Detection and Analysis of Plant Leaf Diseases using Image Processing

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ABSTRACT
The urgent need is that many plants are at the risk of extinction. About 50% of Ayurveda medicines are prepared using plant leaves and many of these plant species belong to the endanger group. So it is very necessary to set up a database for plant protection.Here first step is to teach a computer how to classify plants. Herein this project employ Probabilistic Neural Network (PNN) with image and data processing techniques to implement general purpose automated leaf recognition for plant classification. 12 leaf features are extracted and orthogonalized into 5 principal variables which consists the input vector of the PNN. The PNN is trained by 30 leaves to classify 5 kinds of plants with accuracy greater than 90%. Compared with other approaches, this algorithm is an accurate artificial intelligence approach which is fast in execution and easy in implementation. The detection of plant leaf disease is a very important factor to prevent serious outbreak. The developed processing scheme consists of four main steps, first a color transformation structure for the input RGB image is created. Then green pixels are masked and removed using specific threshold value, then the image is segmented and the useful segments are extracted, finally the texture statistics is computed from SGDM matrices. Finally the presence of diseases on the plant leaf is evaluated.

Keywords
Image Processing, PNN, ANN

1. INTRODUCTION
Plants exist everywhere we live, as well as places with out us. Many of them carry significant information for the development of human society. The urgent situation is that many plants are at the risk of extinction. So it is very necessary to set up a database for plant protection. This project believes that the first step is to teach a computer how to classify plants. Compared with other methods, such as cell and molecule biology methods, classification based on leaf image is the first choice for leaf plant classification. Sampling leaves and photoing them are low-cost and convenient. One can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques.

2 BRIEF WORKING OF PROPOSED APPROACH

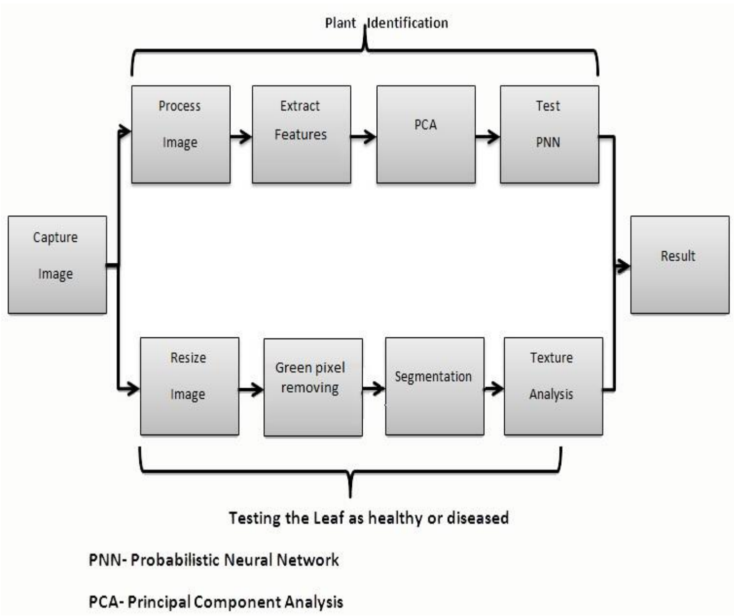


Figure 2.1: Block diagram of plant leaf recognition and disease detection.

As shown in the block diagram there are two stages.

1. Plant identification.
2. Testing the leaf as healthy or diseased.

2.1 Plant Identification
Following steps to be performed for identification of the plant.

2.1.1 Capture Image
First, the images of various leaves are acquired using scanners or digital camera. The images are in the RGB format.

2.1.2 Process Image
Converting RGB image to binary image. The leaf image is acquired by scanners or digital cameras. Since we have not found any digitizing device to save the image in a lossless compression format, the image format here is JPEG. All leaf images are in 800 x 600 resolutions. There is no restriction on the direction of leaves when photo'ing. An RGB image is firstly converted into a gray scale image.

2.1.3 Extract features
Firstly, obtain 5 basic geometric features. Then we derive 12 digital morphological features used for leaf recognition.

2.1.4 Principal Component Analysis (PCA)
To reduce the dimension of input vector of neural network, PCA is used to orthogonalize 12 features. The purpose of PCA is to present the information of original data as the linear combination of certain linear irrelevant variables.

2.1.5 Test and Train Probabilistic neural network
An artificial neural network (ANN) is an interconnected group of artificial neurons simulating the thinking process of human brain. One can consider an ANN as a "magical" black box trained to achieve expected intelligent process, against the input and output information stream. Thus, there is no need for a specified algorithm on how to identify different plants. PNN is derived from Radial Basis Function (RBF) Network which is an ANN using RBF.

2.2 Testing The Leaf As Healthy Or Diseased
To test the leaf whether leaf is healthy or partially healthy or diseased the following steps are to be performed.

2.2.1 Resize Image
The captured RGB image is resized into 256*256 pixels. It helps for the further analysis of the detection.

2.2.2 Masking and Green pixel removing
Masking means setting the pixel value in an image to zero or some other background value. In this step, we identify the mostly green coloured pixels. After that, based on specified threshold value that is computed for these pixels. The green components of the pixel intensities are set to zero if it is less than the pre-computed threshold value. Then red, green and blue components of the pixel are assigned to a value of zero by mapping of RGB components. The green coloured pixels mostly represent the healthy areas of the leaf and they do not add any valuable weight to disease identification.

The green coloured pixels mostly represent the healthy areas of the leaf and they do not add any valuable weight to disease identification so green pixel is removed.

2.2.3 Segmentation
In this step the useful segments are obtained. The size of the patch is chosen in such a way that the significant information is not lost. Not all segments contain significant amount of information. So the patches which are having more than fifty percent of the information are taken into account for the further analysis. In this process image is divided into 32*32 patches.

2.2.4 Texture analysis
Properties of Spatial Gray-level Dependence Matrices (SGDM) like Contrast, Energy, Local homogeneity, and correlation are computed for the image is taken for analysis.The result leaf is healthy or diseased is obtained based on the number of high contrast patches.

2.3 Plant Recognition Using PCA & PNN

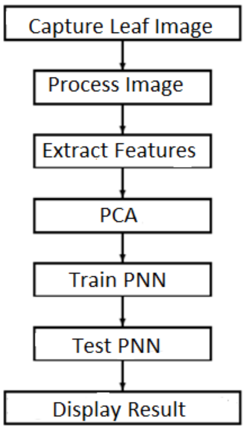


Figure 2.2: Flow diagram of proposed scheme.

2.3.1 Image pre-processing
Converting RGB image to binary image. The leaf image is acquired by scanners or digital cameras. Since we have not found any digitizing device to save the image in a lossless compression format, the image format here is JPEG. All leaf images are in 800 x 600 resolutions. There is no restriction on the direction of leaves when photo'ing. An RGB image is firstly converted into a grayscale image.

Eq. 1 is the formula used to convert RGB value of a pixel into its grayscale value.

gray = 0.2989 ∗ R + 0.5870 ∗ G + 0.1140 ∗ B (1)

Where R, G, B correspond to the colour of the pixel, respectively. The level to convert grayscale into binary image is determined according to the RGB histogram.We choose the level as 0.95.

The output image replaces all pixels in the input image with luminance greater than the level by the value 1 and replaces all other pixels by the value 0. A rectangular averaging filter of size 3 × 3 is applied to filter noises. Then pixel values are rounded to 0 or 1.

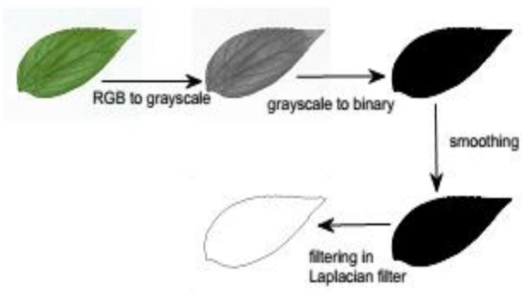


Figure 2.3: Image pre-processing

2.3.2 Feature extraction
Basic Geometric Features Firstly, obtaining 5 basic geometric features.

2.3.3 Diameter
The diameter is defined as the longest distance between any two points on the margin of the leaf. It isdenoted as D.

2.3.4 PhysiologicalLength

The only human interfered part of this algorithm is that you need to mark the two terminals of the main vein of the leaf via mouse click. The distance between the two terminals is defined as the physiological length. It is denoted as Lp.

2.3.5 Physiological Width

Drawing a line passing through the two terminals of the main vein, one can plot infinite lines orthogonal to that line. The number of intersection pairs between those lines and the leaf margin is also infinite. The longest distance between points of those intersection pairs is defined at the physiological width. It is denoted as Wp. Since the coordinates of pixels are discrete, we consider two lines are orthogonal if their degree is 90± 0.5

The relationship between physiological length and physiological width is illustrated in Figure.

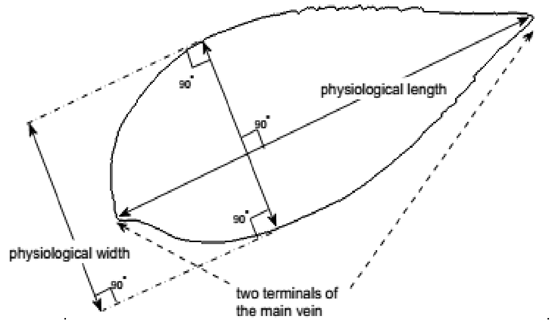


Figure 2.4: Relationship between Physiological Length and Physiological Width.

2.4 Digital Morphological Features

Based on 5 basic features introduced previously, we can define 12 digital morphological features used for leaf recognition.

2.4.1 Smooth factor

In this project the effect of noises to image area to describe the smoothness of leaf image. In this paper, smooth factor is defined as the ratio between area of leaf image smoothed by 5 × 5 rectangular averaging filter and the one smoothed by 2 × 2 rectangular averaging filter.

2.4.2 Aspect ratio

The aspect ratio is defined as the ratio of physiological length Lp to physiological width Wp, thus Lp/Wp.

2.4.3 Form factor

This feature is used to describe the difference between a leaf and a circle. It is defined as 4πA/P2, where A is the leaf area and P is the perimeter of the leaf margin.

2.4.4 Rectangularity

Rectangularity describes the similarity between a leaf and a rectangle. It is defined as LpWp/A, where Lp is the physiological length, Wp is the physiological width and A is the leaf area.

2.4.5 Narrow factor

Narrow factor is defined as the ratio of the diameter D and physiological length Lp, thus D/Lp.

2.4.6 Perimeter ratio of diameter

Ratio of perimeter to diameter, representing the ratio of leaf perimeter P and leaf diameter D, is calculated by P/D.

2.4.7 Ratio of perimeter to physiological length and width

This feature is defined as the ratio of leaf perimeter P and the sum of physiological length Lp and physiological width Wp, thus P/ (Lp + Wp).

2.4.8 Vein features

To perform the morphological opening on grayscale image with flat, disk-shaped structuring element of radius 1,2,3,4 and subtract remained image by the margin. The results look like the vein. That is why following 5 feature are called vein features. Areas of left pixels are denoted as Av1, Av2, Av3 and Av4 respectively.

Then we obtain the last 5 features:

1) Av1/A,
2) Av2/A,
3) Av3/A,
4) Av4/A,
5) Av4/Av1.

2.5 Principal Component Analysis

Principal Component Analysis (PCA) is a statistical method that the main goal is to reduce dimension of data.

To reduce the dimension of input vector of neural network,PCA is used to orthogonalize 12 features. The purpose of PCA is to present the information of original data as the linear combination of certain linear irrelevant variables. Mathematically, PCA transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate, the second greatest variance on the second coordinate, and so on. Each coordinate is called a principal component.

The algorithm of PCA is described as follow .

1. Calculate the mean of data and store to u:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$

2. Subtract all data with u:

$$(\bar{x} \leftarrow x - \mu).$$

3. Calculate the covariance of the data

$$\mathrm{cov}(x,y) = \frac{\sum_{i=1}^{n}(x_i - \mu)(y_i - \mu)}{n-1}$$

4. Calculate the eigenvalues and the eigenvectors based on the covariance matrix
5. Calculate the new data set by using the following formula:
   s= (data(x)-mean(x))*coefficient(x,y);

2.6 Probabilistic Neural Network

An artificial neural network (ANN) is an interconnected group of artificial neurons simulating the thinking process of human brain. One can consider an ANN as a "magical" black box trained to achieve expected intelligent process, against the input and output information stream. Thus, there is no need for a specified algorithm on how to identify different plants. PNN is derived from Radial Basis Function (RBF) Network which is an ANN using RBF. RBF is a bell shape function that scales the variable nonlinearly. PNN is adopted for it has many advantages. Its training speed is many times faster than a BP network. PNN can approach a Bayes optimal result under certain easily met conditions. Additionally, it is robust to noise examples. We choose it also for its simple structure and training manner. The most important advantage of PNN is that training is easy and instantaneous. Weights are not "trained" but assigned. Existing weights will never be alternated but only new vectors are inserted into weight matrices when training. So it can be used in real time. Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast.

The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers:

1)Input layer,
2) Radial Basis Layer and
3) Competitive Layer.

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. Then the Competitive Layer finds the shortest distanceamong them, and thus finds the training pattern closest to the input pattern based on theirDistance.

2.6.1 Input Layer

The input vector, denoted as p, is presented as the black vertical bar in Fig. 2.5Its dimension is R × 1.

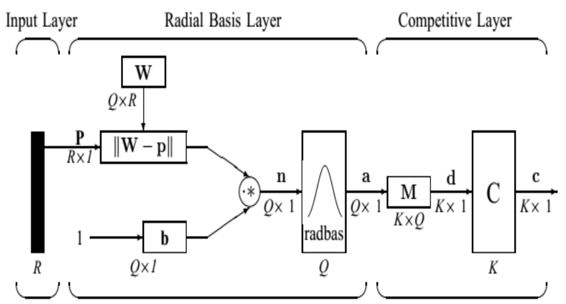


Figure 2.5: PNN Network Structure.

2.6.2 Radial Basis Layer

In Radial Basis Layer, the vector distances between input vector p and the weight vector made of each row of weight matrix W are calculated. Here, the vector distance is defined as the dot product between two vectors. Assume the dimension of W is Q × R. The dot product between p and the i-th row of W produces the i-the element of the distance vector ||W − p||, whose dimension is Q × 1, as shown in Fig. 5. The minus symbol, "–", indicates that it is the distance between vectors.Then, the bias vector b is combined with ||W − p|| by an element-by-element multiplication, represented as "·∗ " in Fig. 2.5 The result is denoted as

$$n = ||W - p|| \cdot *p.$$

The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, we define it as

$$radbas(n) = e^{-n^2} \quad (2)$$

Each element of n is substituted into Eq. 2 and produces corresponding element of a, the output vector of Radial Basis Layer. We can represent the i-th element of a as

$$a_i = radbas(||\mathbf{W}_i - \mathbf{p}|| \cdot *\mathbf{b}_i) \quad (3)$$

Where Wi is the vector made of the i-th row of W and bi is the i-th element of bias vector b.

2.6.3 Some characteristics of Radial Basis Layer

The i-th element of an equals to 1 if the input p is identical to the i-th row of input weight matrix W. A radial basis neuron with a weight vector close to the input vector p produces a value near 1 and then its output weights in the competitive layer will pass their values to the competitive function which will be discussed later. It is also possible that several elements of a are close to 1 since the input pattern is close to several training patterns.

2.6.4 Competitive Layer

There is no bias in Competitive Layer. In Competitive Layer, the vector a is firstly multiplied with layer weight matrix M, producing an output vector d. The competitive function, denoted as C in Fig. 2.5, produces a 1 corresponding to the largest element of d, and 0's elsewhere. The output vector of competitive function is denoted as c. The index of 1 in c is the number of plant that our system can classify. It can be used as the index to look for the scientific name of this plant. The dimension of output vector, K, is 32 in this paper.

2.7 Crop Disease Detection

First, the images of various leaves are acquired using a digital camera. Then image-processing techniques are applied to the acquired images to extract useful features that are necessary for further analysis.

The step-by-step procedure of the proposed system:

1) RGB image acquisition
2) Masking the green-pixels
3) Removal of masked green pixels
4) Segment the components
5) Obtain the useful segments
6) Computing the texture features using colour-Co-Occurrence methodology

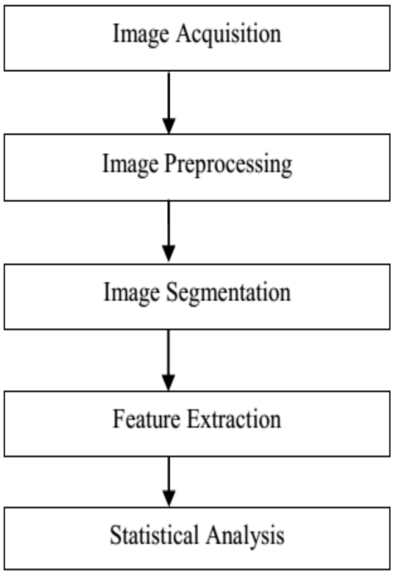


Figure 2.6: Crop disease detection.

2.7.1 RGB Image Acquisition

First, the images of various leaves are acquired using a digital camera. The images are in the RGB format.

2.7.2 Masking and Removing of green pixels

Masking means setting the pixel value in an image to zero or some other background value. In this step, normally human beings can identify the mostly green colored pixels. After that, based on specified threshold value that is computed for these pixels. The green components of the pixel intensities are set to zero if it is less than the pre-computed threshold value. Then red, green and blue components of the pixel are assigned to a value of zero by mapping of RGB components.The green colored pixels mostly represent the healthy areas of the leaf and they do not add any valuable weight to disease identification.

2.7.3 Segmentation

From the above steps, the infected portion of the leaf is extracted. The leaf region is then segmented into a number of patches of equal size. The patches are overlapping patches. In this approach patch size of 32X32 is taken .

2.7.4 Obtaining Useful Segments

In this step the useful segments are obtained. The size of the patch is chosen in such a way that the significant information are not lost. Not all segments contain significant amount of information. So the patches which are having less than fifty percent of the information are set to zero value and the patches which are having more than fifty percent of the information are taken into account for the further analysis.finally segmented image is formed.

2.7.5 Colour co-occurrence method

The colour co-occurrence texture analysis method is developed through the SGDM. The gray level co-occurrence methodology isa statistical way to describe shape by statistically sampling the way certain gray-levels occur in relation toother gray levels.These matrices measure the probability that a pixel at one particular gray level will occur at a distinct distance and orientation from any pixel given that pixel has a second particular gray level. The SGDM's are represented by the function P (i, j, d, θ) where I represent the gray level of the location (x, y), and j represents the gray level of the pixel at a distance d from location (x, y) at an orientation angle of θ. SGDM's are generated for H image.

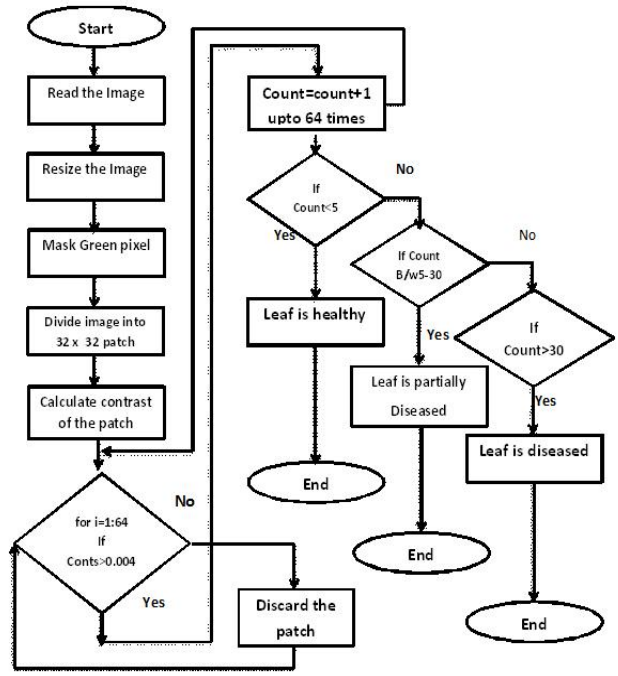
Spatial Gray-level Dependence Matrices (SGDM) method is a way of extracting statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i, j \mid \Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance $(\Delta x, \Delta y)$ occur within a given neighborhood, one with intensity i and the other with intensity j.

2.7.6 Texture Features

Properties of Spatial Gray-level Dependence Matrices (SGDM) like Contrast, Energy, Local homogeneity, correlation ,cluster shed, cluster prominence are computed for the Hue content of the image as given in following Eqns..

3 IMPLEMENTATION

The following section deals with the algorithm used for the program, identification and disease detection of a leaf.



The captured image is first resized and the green pixels of the leaf are masked. The green pixel masked image is divided into 32X32 patches. The contrast of the patch is calculated. The count can be increased upto 64 times.If the count is less than 5 then the leaf is said to be healthy. If the count is between 5 to 30, then the leaf is said to be diseased partially. If the count is greater than 30, the leaf is diseased.

4 ADVANTAGES FUTURE WORK

1) PNN Algorithm is speed & efficient compared to k-nearest neighbour (k-NN) & MMC hyper sphere classifier.
2) Black Spot disease is identified in various types of leaves.
3) If we set a database for endangered plant species, then it is easy to identify & protect those plants.
4) We can identify plant species without requiring the expertise of botanists.
5) Photo'ing of leaf can be done in any direction.

Since the essential of the competitive function is to output the index of the maximum value in an array, we plan to let this algorithm output not only the index of maximum value, but also the indices of the second greatest value and the third greatest value. It is based on this consideration that the index of the second greatest value corresponds to the second top matched plant. So does the index of the third greatest value. Sometimes, maybe the correct plant is in the second or the third most possible plant. So all the three values can be provided to user.

5 CONCLUSION

The computer can automatically classify 6 kinds of plants via the leaf images loaded from digital cameras or scanners. PNN is adopted for its speed on training and simple structure. Compared with other methods, this algorithm is fast in execution, efficient in recognition and easy in implementation.

Proposed leaf analysis algorithm is tested on all recognized leaves. The experimental results indicate that the proposed approach is a valuable approach, which can significantly support an accurate detection of leaf diseases in a little computational effort. Future work is under consideration to improve it.

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