

Botanical Biometrics using Artificial Neural Networks based Pattern Classification of Plant Species.

Shardul S. Thakre, Amitkumar V. Wankhede

Abstract— We present a neural network-based pattern classification system. A rationally connected neural network examines small windows of an image, and classifies the leaf into its particular species. This eliminates the difficult task of manually selecting non-mango image training examples, which must be chosen to span the entire space of non-mango images. it is based on the geometrical and morphological features of the leaf but not the texture of the leaf in the image.

Index Terms—Morphological Features, Artificial neural network, receiver operating characteristic, performance plot, training state.

I. INTRODUCTION

India is an agriculture based country. Its economy is solely dependent on agriculture. The food inflation is a national challenge. Scientists, agriculturists work day and night to promote the yield of food grains. It is very difficult to infer the varieties of a plant species by simple visual observation. It is very time consuming and can be accomplished by the trained botanists [1-2].

In this paper, we present a neural network-based algorithm to detect frontal views of the leaf images in gray-scale images. The algorithm works by applying one neural network directly to portions of the input image, and arbitrating their results. The network is trained to output the presence or absence of the trained leaf image. The algorithms and training methods are designed to be general, with little customization for leaf images. MATLAB has been used for implementation of this research.

The images can be characterized by probabilistic models of the set of leaf images or implicitly by neural networks or other mechanisms. The parameters for these models are adjusted either automatically from example images (as in our work) or by hand. Training a neural network for the image detection task is challenging because of the difficulty in characterizing prototypical “Non-Mango-Leaf” images.

In our work we have tried to identify the varieties of mango plant. Mango (*Mangifera indica* L.) is considered as the king of fruits due to its nutritional value and taste. Mango trees

have a large no. of varieties ranging from Alphonso to Amrapali.

II. PROPOSED SYSTEM

This system operates in three stages:

In the First stage, the given Colored image is converted to the Edge-detected image. This stage involves four steps: the Colored image is converted to gray-scale image, which is then converted to a Median Filtered image, this image is then converted to the Binary image and finally it is converted to an Edge-detected image [8-9].

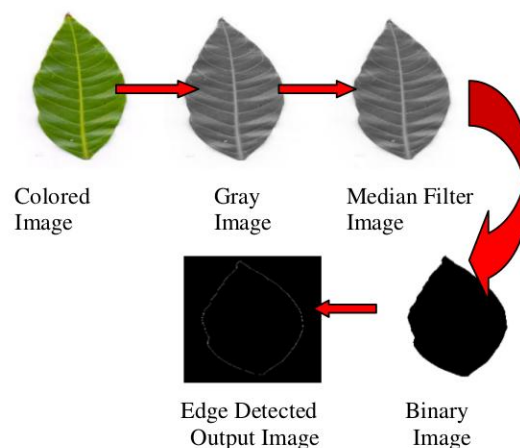


Fig -1: Colored image converted to Edge-detected image.

In the Second stage, the calculation of the Leaf Features (viz. Length, width, area and so on) and the Statistical Features (viz. Entropy, Homogeneity and so on.) is processed [7]. This stage defines the complete leaf. All the calculated factors are stored in the matrix, which is further used for system training and classification.

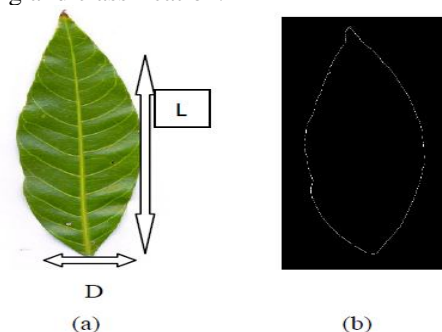


Fig -2: Sample Morphological features.

Manuscript received Oct, 2015.

Shardul S. Thakre, Dept. of Computer Science and engineering, Shri Guru Gobind Singhji Institute of Engineering, and Technology, Nanded, Nanded, India, 8097158723

Amitkumar V. Wankhede, Dept. of Computer Science and engineering, Shri Guru Gobind Singhji Institute of Engineering, and Technology, Nanded, Nanded, India, 7406060003

In the Third stage, we use the neural network training tool for system training and classification. This stage gives us a Confusion Matrix which shows us the result of training.

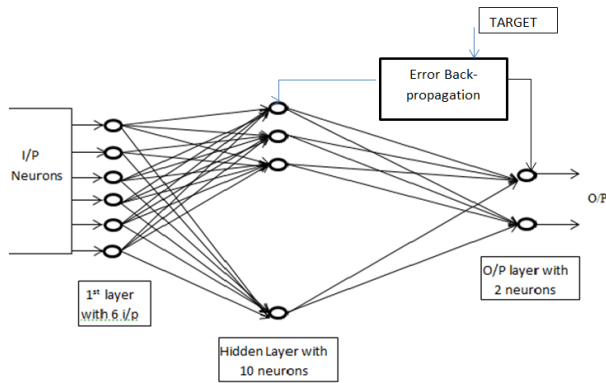


Fig -3: Artificial neural network with Back propagation.

III. METHODOLOGY

A. Feature Extraction

Plants are basically identified according to their morphological and geometrical features of their leaves [5-6]. These features of leaves are captured with the data acquisition system e.g. Digital scanner or a Digital camera. The acquired image is processed by digital Image processing technique. Brief accounts of the two significant leaf features are detailed below.

Geometrical and Morphological Features:

The geometrical features are associated with the shape of the leaves such as length, width, aspect ratio and so on.

Leaf length: In the Fig.-2 (a), the length, L of the leaf is the distance between the points A and B.

```
'function length=findlength(cleanimage)
st=regionprops(cleanimage,'MajorAxisLength');
length=st.MajorAxisLength;'
```

Above is the function used to get the length of the leaf.

Leaf width: The maximum horizontal distance between the two points C and D laying on the edge of the leaf is considered as the width, W of the leaf.

```
'function width=findwidth(cleanimage)
st=regionprops(cleanimage,'MinorAxisLength');
width=st.MinorAxisLength;'
```

Above is the function used to get the width of the leaf.

Aspect ratio: It is defined as the ratio of length, L to the width, W of the leaf. Thus L/W is the aspect ratio.

```
'function aspectratio=asratio(length,width)
aspectratio=length/width;'
```

Above is the function used to get the aspect ratio of the leaf.

Area: The area of the leaf is calculated by counting the no of pixels of binary value 1 on smoothed leaf image and it is denoted by A [7].

```
'function area=findarea(cleanimage)
[i,j]=size(cleanimage);
area=0;
for x=1:i
for y=1:j
if(cleanimage(x,y))
```

```
area=area+1;
end
end
end'
```

Above is the function used to get the area of the leaf.

Perimeter: The leaf perimeter, P is calculated by evaluating the total no. of pixels present on the leaf margin.

```
'function perimeter=findperimeter( edgedetectedoutput)
[i,j]=size( edgedetectedoutput);
perimeter=0;
for x=1:i
for y=1:j
if( edgedetectedoutput(x,y))
perimeter=perimeter+1;
end
end
end'
```

Above is the function used to get the Perimeter of the leaf.

Form factor: This feature is used to describe the difference between a leaf and a circle. It is defined as $FF = 4\pi A/P^2$, where A is the area of the leaf with P being its perimeter [7].

```
'function formfactor=findformfactor(area,perimeter)
formfactor=(area)/(perimeter^2);'
```

Above is the function used to get the Form Factor of the leaf.

Statistical Features:

Entropy: If an image has G gray levels and probability of gray level k is P(k) then the entropy H, not considering correlation of gray levels is defined as

```
'E=entropy(grayimage);
Ent=mu2str(E);'
```

$$H = - \sum_{k=0}^{G-1} P(k) \log[P(k)] \quad (1)$$

2. **Contrast:** A measure of the intensity contrast between a pixel and its neighbor over whole image. Contrast is zero for a constant image.

```
'glcm=graycomatrix(grayimage);
Stats=raycoprops(glcm,{'contrast'});
Contrast=stats(1).Contrast;
Cont=num2str(contrast);'
```

$$C = \sum_{i,j} |i - j|^2 P(i, j) \quad (2)$$

3. **Homogeneity:** In, a measure of local homogeneity has been used in one-dimensional histogram thresholding. The homogeneity consists of two parts: the standard deviation and the discontinuity of the intensities at each pixel of the image. The standard derivation S_{ij} at pixel P_{ij} can be written as:

```
'homo=graycoprops(glcm,{'homogeneity'});
Homogeneity=homo(1).Homogeneity;
H=mu2str(homogeneity);'
```

$$S_{ij} = \sqrt{\frac{1}{n_w} \sum_{l_w, w_d} P(ij) (l_w - m_{ij})^2} \quad (3)$$

Where m_{ij} is the mean of n_w intensities within the window $P(i,j)$, which has a size of d by d and is centered at P_{ij} . A measure of the discontinuity D_{ij} at pixel P_{ij} can be written as:

$$D_{ij} = \sqrt{(G_x^2 + G_y^2)} \quad (4)$$

Where, G_x and G_y are the gradients at pixel P_{ij} in the x and y direction. Thus, the homogeneity H_{ij} at P_{ij} can be written as:

$$H_{ij} = 1 - \left(\frac{S_{ij}}{S_{max}}\right) \times \left(\frac{D_{ij}}{D_{max}}\right) \quad (5)$$

From the equation (5), we can see that H value ranges from 0 to 1.

B. Artificial Neural Network and Training

Artificial Neural Network (ANN) is a powerful general purpose software tool used for number of data analysis such as prediction, classification and clustering and so on [3]. An ANN consists of a set of processing elements, also known as neurons or nodes, which are interconnected. It can be described as a directed graph in which each node k performs a function f_k of the form

$$y_k = f_k \left(\sum_{j=1}^p w_{kj} x_j - \theta_k \right) \quad (7)$$

Where z_k is the output of the node k , y_j is the j th input to the node and x_{kj} is the connection weight between nodes k and j . θ_k is the threshold (or bias) of the node. Usually f_k is nonlinear, such as a Heaviside, sigmoid, or Gaussian function.

In equation (7), each term in summation only involves one input y_j . Higher-order ANN's are those that contain higher-order nodes, i.e. nodes in which more than one input are involved in some of the terms of the summation. For example, a second-order node can be described as

$$y_k = f_k \left(\sum_{i=1}^p w_{kji} x_j x_i - \theta_k \right) \quad (8)$$

Where, all the symbols have similar definitions as on equation no (7).

C. Defining Architecture of Neural Network

For the current problem we define a neural network with one input layer, one hidden layer and one output layer. The input layer encodes a sliding window in each input features extracted from the Mango Leaf. Each window position is encoded using a binary array of size 20, having one element for each input type. In each group of 20 inputs, the element corresponding to the input type in the given position is set to 1, while all other inputs are set to 0. Thus, the input layer

consists of $R = 6 \times 20$ input units, i.e. 6 groups of 20 inputs each.

The output layer of our neural network consists of two units, one for each of the considered structural states (or classes), which are encoded using a binary scheme. To create the target matrix for the neural network, we first obtain, from the data, the structural assignments of all possible subsequences corresponding to the sliding window. Then we consider the central position in each window and transform the corresponding structural assignment using the following binary encoding: 1 0 for Mango Leaf and 0 1 for Other Leaf.

D. Training the Neural Network

The pattern recognition network uses the default Scaled Conjugate Gradient algorithm for training, but other algorithms are available (see the Neural Network Toolbox documentation for a list of available functions). At each training cycle, the training sequences are presented to the network through the sliding window defined above, one row at a time. Each hidden unit transforms the signals received from the input layer by using a transfer function 'logsig' to produce an output signal that is between and close to either 0 or 1, simulating the firing of a neuron. Weights are adjusted so that the error between the observed output from each unit and the desired output specified by the target matrix is minimized.

During training, the training tool window opens and displays the progress. Training details such as the algorithm, the performance criteria, the type of error considered, etc. are shown [10].

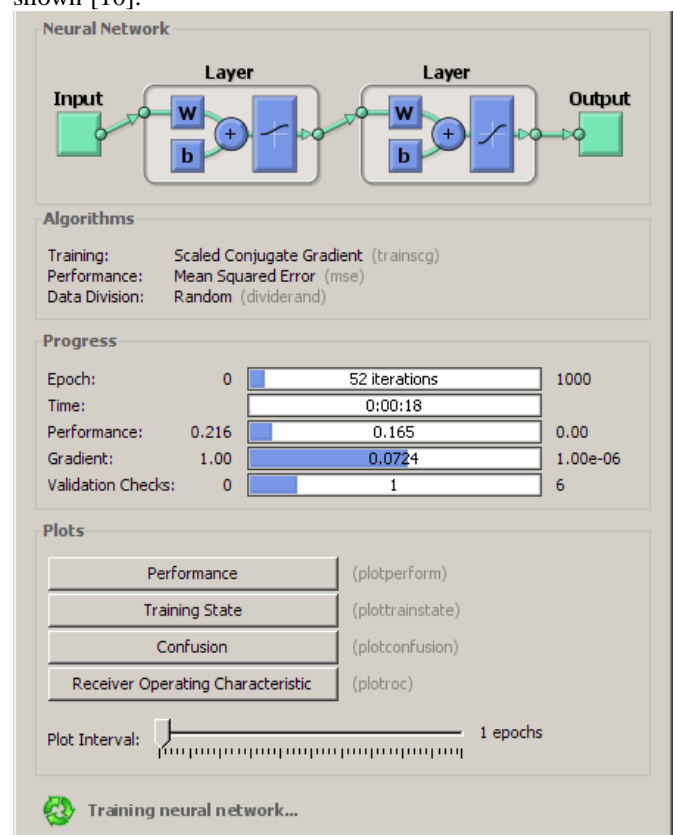


Fig -4: Training of Neural Network.

One common problem that occurs during neural network training is data over fitting, where the network tends to memorize the training examples without learning how to

generalize to new situations. The default method for improving generalization is called early stopping and consists in dividing the available training data set into three subsets:

- (i) The training set, which is used for computing the gradient and updating the network weights and biases;
- (ii) The validation set, whose error is monitored during the training process because it tends to increase when data is over fitted;
- (iii) The test set, whose error can be used to assess the quality of the division of the data set.

IV. RESULTS AND ANALYSIS

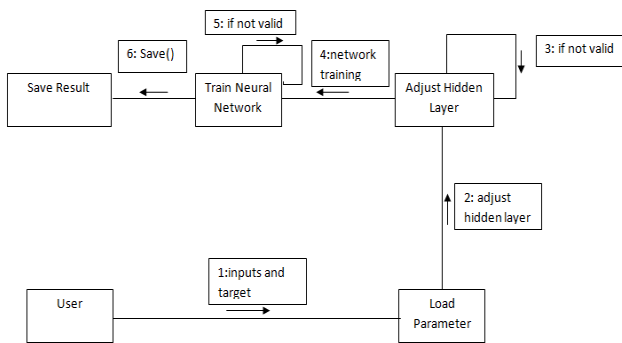


Fig -5: Data flow in the neural network.

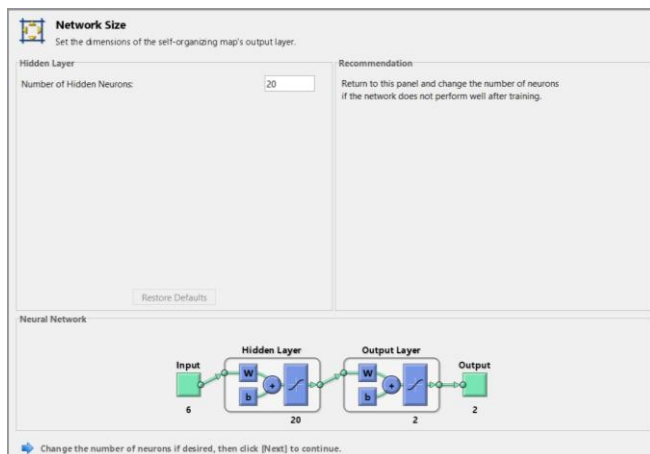


Fig -6: Artificial neural network.

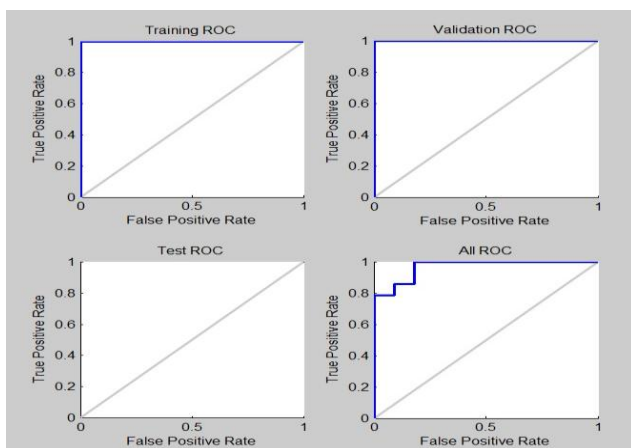


Fig -7: Receiver Operating Characteristic

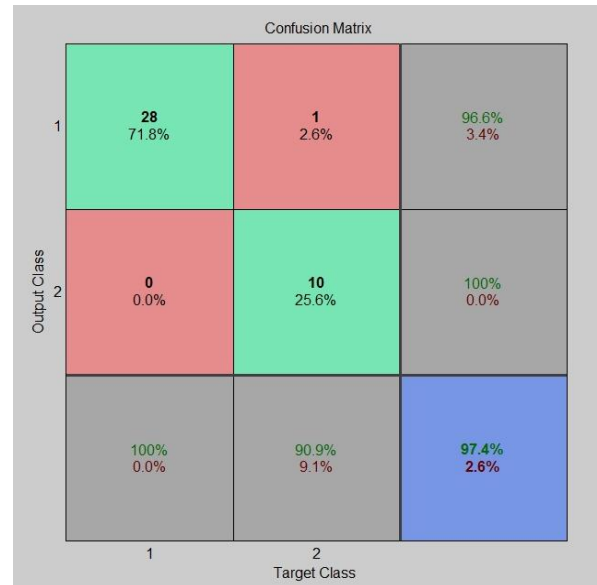


Fig -8: Confusion Matrix

As the training ends, the **Confusion matrix** (Fig -8) and the **Receiver Operating Characteristics** (ROC -- Fig -7) show us the result of the training and the degree of correctness of the given input [10].

To analyze the network response, we examine the **confusion matrix** by considering the outputs of the trained network and comparing them to the expected results (targets). The diagonal cells show the number of input leaves that were correctly classified for each structural class. The off-diagonal cells show the number of residue positions that were misclassified. The blue cell shows the total percentage of correctly predicted Mango Leaf (in green) and the total percentage of incorrectly predicted Mango Leaf (in red).

We can also consider the **Receiver Operating Characteristic** (ROC) curve, a plot of the true positive rate (sensitivity) versus the false positive rate (1 - specificity). The Receiver Operating Characteristic is a metric used to check the quality of classifiers. For each class of a classifier, *roc* applies threshold values across the interval [0, 1] to outputs. For each threshold, two values are calculated, the True False Ratio (the number of outputs greater or equal to the threshold, divided by the number of one targets), and the False Positive Ratio (the number of outputs less than the threshold, divided by the number of zero targets).

V. CONCLUSION

In this paper the image processing technique and artificial neural network approach is used for the classification of the four varieties of mango leaves. The neural network is trained by 80 samples of mango leaves and it is then tested by an additional 20 unknown sample of mango leaves. Out of 20 test sample 15 are correctly classified while remaining 5 samples could not be classified by the system. The reasons for the miss classification could be probably the closed approximation of geometrical of morphological feature of the other kinds.

After testing it is found that their geometrical features are very close to those work is under consideration to improve the performance with a larger variety of mangoes. We are also trying to extract the color feature from the mango leaves

so that the classification can be done on the basis of color component also

ACKNOWLEDGMENT

We would like to express our gratitude to all those who helped us to complete this work. We want to thank our guide **Mr. Chavan R. K.** for his continuous help and generous assistance. He helped in a broad range of issues from giving us direction, helping to find the solutions, outlining the requirements and always having the time to see us.

We have furthermore to thank **Mr. Nalwade P S**, Head of the Department of Computer Science & Engineering, to encourage us to go ahead and for continuous guidance.

We would like to thank our friend Mr. Hambarde S. for his help in providing us the raw material specifically the leaves required for the system training of project. We would like to thank our colleagues who helped us time to time from preparing report and giving good suggestions. We also extend sincere thanks to all the staff members of Department of Computer Science & Engineering for helping us in various aspects. Last but not least we are grateful to our parents for all their support and encouragement.

REFERENCES

- [1] Jiazhi Pan, Yong He, "Recognition of plant by leaves digital image and neural network", International conference on Computer Science and Software Engineering, Vol. 4, pp. 906-910, December 2008.
- [2] Caner Uluturk, Aybars Ugur, "Recognition of Leaves based on Morphological Features Derived From Two Half – Regions", International Symposium on Innovation in Intelligent Systems and Application (IN ISTA), pp. 1-4, 2-4 July, 2012.
- [3] Dr. Jacek M. Zurada "Use Artificial Neural Network for Images", IEEE transaction on Image Processing, Vol 8, No. 02 Sep 2005 Page No. 145-167.
- [4] Suhas S Gajre, Mahesh B. Kokare, "Content Based Image retrieval of Biomedical images", IEEE transaction on Biomedical Imaging, Vol 34 NO.12 Dec 2007, Page No.106-112.
- [5] Jyotismita Chaki, Ranjan Parekh, "Plant Leaf Recognition using Shape Based Features and Neural Network Classifiers", International Journal of Advanced Computer Science and Application (IJACSA), Vol.2 , No. 10, 2011.
- [6] A Gopal, S. Prudhveeswar Reddy , V. Gayatri, "Classification of Selected Medicinal Plants Leaf using Image Processing", International conference on Machine Vision and Image Processing (MVIP), pp. 5-8, 14-15 Dec, 2012.
- [7] Stephen Gang Wu, Forrest Sheng Bao, Eric You Xu, "A leaf Recognition Algorithm for Plant classification Using Probabilistic Neural Network", 7th IEEE International conference on signal Processing and Information Technology, Dec 2007.
- [8] A. K. Jain, Fundamental of Digital Image processing, Pearson Education, 2nd edition, 2004.
- [9] R.C. Gonzalez, R.E. Woods, "Digital image processing", Pearson Education India, Third Edition, 2002.

[10] The Math Works Inc, Neural Networks Toolbox User's Guide, 2010.

Shardul S. Thakre - B.Tech Computer Science and Engineering, SGGSIET, Nanded. Currently working as a software engineer with a private firm an information analytics and security. Worked on various projects of image processing and Internet of Things.

Amitkumar V. Wankhede - B.Tech Computer Science and Engineering, SGGSIET, Nanded. Currently working as a software engineer with a private firm as a Java developer.