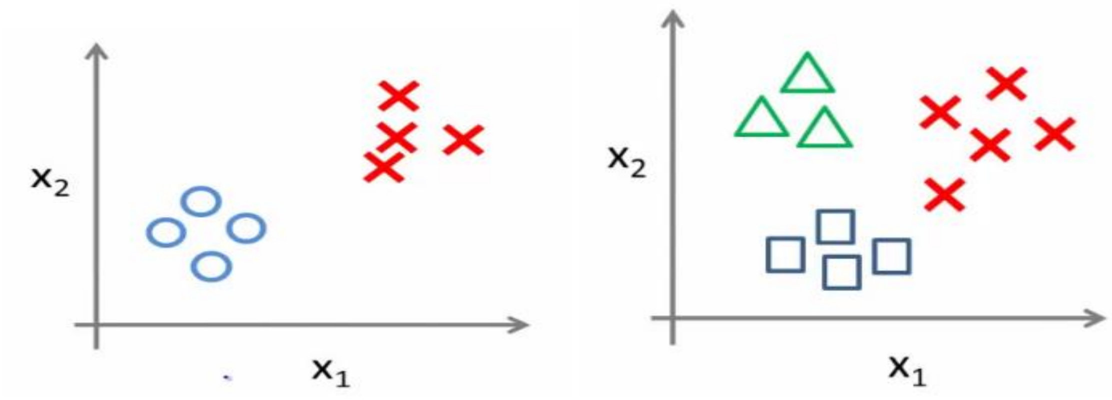


Fig: 1.4: Classifier

The classifiers can be classified as binary and multiclass classifiers.

- **Binary Classifiers:** The binary classifiers are used to classify the data between two classes only. The various binary classifiers are Decision trees, KNN, Support vector machines etc.
- **Multiclass classifiers:** The multiclass classifiers can classify the data between two or more classes. The inherent multiclass classifiers are Ensemble classifiers, Naïve Bayes Perceptron etc.

The multi class classifiers can be implemented using binary classifiers concept by decomposing multiclass into several binary classifiers using different methods like one versus one, one versus all and error correcting output codes [9].



(a) (b)

Fig: 1.5: (a) Binary classification (b) Multiclass classification

The number of the classifiers can be combined based on the different techniques to obtain combined classifier. In the combined classifiers basically the output of the individual classifiers are combined based on different classifier combination techniques. The results obtained as the output of the combined classifier are better than parent classifiers.

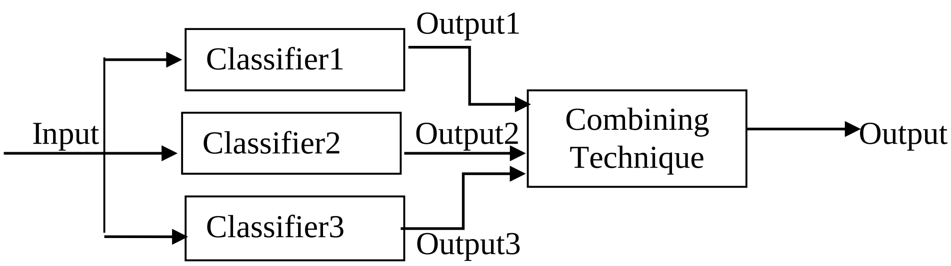


Fig: 1.6: Combined Classifier

1.4 Plant Classification Based on Leaf Image

Plants can be distinguish on the basis of the many parameters such as fruits, flowers, leaves and so on. Flowers and fruits of the plants are seasonal and may dry up but leaves remain whole year thus leaves are the best parameter for their identification [21].

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

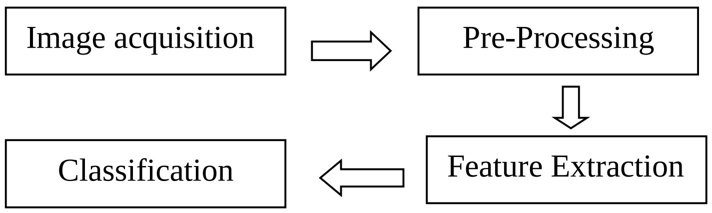


Fig: 1.7: Plant Classification System

The acquired image is input to the system for preprocessing that includes resizing, segmenting, removing noise from image etc. Features are extracted from the pre-processed image using various feature extraction techniques. Extracted features are fed to the classifier for classification purposes.

1.5 Rationale and Scope of the Study

The main objective is to develop plant identification and classification system that correctly identifies and classifies plants based on their visual descriptors and thereby enhancing the scope of improvement in the classification system.

1.5.1 Problem Statement

With the increase in the population and advancement in technologies, destruction of the nature is also increasing. Forests are severely getting chopped for land. Therefore there is need to protect plants by preparing a record of extinct and endangered plants with the correct identification of their species. Humans and animals are dependent on plants in many ways thus usage of toxic plants by humans and animals may risk their lives. Scientist are using plants for research purpose, during research work manual identification of plants may get wrong. Farmers have good knowledge about plants but alike looks of plants may confuse them in identifying correct plant. Many plants looks identical thus manual identification of plants by humans is difficult task and may result in inappropriate results.

1.5.1 Solution to the Existing Problem Statement

To serve all these reasons of correct plant identification, an automated system of plant classification and identification from leaves has been proposed using digital image processing and machine learning.

1.6 Motivation and Objective of the Thesis

Drastic need of correct identification of the plants for consumption of humans and animals, scientific research purposes, making of herbal cosmetic products and Ayurveda medicines for humans is the reason of the encouragement for working on developments of automated plant identification system from visual descriptors. With this system small contribution to the welfare of the mankind can be done.

1.7 Application and Scope of the Research Work

The plants are essential for the existence of the life on the earth. The humans and animals depends on the plants for the fulfillment of their needs. Humans acquire their essential from plants like food, medicines, cloth etc. With the advancement in the technology a huge research is taking in this field. There exists both virulent and non-virulent plants on the earth and it is mandatory to properly differentiate between both for the sake of the life. It is onerous for one to recall all the existing plant categories on the earth thus the automated plant leaf identification and identification system will be worthwhile in one or another way as mention below.

- The system will be helpful for the common people to identify the unknown plant categories in their surroundings.
- The botanist and researchers deals with the enormous plants, since manual identification of plants by them can also be awry thus the system will prove useful for them in correct identification of desired plant category.
- The system also finds its application in the case of farming since it will be useful for the farmers to explore new plant categories.
- The home gardeners will also attain the profit of this system in exploring different plants.

The mobile or online application of this system will profit the population of the earth in one or the way as mentioned above.

CHAPTER 2
LITERATURE REVIEW

Plants are crucial to maintain the requisite balance of life on the earth. There exists plants of divergent and immense categories, some are consumable while some are noxious and threat to the life. Thus it is indispensable for one to be aware of the existing plants. Since manual identification and recalling of entire plant categories is impracticable for humans thus, digital system is required for correct automatic classification and identification of plant categories with minimal human interference. Various research papers as mentioned below describes that the research work in this field

2.1 Literature Survey

Q. Wu et al. [10] demonstrates the automated plant leaf identification system based on the shape and vein features. The slimness ratio, roundness, solidity has been extracted as shape features along with moment invariants to represent the leaf shape properly. Other than leaf's general shape, leaf margin and leaf dent contains important information in regard to the classification purposes. The leaf margin coarseness has been calculated along with the wavelet local extrema which represents the size, sharpness and angle of the leaf dent. Ramification and camber has been used to represent the leaf's main vein features. Ramification represents the water diffluent along the main vein and camber represents the degree of the crook in the main vein. The neural network trained with back propagation algorithm has been used for classification purpose.

The proposed system is unable to work on colored leaves due to the absence of the color features. The system is unable to work on background consisting of multiple objects.

S. G. Wu et al. [11] demonstrates the combination of the PNN with image processing techniques has been proposed for the formulation of the automated plant leaf identification system. The binary image has been obtained from the input leaf image using RGB histograms. For the extraction of leaf boundary the image has been convolved with 3x3 spatial mask. The five basic geometric features diameter, width, area, perimeter and length of the leaf in the image has been extracted from the image based on these other twelve digital morphological features smooth factor, aspect ratio, perimeter ratio to length and width, perimeter ratio to diameter, rectangularity, form factor, narrow factor and five vein features has been calculated. The five vein features has been calculated using morphological opening operations. The average accuracy of the 90.312% has been achieved on flavia dataset.

J. X. Du et al. [12] demonstrates the application of the digital morphological features along with move median centers (MMC) hypersphere classifier. The extracted shape features includes aspect ratio, area ratio of convex hull, rectangularity, circularity, sphericity, perimeter ratio of convex hull, eccentricity, form factor and invariant moments. The descriptors used are more robust than contour based methods since in contour based methods it is difficult to locate appropriate curvature points. The extracted features has been to MMC classifier. The performance of the MMC classifier has been proved better than KNN classifier as it provides good accuracy along with reduced computational time.

K. Singh et al. [13] describes three techniques SVM-BDT, PNN and Fourier moments has been used as a solution to the multiclass classification problem. The edge extraction algorithm has been implemented on the binary image that has been acquired using histogram for the extraction of the boundary image. The convolution of the image with 3x3 rectangular averaging filter removed any noise present in the image. For the shape feature extraction the five basic geometric features diameter, width, area, perimeter and width of the leaf in the image has been calculated and based on these other twelve digital morphological features smooth factor, aspect ratio, perimeter ratio to length and width, perimeter ratio to diameter, rectangularity, form factor, narrow factor and five vein features has been calculated. The 96% has been achieved with SVM-BDT, 91% with PNN and 62% with Fourier moments on flavia dataset.

The system proposed fails to classify colored leaves due to the absence of the color features.

D. Wijesingha et al. [14] proposed that the leaf images has been enhanced and segmented for the extraction of the shape features. The shape features extracted are leaf perimeter, width, area and length. The count of the number of the pixels on the leaf margin gives perimeter and the number of the pixels in binary images gives area. The image pixel value spatial variation has been characterize using pixel- value run length which gives the set of pixels having same value in particular direction. The extracted four feature vectors has been given as input to the probabilistic neural network (PNN) for classification. The accuracy of

85% has been achieved for the test set and 95% for training set of Stemonoporus, Dipterocarpacea a plant genus having 30 species of plants.

The proposed works for only similar input patterns, lack of rotation and scale invariance. The system misclassifies colored leaves due to the absence of the color features.

A. Kadir et al. [15] introduced that the plant classification system has been proposed for foliage plants that has fancy colored leaves. The combination of shape, vein, texture and color features has been considered with PNN as classifier for identification purpose. The three geometric features roundness, slimness and dispersion has been extracted as shape features along with PFT. The vein features has been extracted using morphological opening. The first three color moments has been used for the extraction of color features from each color channel. The five GLCM features correlation, angular second moment, inverse different moment, angular second moment, correlation, inverse different moment (IDM), contrast and correlation has been attained as texture features. The results are normalized and are classified using PNN. The 94.6875% accuracy has been achieved on Flavia dataset.

A. Kadir et al. [16] represents the shape, vein, texture and color features has been represented for the classification of the leaf images along with PNN as classifier. The slimness, roundness and dispersion has been extracted as shape features along with the PFT from the segmented image. The image has been segmented with the use of the intensity histogram. Dispersion is for the irregular leaves. The features extracted with the PFT are rotation, scale and translation invariant. The vein features has been extracted using morphological opening. The first three color moments has been used for the extraction of color features from each color channel. The fractal measure lacunarity that distinguishes between two fractals has been used as texture descriptor. The extracted features are normalized and fed to PNN for classification purposes. The average accuracy of 93.75% has been achieved on Flavia dataset.

M. Swain et al. [17] aimed at the development of the system for the detection of the iris plant based on the measurement of the plant attributes. The petal and petal of the flower has been considered for the measurement of the parameters. The sepal length, width and the petal length and width has been considered as shape features. These features has been input to the multilayer feed forward neural network trained with back propagation algorithm. The accuracy has been achieved in the range of 83.33% to 96.66% by varying the number of epochs required to train the neural neutral in the range of 500 to 50000 for iris dataset.

Increasing the number of epochs increases the computation time and the system developed is species specific.

K. Jayamala et al. [18] represents a content based image retrieval system for diseased plants has been represented using color moments. The color feature matrix has been formed using first three color moments mean, standard deviation and skewness. The distance has been measured between testing image feature vector and database feature vector for feature matching. The comparative study has been done between three color spaces RGB, HSV and HSI. It has been observed that HSV outperforms other two with 43% accuracy. The color images contains more information than gray images since only limited gray levels can be perceived by humans. The color features are robust to image size, background complications and are invariant to scaling and orientation.

C. Arunpriya et al. [19] proposed a tea leaf identification system using various features. In the pre-processing stage fuzzy denoising has been performed using dual tree discrete wavelet transform. The boundary image has been extracted by convolving the image with 3x3 spatial mask laplacian filter. The seven digital morphological features leaf length, width, aspect ratio, serration angle (teeth angle), segment, segment maximum width to physiological length ratio and tip angle has been extracted as shape features. The extracted features has been input to the artificial neural network that has been trained using gradient descent Momentum for classification purpose. The system attained can only be used for the extraction tea leaves.

P. Pallavi et al. [20] describes a leaf identification system has been developed using shape, texture, color and vein features along with the use of neural network approach as classifier. The apex ratio, circularity, moment ratio, base angle, apex angle and width ratio has been extracted as shape features along with the Zernike moments from the pre-processed image. The first four color moments mean, standard deviation, skewness and kurtosis representing the color distribution in the image has been used as color features. The vein features has been obtained using morphological opening operation. The GLCM has been used for the extraction of the texture features at 0, 45, 90 and 135 degree angle.

S. D. Chothe et al. [21] signifies the automated plant leaf identification based on shape and vein features along with Euclidean classifier. The leaf images has been preferred for feature extraction over other traits since leaves can be easily obtained. The input image has been pre-processed and filtered using median filtering. The five basic features diameter, width, area, perimeter and width has been extracted from the image and based on these features other six features aspect ratio, narrow factor, form factor, perimeter ratio of length and width, rectangularity and perimeter ratio of diameter has been derived. Along with these vein features has also been extracted using morphological opening. The extracted features has been input to the Euclidean classifier for classification. The system has been tested on two dataset for one the accuracy is 78.12 % and for another 85%.

A plant classification system has been proposed by **S. Singh et al.** [21] that attains good efficiency with less complexity and computation time. The combination of image processing and artificial neural networks has been used in this system. The eight morphological features eccentricity, area, perimeter, aspect ratio, major axis and minor axis length, area ratio of perimeter and solidity has been extracted from the image after the segmentation process. The extracted features has been input to the artificial neural network that has been trained using gradient descent Momentum for classification purpose. This system has a drawback of efficient only at low input, misclassification increases with the increase in the number of inputs.

S. Sharma et al. [23] aim at the development of the classification system for medical and Ayurveda plants. The combination of the image processing and neural networks has been used to serve the purpose. The input are preprocessed by resizing to 256x256, segmenting and removing any noise present. The boundary image has been extracted by convolving the image with 3x3 spatial mask laplacian filter or prewitt edge detector. The twelve digital morphological features major axis length, area, minor axis length, convex area, eccentricity, filled area, perimeter, orientation, solidity, equivdiameter, euler number and extent has been extracted as shape features. The extracted features has been input to the back propagation trained multilayer feed forward neural network for classification. The system yields the accuracy of the 91.13%.

Trishen et al. [24] introduced a recognition system has been developed for plant identification. The mobile application has been developed based on this system. In the pre-processing multiple operation are performed on the image such as rotation when width is greater than height, grey scaling, thresholding using Ostu’s method to obtain binary image, inverse threshold to inver binary image, edge extraction and edge filtering eliminates contours with small length. The shape features has been extracted using convex hull, leaf width and length and distance maps. The color histogram provides color information. The extracted features has been classified using KNN and accuracy above 80% has been achieved on Flavia dataset.

N. Ahmed et al. [25] represents the efficient plant identification system, developed based on the series of process i.e. image pre-processing, feature extraction, normalization, dimensionality reduction with PCA and classification. The image has been pre-processed by changing the image color space from RGB to L*a*b since RGB is device dependent color space, segmenting the image and removing the noise from the image by convolving it with 3x3 rectangular smoothing filter. The fifteen digital morphological features diameter, width, area, perimeter, length, smooth factor, narrow factor, aspect ratio, rectangularity, perimeter ratio to diameter and five vein features using morphological opening has been extracted along with Fourier descriptors as shape features. The extracted features are normalized to have the value of features in certain range. The output of normalization is orthogonalized using PCA and the resultant is fed to SVM classifier for classification. The accuracy of 87.40% has been achieved for SVM classifier.

2.2 Analysis of the Literature Survey

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

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

CHAPTER 3

RESEARCH METHEDOLOGY

In this research work, a plant classification and identification system based on visual descriptors of the image leaf has been proposed. Dataset that has been used in this work is Flavia dataset [109] containing 1908 leaves of 33 categories of plants. Visual descriptors of the image are shape, color, texture of the leaf in the image. These descriptors provides useful feature information for classification purposes about the object in the image and are extracted using various feature extraction techniques. Combination of these descriptors enhances accuracy. Along with these descriptors, vein pattern features of the leaf are also extracted from image, since vein pattern of the leaves of the different species are different. Therefore provides useful information in distinguishing different species of plants. For classification purpose use of combined classifier has been proposed

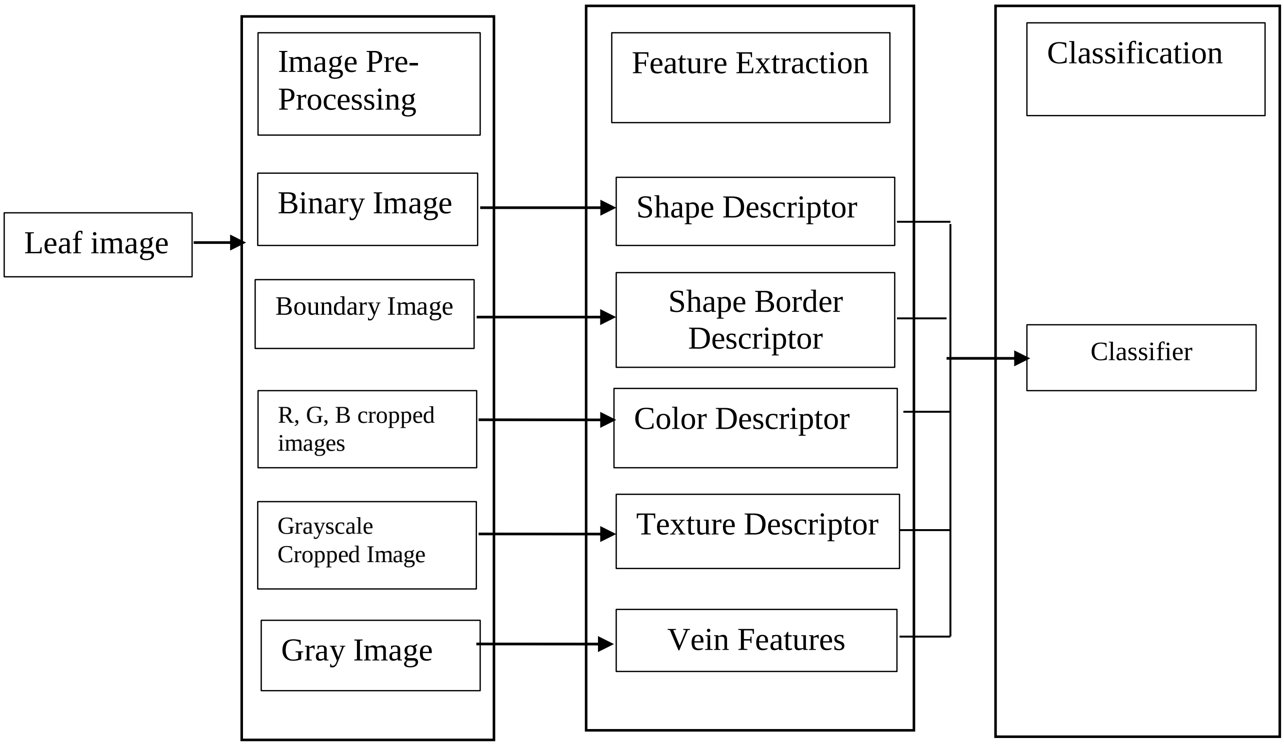


Fig 3.1: Proposed Methodology

3.1 Image Pre-Processing

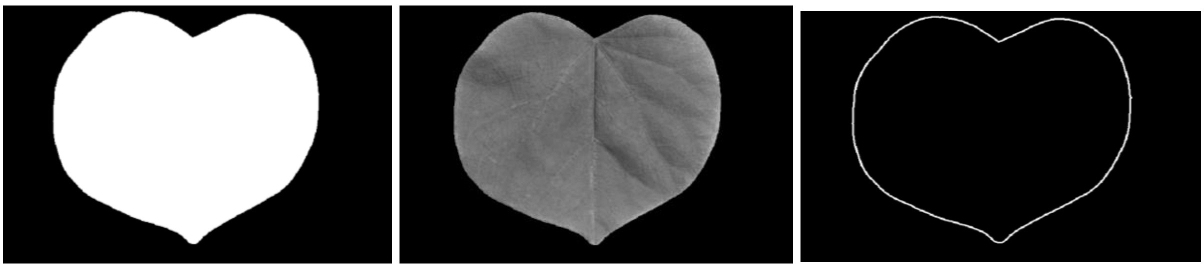
Data set used is Flavia dataset with all leaves on white background. The input to the digital system is the colored digital image of the leaf which is in three dimensional space. Three dimensional space colored image is transformed into two dimensional space by converting it into the gray image. All images are resize to 256*256 for appropriate processing.

Input image is in RGB color space. R, G, B components of the image are extracted for segmentation purpose. In order to obtain segmented image, OR operation is performed on the extracted R, G, B components and the resultant is a black image on the white background. The segmented white image on black background for further processes is obtained by complementing the result of the OR operation. The resultant segmented image obtained is not a clean image at all of its parts due to the presence of white holes on black background and black holes on white area thus to obtain clean image morphological hole filling operation is performed on it.

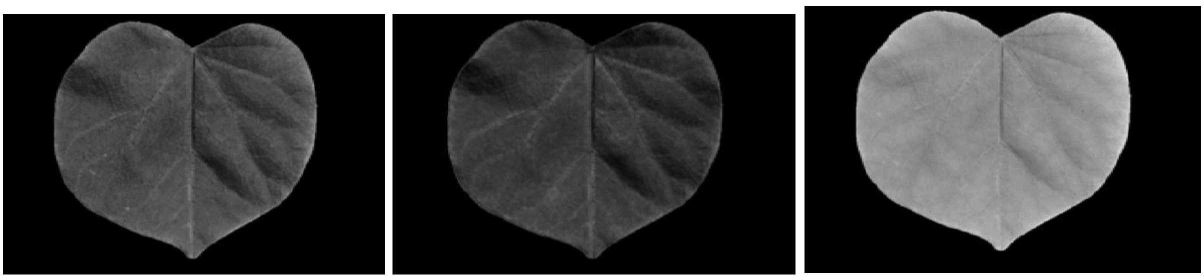
In order to obtain Leaf boundary image only the pixels that forms the boundary of the image are retained and rest are discarded. Thus to attain leaf boundary image dilated image is subtracted from the original image.

Gray scale cropped and R, G, B components cropped images are obtained for extracting texture features and color features respectively.

(a) (b) (c)



(d) (e) (f)

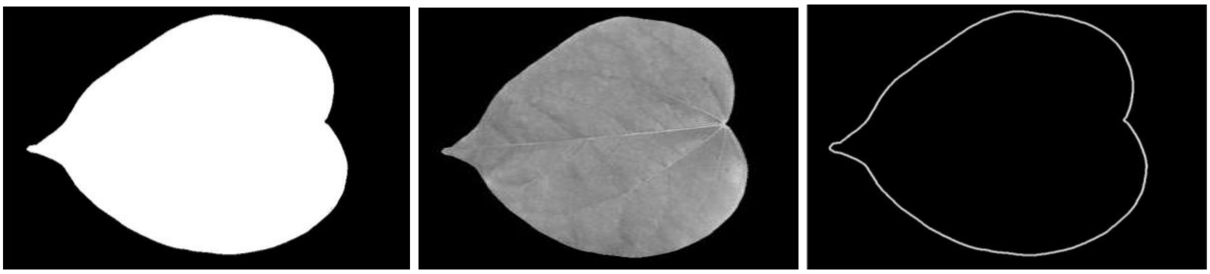


(g) (h) (i)

Fig 3.2: Leaf Image Pre-Processing: (a) RGB Scaled Image, (b) Gray Level Image, (c) Binary Image, (d) Binary Complement Image, (e) Gray Scale Cropped Image, (f) Boundary Extracted Image, (g) R Component Cropped Image, (h) G Component Cropped Image, (i) B Component Cropped Image

The image (a) is given as input to the system. The image is pre-processed to obtain the various desired images. The gray scale operation performed on the input RGB image (a) converted it into the gray scale image (b). The various operations has been performed on R G B components (g) (h) (i) respectively extracted from the input image (a) to obtain binary segmented image (c) and binary complemented image (d). (e) Shows gray cropped image.

(a) (b) (c)



(d) (e) (f)

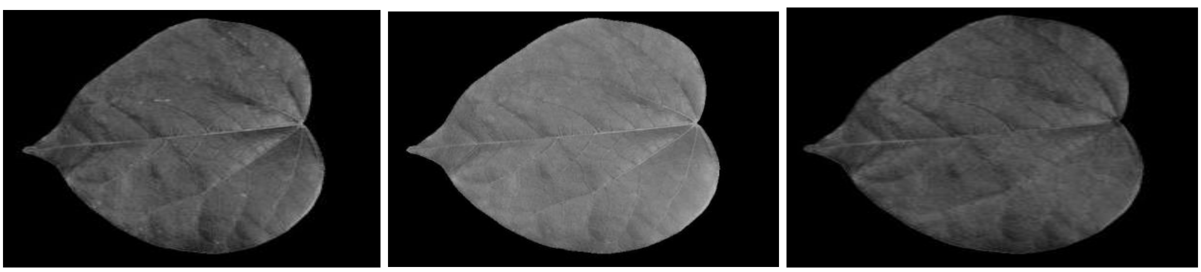
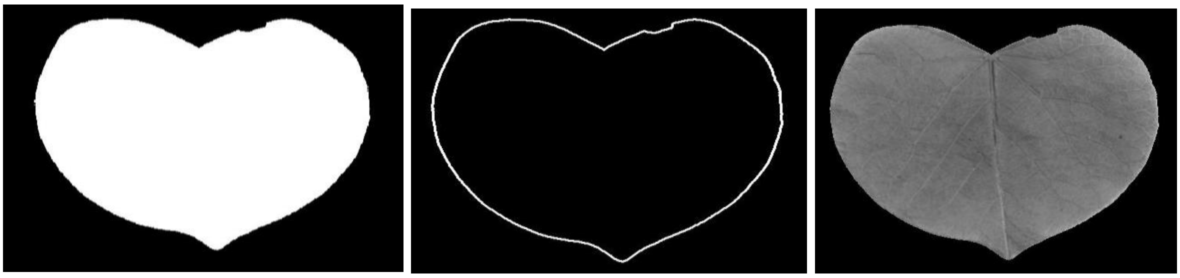


Fig 3.3: 90 Degree Rotated Leaf Image Pre-Processing: (a) RGB Scaled Image, (b) Gray Level Image, (c) Binary Image, (d) Binary Complement Image, (e) Gray Scale Cropped Image, (f) Boundary Extracted Image, (g) R Component Cropped Image, (h) G Component Cropped Image, (i) B Component Cropped Image

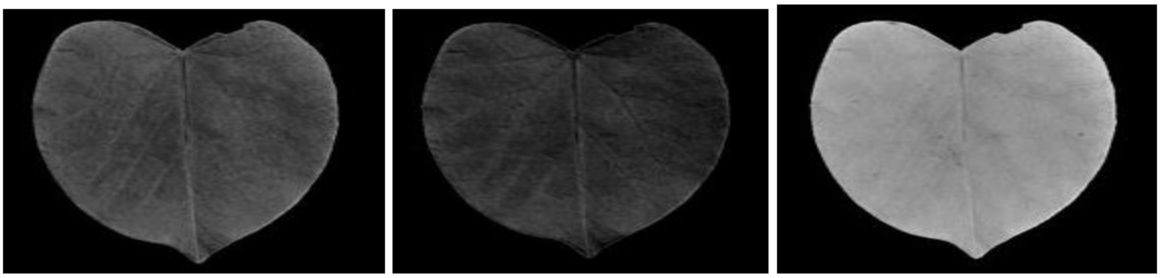
The pre-processing methods are effeciently implemented on the 90 degree rotated image in order to obtain (a) RGB scaled image, (b) Gray level image, (c) Binary image, (d)

Binary complement image, (e) Gray scale cropped image, (f) Boundary extracted image, (g) R component cropped image, (h) G component cropped image, (i) B component cropped image without any distortion in the extracted images.

(a) (b) (c)



(d) (e) (f)



(g) (h) (i)

Fig 3.4: Distorted Leaf Image Pre-Processing: (a) RGB Scaled Image, (b) Gray Level Image, (c) Binary Image, (d) Binary Complement Image, (e) Gray Scale Cropped Image, (f) Boundary Extracted Image, (g) R Component Cropped Image, (h) G Component Cropped Image, (i) B Component Cropped Image

The pre-processing methods are effeciently implemented on the 90 degree rotated image in order to obtain (a) RGB scaled image, (b) Gray level image, (c) Binary image, (d) Binary complement image, (e) Gray scale cropped image, (f) Boundary extracted image, (g) R component cropped image, (h) G component cropped image, (i) B component cropped image without any distortion in the extracted images.

3.2 Shape features

There are various shape features extracted in our work. Starting from the binary image 28 shape descriptors also known as basic and derived morphological features has been extracted. Out of these extracted features 15 are boundary descriptors, 12 are regional descriptors and euler number. The boundary descriptors extracted are perimeter, diameter, radius, minor axis length, bounding box height and width, eccentricity, major axis length, convex perimeter, elongation, perimeter ratio of length and width, perimeter ratio to diameter, narrow factor, extent, equivdiameter. area, compactness, convex area, circularity ratio, rectangularity, solidity, convexity, smooth factor, minimum bounding box area, filled area, and orientation forms the regional descriptors. These shape descriptors have the ability of discriminating the various shapes thus helpful in discriminating different leaves species.

Dispersion is calculated for the irregularity in the shape of the leaves [1].

$$D = \frac{\max\sqrt{((x(i)-x^{\wedge}2)+(y(i)-y^{\wedge}2))}}{\min\sqrt{((x(i)-x^{\wedge}2)+(y(i)-y^{\wedge}2))}} \tag{1}$$

Where coordinates of the leaf centroid are represented by (x, y) and the coordinates of the leaf contour pixel by (x (i), y (i)).

3.3 Vein Features

Vein features of the leaves are extracted by implementing morphological opening operation with flat disk shaped structuring element of radius 1,2,3,4 on grayscale image. Resultant images are subtracted from the grayscale image. Thus on total we have five vein features v1 = a1/a, v2 = a2/a, v3 = a3/a, v1 = a4/a, v5 = a4/a1. a1, a2, a3, a4 corresponds to the areas of the images obtained after subtraction operation. a corresponds the area of the binary input image.

The algorithm can be explained as:

1) Input RGB scale image is converted into grayscale image fig: 3.2 (g) and binary image fig: 3.2 (b).
2) Four flat disk shaped structuring elements S1, S2, S3, S4 are considered with radius of 1,2,3,4 respectively.

3) Opening operation is performed on grayscale image with S1, S2, S3, S4 thus at output i1, i2, i3, i4 are obtained respectively.

   i1 = opening (g, S1)

   i2 = opening (g, S2)

   i3 = opening (g, S3)

   i4 = opening (g, S4)

4) Output images are subtracted from grayscale image, thus as a resultant we have o1, o2, o3, o4 images representing veins of image fig (3.3).

   o1 = subtract (g, o1)

   o2 = subtract (g, o2)

   o3 = subtract (g, o3)

   o4 = subtract (g, o4)

5) Area of images b, o1, o2, o3, o4 are calculated as a, a1, a2, a3, a4 respectively for calculating vein features v1, v2, v3, v4, v5.

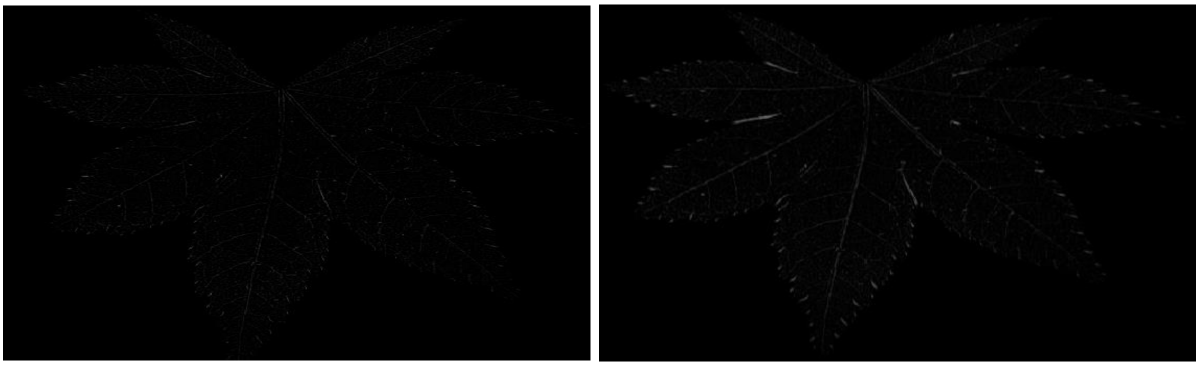
$$v1 = \frac{A1}{A} \tag{2}$$

$$v2 = \frac{A2}{A} \tag{3}$$

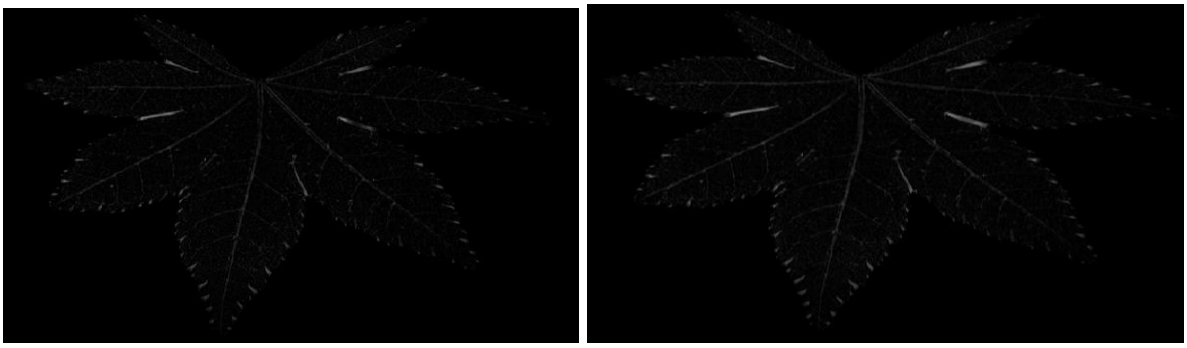
$$v3 = \frac{A3}{A} \tag{4}$$

$$v4 = \frac{A4}{A} \tag{5}$$

$$v5 = \frac{A4}{A1} \tag{6}$$



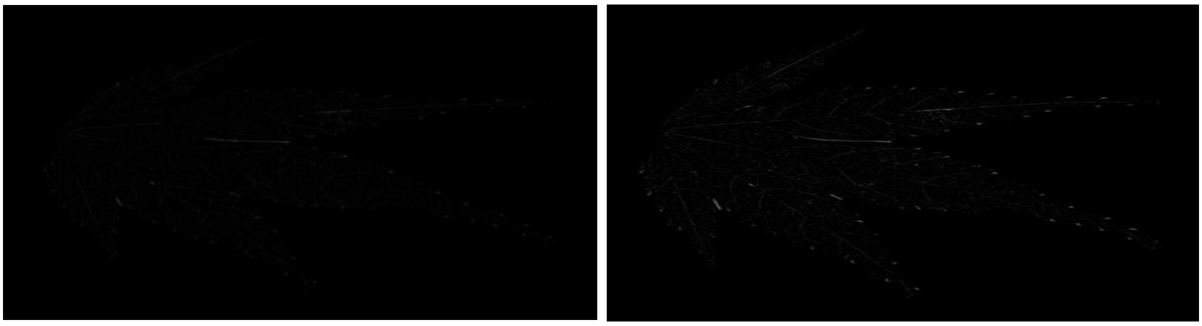
(a) (b)



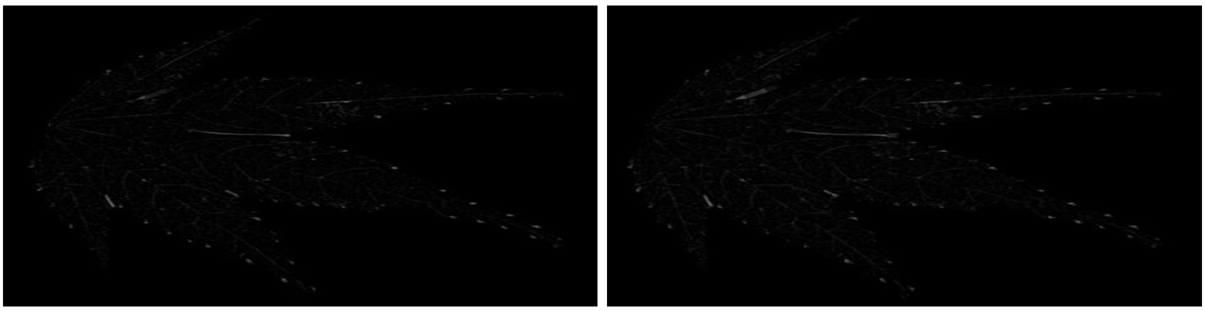
(c) (d)

Fig 3.5: Leaf Vein Images obtained with Structuring Disk 1, 2, 3, 4 respectively

The various vein features equation (1-5) has been obtained as a result of the distinct operations performed on the grayscale image fig: 3.2 (g) and binary image fig: 3.2 (b). Fig: 3.5 (a) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 1 from gray scale image. Fig: 3.5 (b) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 2 from gray scale image. Fig: 3.5 (c) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 3 from gray scale image. Fig: 3.5 (d) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 1 from gray scale image.



(a) (b)



(c) (d)

Fig 3.6: Leaf Vein Images obtained with Structuring Disk 1, 2, 3, 4 respectively for 90 Degree Rotated Leaf Image

The feature extracted from the images should be rotation invariant i.e. feature extraction techniques must be able to extract features properly from the rotated image as they are from the original image. The vein features extracted using vein feature extraction algorithm mentioned above are rotation invariant. Fig 3.5 and Fig 3.6 shows the rotation invariant property of the features extracted using vein feature extraction algorithm mentioned above. Fig 3.6 shows the results obtained by implementing the vein feature extraction technique on the 90 degree rotated image. Fig: 3.6 (a) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 1 from gray scale image. Fig: 3.6 (b) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 2 from gray scale image. Fig: 3.6 (c) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 3 from gray scale image. Fig: 3.6 (d) is the result obtained by the subtracting the result of the operation performed on grayscale image with structuring disk of radius 1 from gray scale image.

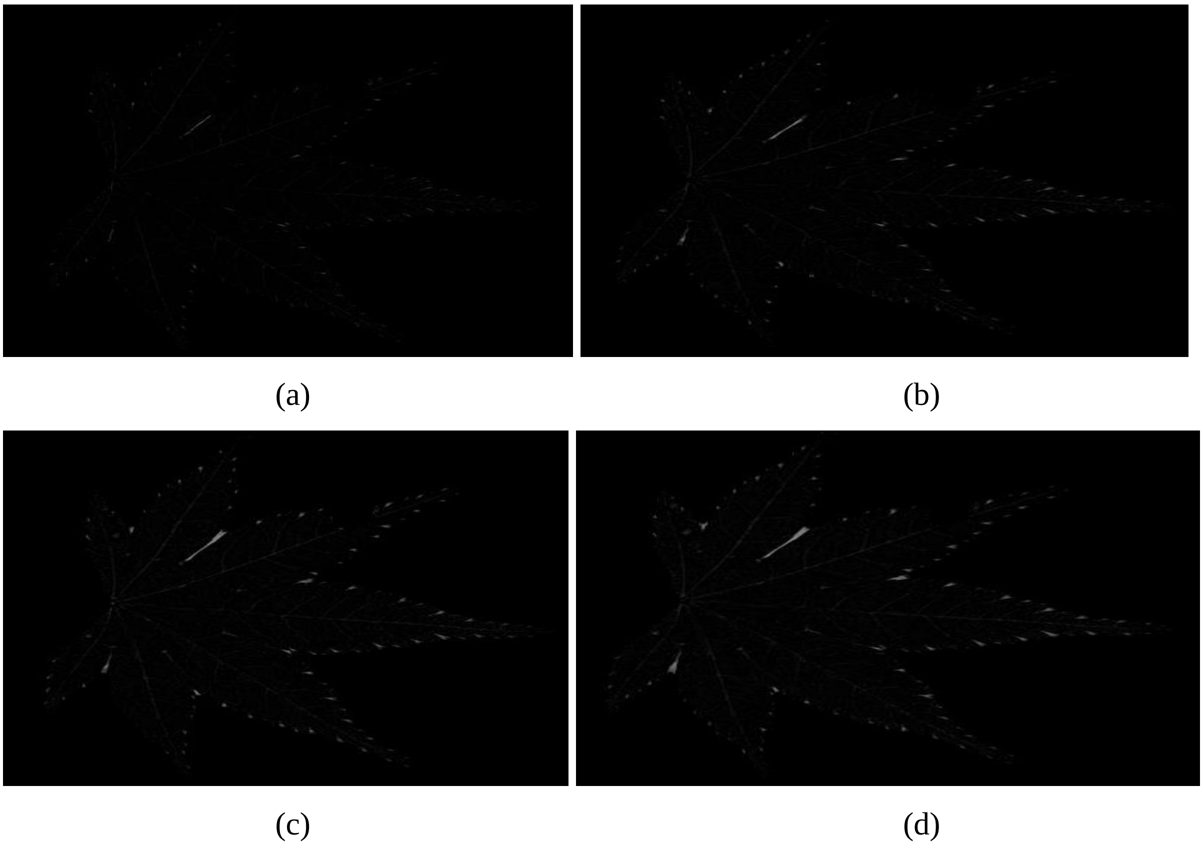


Fig 3.7: Leaf Vein Images obtained with Structuring Disk 1, 2, 3, 4 respectively for Distorted Leaf Image

The vein feature extraction algorithm must be able to extract features appropriately from the distorted images also. Fig: 3.7 shows the vein feature extraction method is able to extract features properly from the distorted torn leaf image.

3.4 Color Features

Color features are robust descriptor as these are independent of image size and orientation. Color features denote joint probability distribution of the intensities of three color channels of color space hence, an image color distribution can be consider as a probability distribution. Color histograms are invariant with position and orientation changes but doesn't consider spatial information in image as a result discriminating power is limited. This drawback is overcome in color color coherence vector and color correlogram but these suffers the drawback of expensive computation [13]. Probability distributions of colors can be characterized by set of unique moments. Therefore if colors in an image follows certain probability distribution than color moments can be used for color feature extraction and moments of that distribution are feature. Matching of color features based on color moments are more robust compared to the quantization parameters of the color histogram due to drawback of histograms spatial color regions. In addition to this, color moments has the advantage of lowest computational complexity and lowest feature vector dimension as compared to other methods. Low order moments acquires most of the information and these are first moment - mean, second moment - variance and third moment - skewness. Color moments has been proposed for color features extraction since leaves are of one color only thus color distribution in image of leaves follows probability distribution, making use of color moments optimal.

Image is in a RGB color space. The use of seven color moments mean, skewness, kurtosis, standard deviation, entropy, smoothness, uniformity has been proposed. Color moments are calculated for i-th color channel at j-th image pixel as Pij for M total number of pixels in image. Twenty one color moments has been calculated for the image, seven for each color channel.

The algorithm can be explained as:

1) The R, G, B channels are extracted from the image.
2) Mean is calculated for all three channels using expression,

$$\mu = \frac{\sum Pij}{M} \tag{7}$$

3) Standard Deviation is calculated for all three channels using expression,

$$\sigma = \sqrt{(\frac{(\sum Pij-\mu)^2}{M})} \tag{8}$$

4) Skewness is calculated for all three channels using expression,

$$\theta = \sqrt{(\frac{(\sum Pij-\mu)^3}{M*\sigma^3})} \tag{9}$$

5) Kurtosis is calculated for all three channels using expression,

$$\gamma = \sqrt{(\frac{(\sum Pij-\mu)^4}{M*\sigma^4})} \tag{10}$$

6) Smoothness is calculated for all three channels.
7) Entropy is calculated for all three channels using expression,

$$E = -\sqrt{(\sum M * \log_2 M)} \tag{11}$$

8) Uniformity is calculated for all three channels using expression,

$$U = \sum (Pij)^2 \tag{12}$$

9) Thus at output for each channel we get 7*1 matrix.
10) Steps 1-8 are repeated for each image in the database.

3.5 Texture Features

Texture features has been extracted using Gray level co-occurrence matrix (GLCM) since the discrimination rates attained by second order statistics i.e. GLCM are higher than other methods. GLCM gives the position of the pixels with respect to the neighboring pixels. It counts the grey value pixel occurrence at given distance. GLCM twenty features given by Harlick has been calculated at the distance 1 for angles 135, 90, 45, 0 degree thus on total eighty features has been attained. The features calculated are cluster prominence, variance, contrast, dissimilarity, correlation, cluster shade, autocorrelation, energy, information measure of correlation2, entropy, sum average, homogeneity, difference entropy, maximum probability, sum variance, inverse difference normalized, sum entropy, difference variance, inverse difference moment normalized, information measure of correlation1.

3.6 Classification and Identification

The plant classification and identification from leaf image is classifier specified problem. The classifiers are used to serve the purpose of the classification and identification. There are many classifiers available, since the proposed problem is multiclass thus the use of the multiclass classifiers has been preferred to serve the purpose. The comparative analysis has been done with the use of the multiple classifiers. The classifiers used are SVM, PNN, feed forward neural networks with gradient descent and scalar conjugate gradient training algorithm, naive Bayes and decision tree. The SVM is inherently binary classifier thus it has been transformed to multiclass using one versus all technique.

The SVM, PNN, naïve Bayes and decision tree classifiers are able to perform both classification and identification of the class of the leaf in the image whereas feed forward neural network trained with gradient descent and scalar conjugate gradient training algorithm performs only classification.

The output of the SVM, naïve Bayes and decision tree classifiers has been combined to form the combined classifiers using majority voting method. The performance accuracy obtained using combined classifier and ensemble classifier has been enhanced than the accuracy of the individual classifiers.

CHAPTER 4
EXPERIMENTAL RESULTS

The research methodology has been implemented in order to classify and identify the various plant leaf images. The evaluation parameters as mentioned in chapter-1 are applied over the research methodology and it has been analyzed that these parameters like accuracy, precision and recall varies based upon the classifiers used, input parameters like number of input leaf images and number of input classes. The results of the evaluation parameters are also based on the number of features extracted from the leaf image. The confusion matrix representing the accuracy has also been displayed for different classifiers. The system performs both classification and identification for input images.

4.1 Experimental Results

Table-4.1 shows the results based on the implementation of the various classifiers on total 140 distinct extracted features from the plant leaf image.

Table 4.1: System analysis for 140 features using different classifiers

Classifier	**Input Parameters**		**Evaluation Parameters**		
	Number of input leaf images	Number of input classes	Accuracy	Precision	Recall
SVM PNN S.C.G G.D	320	32	100% 100% 97.5% 88%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	640	32	100% 100% 96% 92%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	1280	32	100% 100% 98.5% 98%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	1536	32	99.3651% 100% 98.5% 98%	0.9938 1 - -	0.9948 1 - -

SVM PNN S.C.G GD	1850	32	100% 100% 98.8% 98.5%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	1162	20	100% 100% 96.8% 96.2%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	611	10	100% 100% 99.8% 99%	1 1 - -	1 1 - -
SVM PNN S.C.G GD	301	5	100% 100% 100% 98.3%	1 1 - -	1 1 - -

The comparative analysis of the different classifiers SVM, PNN and forward neural networks with gradient descent and scalar conjugate gradient training algorithm for 140 features concludes that the performance of the PNN is the best amongst all, for different number of input images and classes its performance remains constant to 100% accuracy. The performance of the SVM classifier is also good but it misclassified some images for 1536 inputs of 32 classes. The S.C.G (scalar conjugate gradient) and GD (gradient descent) also gives good results but the number of the iterations and computation time of the GD descent is more and increases with the increase in the number of the inputs. The SVM and PNN are able to identify the class of the input image whereas S.C.G and GD can only perform classification.

Table-4.2 shows the results based on the implementation of the various classifiers on the total 40 distinct extracted features from the plant leaf image.

Table 4.2: System analysis for 40 features using different classifiers

Classifier	**Input Parameters**		**Evaluation Parameters**		
	Number of input leaf images	Number of input classes	Accuracy	Precision	Recall
SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	1850 Train images: 1480 Test Images: 370	32	81.8919% 85.6757% 84.5946% 90.8108% 95.1351%	.8148 .8576 .8190 .9076 .9382	.8148 .8576 .8190 .9076 .9382

SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	1536 Train images: 1229 Test Images: 307	32	76.2215% 82.7326% 79.1531% 87.9479% 92.8339%	.7658 .8322 .7839 .8845 .9168	.7658 .8322 .7839 .8845 .9168
SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	1280 Train images: 1024 Test Images: 256	32	78.9063% 78.1250% 79.2969% 85.9375% 92.5781%	.7847 .7912 .7956 .8611 .9145	.7847 .7912 .7956 .8611 .9145
SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	1162 Train images: 930 Test Images: 232	20	81.4655% 81.0345% 80.6034% 87.0690% 91.8103%	.8090 .8020 .7973 .8660 .9118	. .8090 .8020 .7973 .8660 .9118
SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	611 Train images: 489 Test Images: 122	20	94.2623% 92.6230% 94.2623% 96.7213% 99.1803%	.9385 .9189 .9371 .9636 .9909	.9385 .9189 .9371 .9636 .9909
SVM Naïve Bayes Tree Combined Classifier Ensemble Classifier	640 Train images: 512 Test Images: 128	32	71.0938% 75.7813% 74.2188% 82.8125% 88.2813%	.7125 .7641 .7281 .8313 .8844	.7125. .7641 .7281 .8313 .8844

The performance of the system decreases with the decrease in the number of the features. It is observed that with the 140 features 100% accuracy is achieved with SVM classifier and above 90% with others whereas when the number of inputs are decreased the accuracy achieved with different classifiers also decreased and ranges between 70% - 85% at different inputs for SVM classifier.

The concept of the combined classifier is thus used to increase the accuracy performance of the system. It is observed that implementation of the combined classifier with majority voting technique enhanced the attained accuracy but the ensemble classifier outperformed the results obtained with majority voting technique and improved the results.

The comparative analysis of the different classifiers SVM, Naïve Bayes Decision Tree, combined classifier with majority voting technique and ensemble classifier for 40 features concludes that the performance of the ensemble classifier with bagging is the best amongst all followed by combined classifier with majority voting technique. Thus it can be concluded that results obtained with combined classifiers are better than the individual classifiers.

14	0	0	0	0
0	12	0	0	0
0	0	10	0	0
0	0	0	13	0
0	0	0	0	11

Fig: 4.1 PNN Confusion Matrix for 60 test samples of 301 input 5 class

The confusion matrix summarizes the performance of the PNN classifier. It indicates that trained PNN classifier correctly classifies all the testing leaves images input to it for 301 input of 5 leaves classes. In the figure X axis indicates target class and Y axis output class.

14	0	0	0	0
0	12	0	0	0
0	0	10	0	0
0	0	0	13	0
0	0	0	0	11

Fig: 4.2 SVM Confusion Matrix for 60 test samples of 301 input 5 class

The confusion matrix summarize the performance of the SVM classifier. It indicates that the trained SVM classifier correctly classifies all the testing leaves images input to it for 301 input of 5 leaves classes. In the figure X axis indicates target class and Y axis output class.

Fig 4.3: Neural network gradient descent (GD) Confusion Matrix for 301 input 5 class

The confusion matrix summarize the performance of the neural network trained with gradient descent (GD) classifier for 301 inputs of 5 classes. It indicates that the trained classifier correctly classifies the all leaf images of the two classes but misclassifies the some leaf images of the three classes.

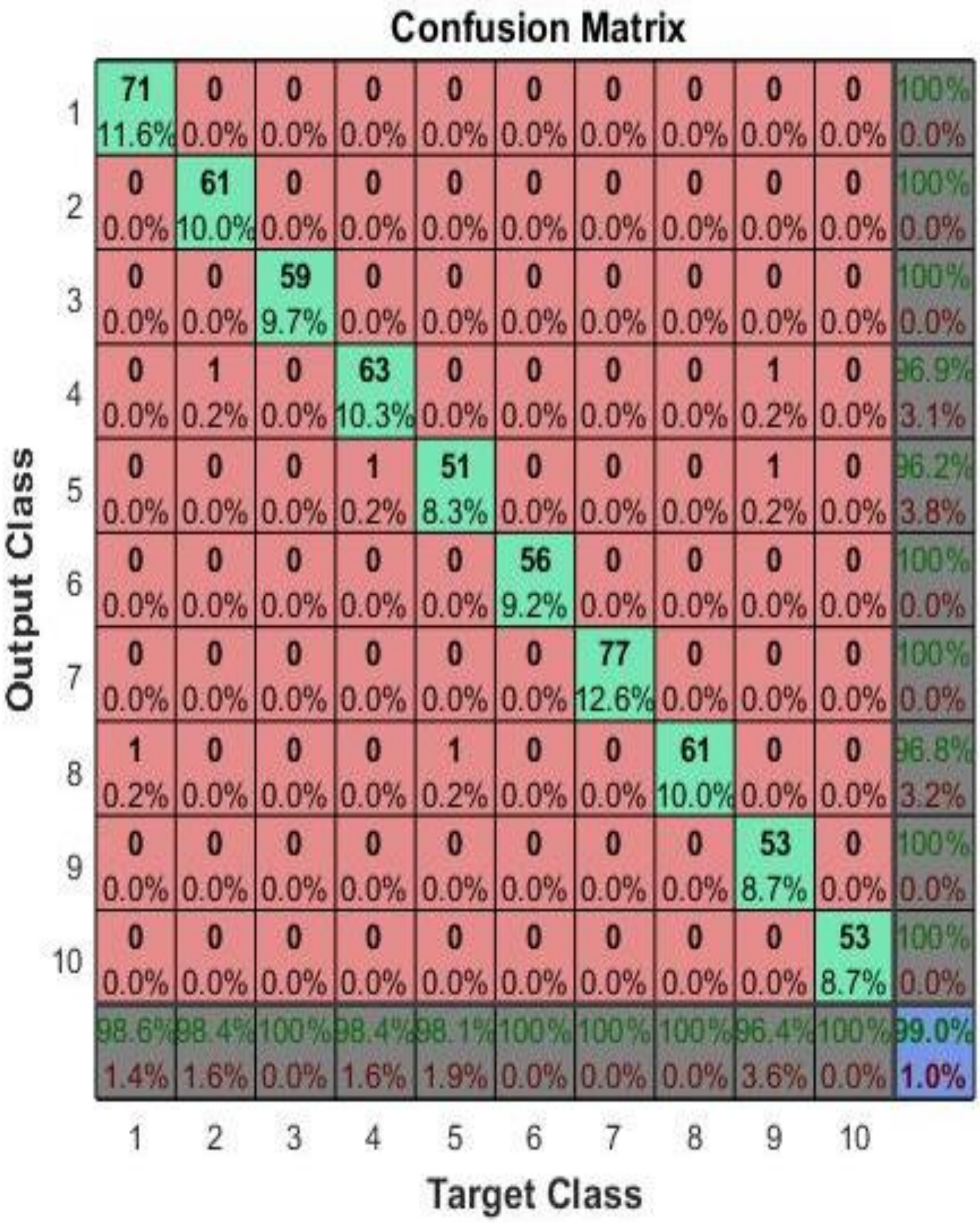


Fig 4.4: Neural network gradient descent (GD) Confusion Matrix for 611 input 10 class

The confusion matrix summarize the performance of the neural network trained with gradient descent (GD) classifier for 611 inputs of 10 classes. It indicates that the trained classifier correctly classifies the all leaf images of the seven classes but misclassifies the some leaf images of the three classes.

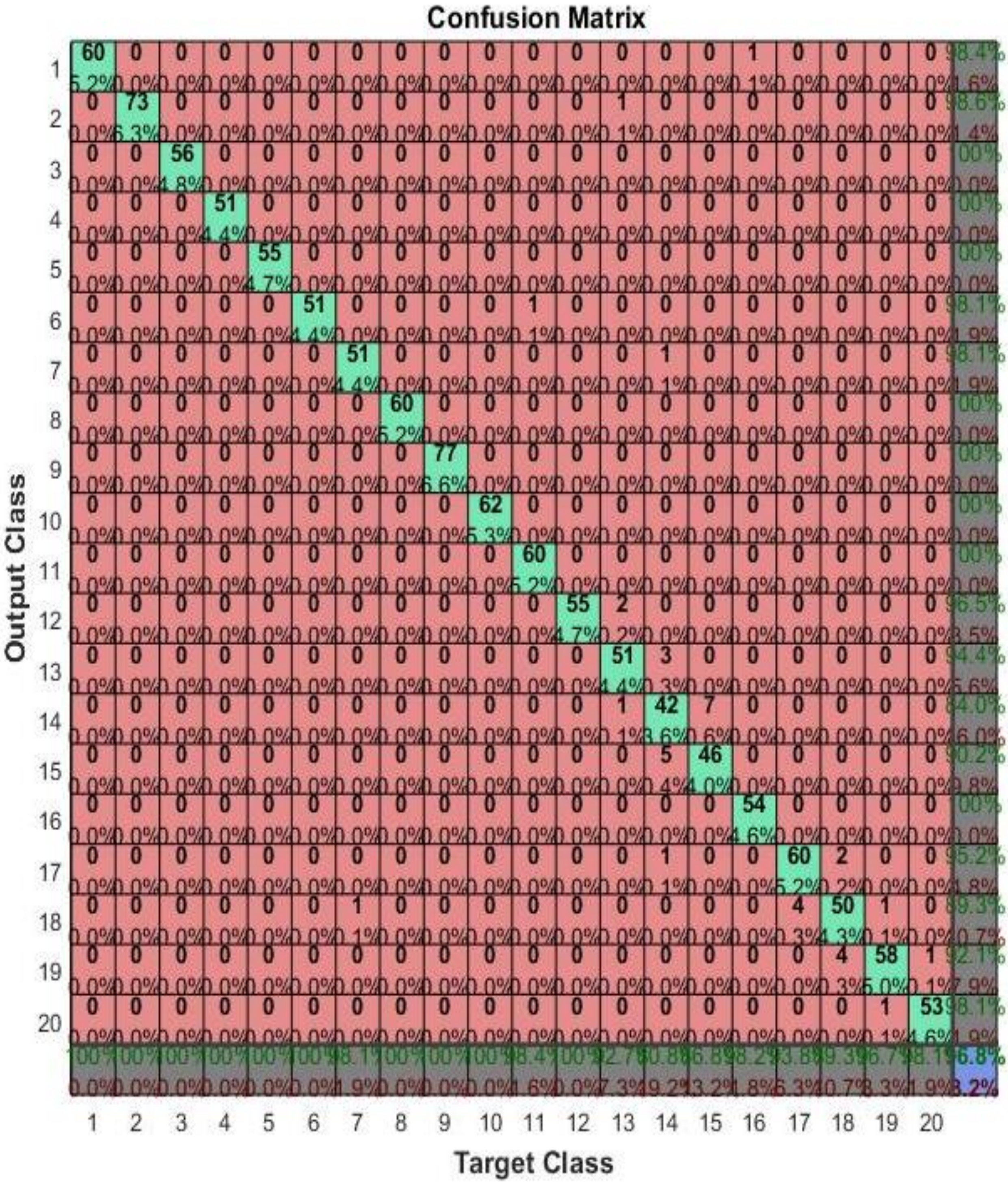


Fig 4.5: Neural network scalar conjugate gradient (S.C.G) Confusion Matrix for 1162 input 20 class

The confusion matrix summarize the performance of the neural network trained with gradient descent (GD) classifier for 1162 inputs of 20 classes. It indicates that the trained classifier correctly classifies the all leaf images of the eight classes but misclassifies the some leaf images of the twelve classes.

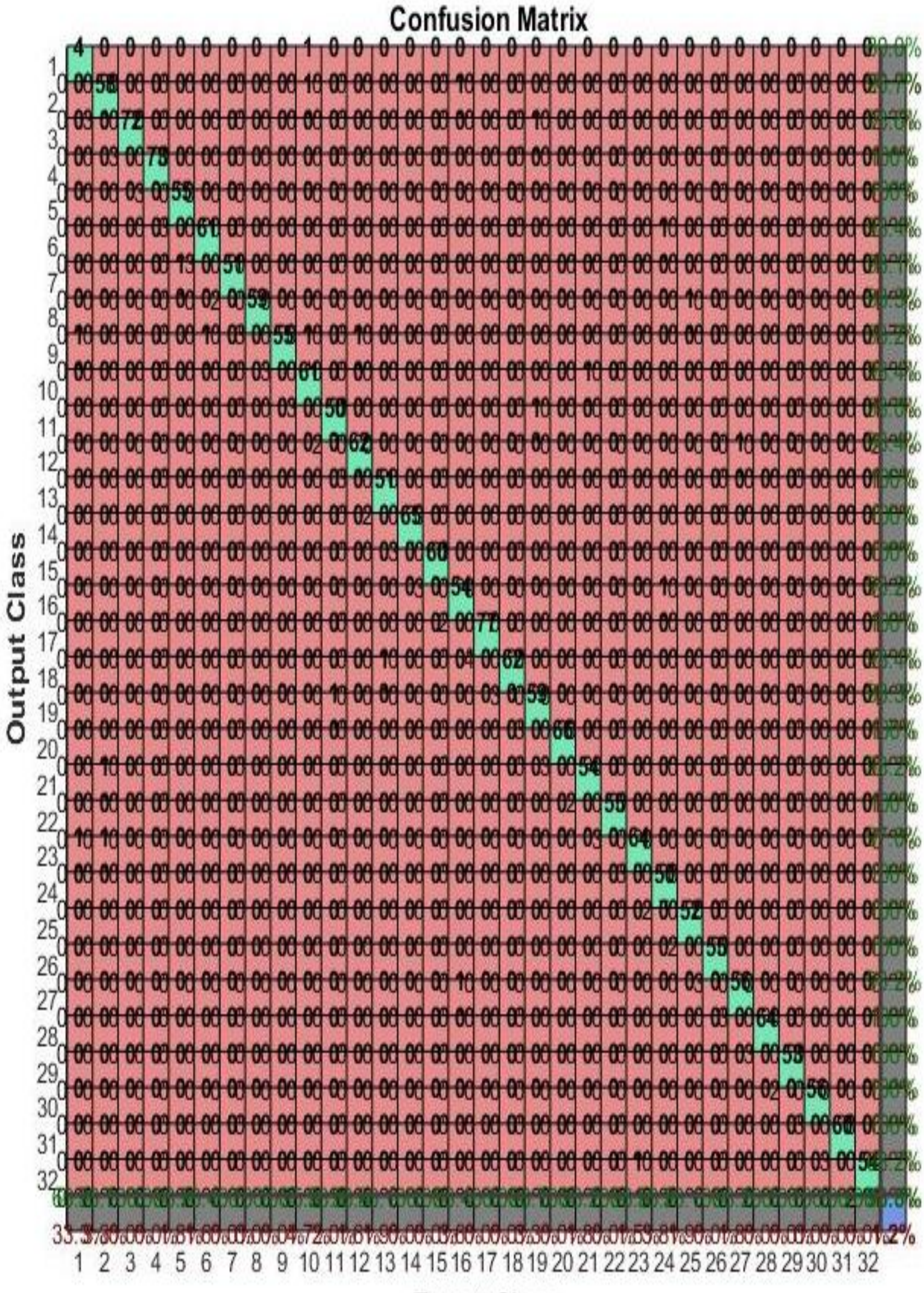


Fig 4.6: Neural network scalar conjugate gradient (S.C.G) Confusion Matrix for 1850 input 32 classes

11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	13	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	1	0	0	9	0	0	0	0	0	0	0	0	0	2	0	0	2	0	0
0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	2	0	0	0	0	10	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0
0	0	0	2	0	0	1	0	0	3	0	0	0	0	1	0	2	2	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	7	0	0	2	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	1	7	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	4	5	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	9	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	10	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	10	1
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	9

Fig: 4.7 Naïve Bayes Confusion Matrix for 1162 input 20 class

The confusion matrix summarize the performance of the naïve Bayes for 1162 inputs of 20 classes. It indicates that the trained classifier correctly classifies the all leaf images of the seven classes but misclassifies the some leaf images of the thirteen classes.

12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	1	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	1	0	0	10	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	11	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	5	0	0	0	0	0	0	1
0	1	0	0	0	0	1	0	0	1	0	0	0	6	0	0	1	0	0	0
1	0	0	0	0	1	0	0	0	0	0	0	1	1	6	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	8	0	0	0	1
2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	6	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	7	2
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	9

Fig: 4.8 SVM Confusion Matrix for 1162 input 20 class

The confusion matrix summarize the performance of the SVM classifier for 1162 inputs of 20 classes. It indicates that the trained classifier correctly classifies the all leaf images of the three classes but misclassifies the some leaf images of the seventeen classes.

15	0	0	0	0	0	0	0	0	0
0	11	0	0	0	1	0	0	0	0
0	0	11	0	0	0	0	0	0	0
0	0	0	12	0	0	0	0	0	0
0	0	0	0	10	0	0	0	1	0
0	0	0	0	2	9	0	0	0	0
0	0	0	0	0	0	15	0	0	0
0	0	0	0	0	0	0	13	0	0
0	0	1	0	2	0	0	0	8	0
0	0	0	0	0	0	0	0	0	11

Fig: 4.9 Decision tree Confusion Matrix for 611 input 10 class

The confusion matrix summarize the performance of the Decision Tree classifier for 611 inputs of 10 classes. It indicates that the trained classifier correctly classifies the all leaf images of the six classes but misclassifies the some leaf images of the four classes.

15	0	0	0	0	0	0	0	0	0
0	12	0	0	0	0	0	0	0	0
0	0	11	0	0	0	0	0	0	0
0	0	0	12	0	0	0	0	0	0
0	0	0	0	10	0	0	0	1	0
0	0	0	0	1	10	0	0	0	0
0	0	0	0	0	0	15	0	0	0
0	0	0	0	0	0	0	13	0	0
0	0	0	0	2	0	0	0	9	0
0	0	0	0	0	0	0	0	0	11

Table: Fig: 4.10 Combined Classifier Confusion Matrix for 611 input 10 class

The confusion matrix summarize the performance of the Combined Classifier for 611 inputs of 10 classes. It indicates that the trained classifier correctly classifies the all leaf images of the seven classes but misclassifies the some leaf images of the three classes.

15	0	0	0	0	0	0	0	0	0
0	12	0	0	0	0	0	0	0	0
0	0	11	0	0	0	0	0	0	0
0	0	0	12	0	0	0	0	0	0
0	0	0	0	11	0	0	0	0	0
0	0	0	0	0	11	0	0	0	0
0	0	0	0	0	0	15	0	0	0
0	0	0	0	0	0	0	13	0	0
0	0	0	0	1	0	0	0	10	0
0	0	0	0	0	0	0	0	0	11

Fig: 4.11 Ensemble Classifier Confusion Matrix for 611 input 10 class

The confusion matrix summarize the performance of the Ensemble Classifier for 611 inputs of 10 classes. It indicates that the trained classifier correctly classifies the all leaf images of the nine classes but misclassifies the some leaf images of the one classes.

4.2 Result Analysis

The proposed algorithm has been implemented with the help of different classification techniques as mentioned above. The results have been obtained after applying evaluation parameters on the obtained outputs of different classifiers and have been compared on the basis of parameters like number of input leaf images and number of classes of leaf images. It has been experimentally found that with the decrease in the number of the extracted features the performance of the system decreases. The system performs well for 140 features but shows degraded performance for 40 features. Thus to enhance the performance of the system the combined classifiers has been used and it is found for the less number of features the system performs better with combined classifier than individual classifiers .

It is observed that there is tradeoff between system complexity accuracy. The more the number of the features the better is the accuracy but at the cost of the more computation time and complexity. On the other hand if the number the features are reduced than the complexity and the computation time of the system decreases but at the system time the performance of the system also degrades.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

Plants are essential for humans and animals survival on earth as they are the sources of many natural resources. The abundance of plants are present on the earth which looks identical. It is difficult to differentiate them from their physical appearance by humans. On contrary correct identification of plants are required in order to avoid any hazard due to poisonous or danger plants. Correct identification of plants also helps botanist in their researchers and ease the work of farmers. Thus there is a requirement of the digital system for the plant identification from digital images.

The plant classification and identification system has been developed using image processing and classifiers. The shape, texture, vein and color features has been extracted from the leaf images using feature extraction descriptors. The extracted 140 features has been input to the classifier for classification and identification purposes. The GLCM has been used for extracting texture features, color moments for color features, morphological opening for vein features and morphological descriptors for shape features.

The comparative analysis of the performance of the system has been done using various classifiers and the results obtained has been evaluated on the basis of the evaluation parameters such as accuracy, precision and recall.

On the basis of the results it has been observed there is tradeoff between the accuracy, system complexity and computation time. On increasing the number of the extracted features the system accuracy increases but at the same time system complexity and computation time also increases. On the other hand if the number the features are reduced than the complexity and the computation time of the system decreases but at the system time the performance of the system also degrades. The accuracy can be enhanced for the less number of the features using combined classifiers as combined classifiers outperforms the performance of the individual classifiers.

There is the tradeoff between the accuracy, system complexity and computation time and the work is based on the dataset that includes the leaf images on the white background with no noise. Thus the work will be extended to resolve these issues furthermore the other parameters of the plants such as bark, roots etc. will be consider for the development of the identification system.

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