Adaptive Neuro-fuzzy Inference System for Recognition of Cotton Leaf Diseases

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Abstract— **The objective of this work was to develop and to evaluate adaptive neuro-fuzzy inference system as methodology to identify the leaf diseases on cotton. This paper presents automatic system for classification of three cotton leaf diseases namely Bacterial Blight, Myrothecium and Alternaria. Graph cut method is used for segmentation of images to extract color layout descriptors as features to train the adaptive fuzzy inference system. The testing samples are collected from Central Institute for Cotton Research, Nagpur and from the fields in Buldana and Wardha district.**

Index Terms— **Cotton leaf diseases, Gaussian filter, Image segmentation, Graph cut, Color layout descriptors.**

I. INTRODUCTION

Indian economy is agriculture based and it is the main source of rural livelihood. Cotton being an important crop has major impact on Indian economy. Cotton has contributed about 14% to the industrial production, 4% to the GDP and 14.42% to the country's export earnings as per the data of 2011. To increase productivity and improvement in quality Government of India launched a scheme called Technology Mission on Cotton in 2000.

The cotton plants suffer from diseases that can drastically affect the quantity and quality of the yield. Usually the detection and identification of cotton leaf diseases is performed by farmers by naked eye observation [4]. It leads to incorrect diagnosis as the farmer's judge the symptoms by their experience. This will also cause needless and excess use of costly pesticides. Therefore the automatic detection of disease is important which will help in early and accurate diagnosis of cotton leaf diseases [5].

II. COTTON LEAF DISEASES

The leaf diseases under study are Bacterial Blight, Myrothecium and Alternaria. The symptoms of these diseases are as:

Bacterial Blight 	Initially many minute water soaked angular spots scattered on the ventral surface of leaves appeared. These spots turn brown and then converted into black dead lesions on both sides of the leaf. The spots on the infected leaves may spread along the major veins of the leaf and turn them brown or black. This symptom is called as "Black vein".
Myrothecium 	Initially circular to semicircular light brown to tan colored spots appear, having violet to reddish brown borders. Shield shaped small fruiting bodies are develop in the central part of the disease spot. When the center gets dry holes appear in the leaves, eventually the leaves fall [8].
Alternaria 	The disease is most severe on lower leaves as compare to upper leaves. Initially small circular brown, grey-brown to tan colored spots of size varying from 1-10mm appear on leaves. In the later stages, these spots enlarge and concentric rings and cracked centre develops. Severe infection causes drying and falling of leaves. The disease spots may get confused with the spots of Bacterial leaf blight.

III. LITERATURE REVIEW

Automatic system for detection and classification of plant diseases was proposed using K-means clustering technique for segmentation and back propagation algorithm for classification to get the average efficiency of 94.67% in 2011[6]. The system for identification of Ramularia disease, Bacterial Blight, Ascochyta Blight on cotton crop was developed in which input image is decomposed in various color channels like *R*, *G*, *B*, *H*, *S*, *V*, *I3a*, *I3b*, and grey levels then DWT is applied to each color channel and the wavelet energy is computed for each sub-band and compose the feature vectors. Support Vector Machine is used for classification [13]. Identification and classification of grey mildew, bacterial leaf blight, leaf curl, alternaria leaf diseases on cotton was performed using edge features and RGB pixel counting features [10]. An image recognition system for identification of diseases like Rice blast, Ricesheath blight and Brown spot in paddy fields of Sri Lanka was proposed in which Sobel method is used to detect the edges of the image and Texture, shape and color feature disease spot are extracted which are used for classification. The accuracy of the system was 80% for Rice blast, 60% for Rice sheath blight and 85% for Brown spot [11]. The model for identification of diseases such as Mosaic virus, Rust and Leaf spot on apple leaf was proposed.The images are acquired using Canon IXUS 850IS digital camera in natural lighting conditions. The color and texture features of diseased apple leaf were extracted. The kernel principal component analysis (KPCA) based feature selection is performed to identify the best features. The classification model based KPCA and GA-SVM has found to have higher classification efficiency than the model based on PCA and GA-SVM [9].

IV. THE PROPOSED APPROACH

The concept for any vision related approach for image classification remains alike as shown in Figure1. Initially the digital images are acquired using a digital camera. Then image preprocessing techniques are applied to these images to smooth the images. The object of interest from the image is separated by using the segmentation method and the features extracted are analyzed to determine the discriminating features. The neural network used for classification is trained with the help of features of the training data set. The images of the testing data set are used to determine accuracy of the system.

V. IMAGE ACQUISITION

The images required for the experimentation are acquired by using Cannon A460 digital camera and Leica Wild M3C stereo zoom microscope. Other set of images was captured using EOS550D digital SLR camera of 18 Megapixel and 18-55mm lens kit in the natural conditions. The testing samples of the images are taken from fields at Central Institute for Cotton Research Nagpur, cotton fields in Buldana and Wardha district

V. IMAGE ENHANCEMENT

The acquired images are sharpened by using unsharp filter. It enhances edges (and other high frequency components in an image) by subtracting an unsharp version of an image from the original image. The process is shown in Figure 2.

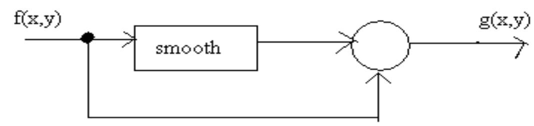


Figure 2 Image filtering using unsharp filter

The function 'fspecial' creates the unsharp filter from the negative of the Laplacian filter with parameter alpha. The selected value for alpha is 0.2. These images are segmented using graph cut method.

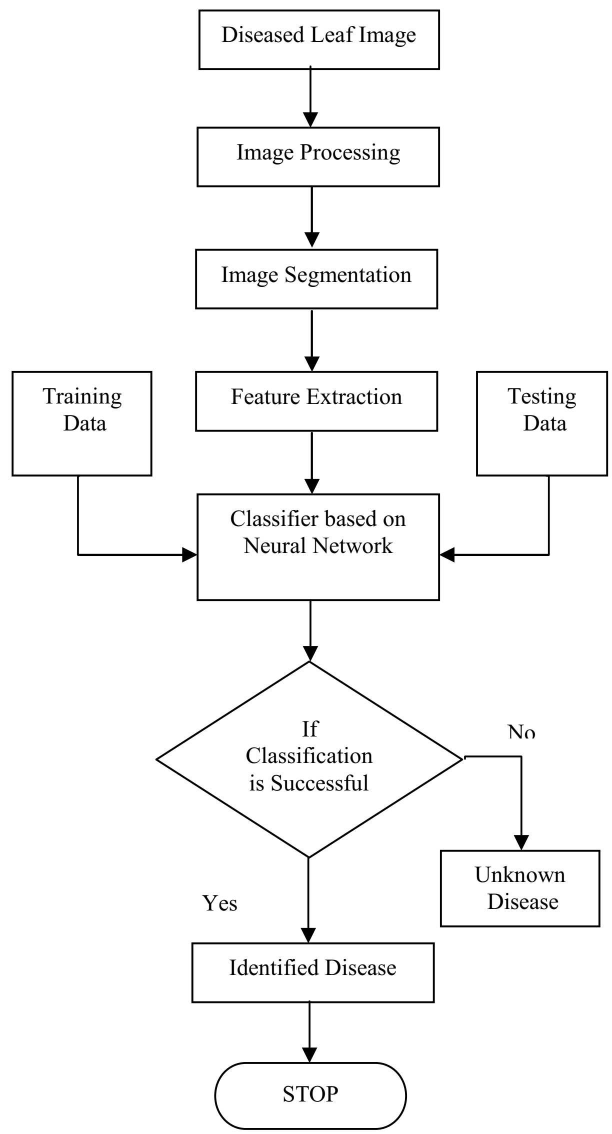


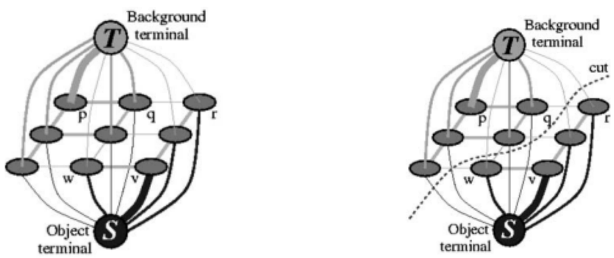
Figure1. The flowchart of proposed approach

VI. IMAGE SEGMENTATION

A graph G = (V, E) is a set of nodes or vertices V and a set of edges E connecting “neighboring” nodes. In the undirected graphs each pair of connected nodes is described by a single edge e = {p, q} ∈ E. The nodes of graph represent image pixels. There are two special terminal nodes called as S (source) and T (sink) which represent “object” and “background”as shown in Figure 4.

A: Seed points in Image B: Segmentation result

Figure3. Segmentation process



Graph Cut

Figure 4 Graph cut Segmentation

The neighboring pixels are interconnected by edges (which are called as n-links) in a regular grid-like fashion. The edges used to connect pixels to terminals are called as t-links. All graph edges including n-links and t-links are assigned non-negative weight. In the above fig the edge weights are indicated by their thickness. The edge weight between pixel i and j will be denoted by W^I_{ij} and the terminal weights between pixel i and the source (s) and terminal (t) as W^S_i and W^T_i respectively and are given by (1), (2) and (3).

$$W^I_{ij} = e^{\left(-\frac{r(i,j)}{\sigma R}\right)} e^{\left(-\frac{\|w(i)-w(j)\|}{\sigma W}\right)} \tag{1}$$

$$W^S_i = \frac{p(w(i)|i \in s)}{p(w(i)|i \in s) + p(w(i)|i \in t)} \tag{2}$$

$$W^T_i = \frac{p(w(i)|i \in t)}{p(w(i)|i \in s) + p(w(i)|i \in t)} \tag{3}$$

An s-t cut is a subset of edges such that the terminals S and T become completely separated by the induced graph. A cut divides the nodes between the terminals. It performs binary partitioning of an underlying image into “object” and “background” segments. The intialisation and result of segmentation is shown in Figure 3. In the above equations ‖ . ‖ denotes the euclidian norm, r (i; j) the distance between pixel i and j and λ, σ_R, and σ_W are tuning parameters weighing the importance of the different features. Hence, W^I_{ij} contains the inter-pixel similarity, that ensures that the segmentation more coherent. W^S_i and W^T_i describes the probability that a pixel belongs to background and foreground respectively. The sample of Myrothecium infected cotton leaf is shown in Figure 5, the image during intermediate stages are shown in Figure 6 and Figure 7, the segmented image is shown in Figure 8.

Initially RGB image is converted to grey image. Kmean clustering is used to partition the input image into two clusters. It is used to minimize the sqEuclidean distance between point and the centroid of cluster. The empty clusters are removed by using parameters ‘emptyaction’ and ‘drop’. The maximum numbers of iterations are set to default value of one hundred. Then graph segmentation is performed to isolate disease spot using RBF kernel. At the end again grey to RGB conversion is performed for display.

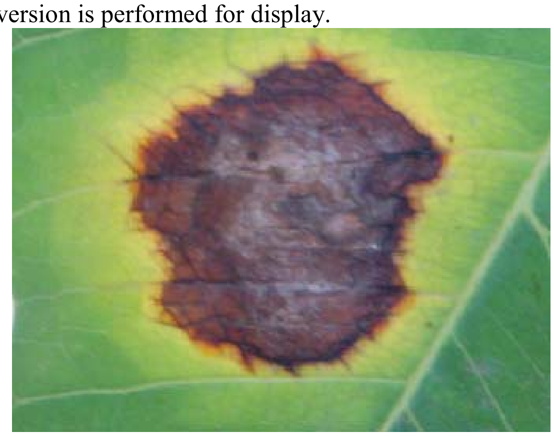


Figure 5 Original Image

Figure 6 Processed Image

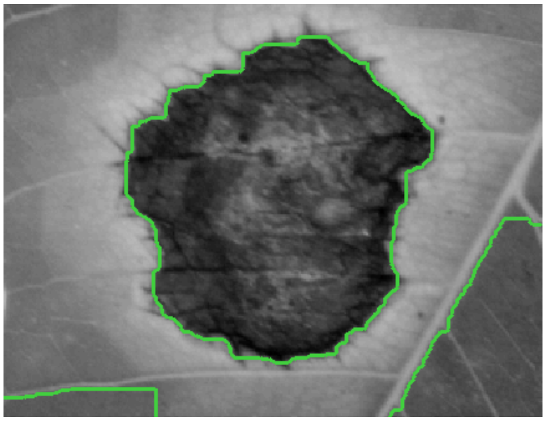


Figure 7 Processed Image

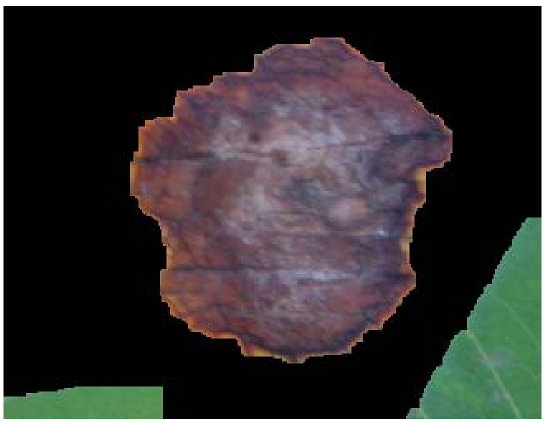


Figure 8 Segmented Image

VII. FEATURE EXTRACTION

Color feature extraction:

The color layout descriptor is a very compact and resolution-invariant representation of color. It efficiently represents the spatial distribution of colors and therefore used for a wide variety of similarity-based retrieval. The extraction process of color descriptor consists of four stages: Image partitioning, Representative color selection, DCT transformation and Zigzag scanning.

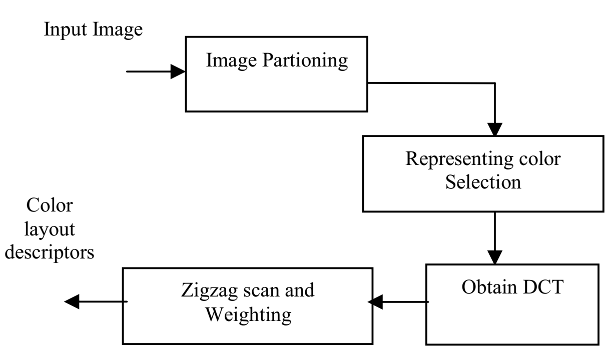


Figure 9 Feature extraction

In the image partitioning stage, the input picture in RGB color space is divided into 64 blocks. Then the average of the pixel color in the block is selected as the representative color for that block. The result is an image of size 8×8 to which color space conversion is applied to convert the image from RGB to YcbCr color space. Next 8×8 DCT is applied to obtain three sets of 64 coefficient for luminenceY, crominance for blue and red color each. To calculate DCT the formule given by (4), (5) and (6) are used.

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N} \qquad (4)$$

$$0 \le p \le M\text{-}1 \text{ and } 0 \le q \le N\text{-}1$$

where

$$\alpha_p = \begin{cases} \frac{1}{\sqrt{M}} & for\ \ p = 1 \\ \sqrt{\frac{2}{M}} & for\ 1 \le p \le M-1 \end{cases} \qquad (6)$$

and

$$\alpha_q = \begin{cases} \frac{1}{\sqrt{N}} & for\ \ q = 1 \\ \sqrt{\frac{2}{N}} & for\ 1 \le q \le N-1 \end{cases} \qquad (7)$$

The result is 3 matrices of size 8×8 representing 64 coefficients for DCTY, DCTCb, and DCTCr. A zigzag scanning is performed with these three sets of 64 DCT coefficients, to group the low frequency coefficients of the 8x8 matrix .These three set of zigzag scanned matrices correspond to the color layout descriptor of the input image. The 192 CLD features of the leaf infected by Myrothecium which is segmented as shown in Figure 8 are given in Table 1:

kmean_time = 0.0765

c = 0.6217
0.3826

Table 1 CLD's for Myrothecium sample image

Columns 1 to 11	Col.12 to 22		Col. 56 to 66		Col.155 to 165		Col. 188 to 192
0.2182	1.0605		1.0605		0.5441		-0.6546
0.5232	-1.3236		-1.3236		-0.5941		-0.9056
0.4515	-0.8025		-0.8025		-0.8344	…	-0.8656
0.6812	0.7672	…	0.7672	…	-0.0589	…	-0.8462
1.3419	1.6358	…	1.6358	…	0.2117	…	-0.8164
1.3483	-1.3026	..	-1.3026	….	0.1882	…	
1.6455	-0.7261		-0.7261		0.3286	…	
1.2118	-1.4720		-1.4720		0.6402	…	
1.4140	1.4942		1.4942		-0.5970	..	
0.7943	0.3978		0.3978		-0.7590		
0.6223	0.2254		0.2254		-0.7841		

VIII. CLASSIFICATION

Adaptive neuro fuzzy inference system is used for classification. It combines the principles of neural network and fuzzy logic therfore it provides advantages of both in a single structure [2].The premise parameters which defines the membership function are updated by using gradient decent method and consequent parameters are identified by using least square method. It has the network consisting of nodes and directional links [7].Since the nodes have the parameters which can affect the ouput of nodes it is reffered as adaptive network. The architecture of ANFIS is shown in Figure 10.

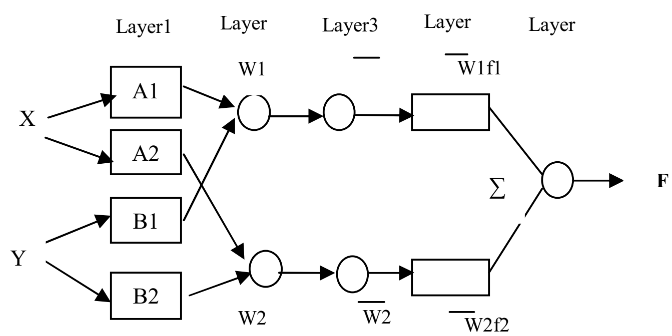


Figure 10 ANFIS architecture

The circular nodes are fixed while the square nodes have parameters to learn. The two rules have the form:

If x is A_1 and y is B_1 *Then $f_1 = p_1x + q_1y + r_1$*
If x is A_2 and y is B_2 *Then $f_2 = p_2x + q_2y + r_2$*

Layer 1:
The output of each node is

$$O_{1,i} = \mu_{Ai}(x) \quad for\ i = 1,2 \qquad (8)$$
$$O_{1,i} = \mu_{Bi-2}(y) \quad for\ i = 1,2 \qquad (9)$$

Layer 2:
Every node in this layer is fixed. The t-norm is used to 'AND' the membership grades.

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad i = 1,2 \qquad (10)$$

Layer 3:

This layer contains the fixed nodes. These nodes calculate the ratio of the firing strengths of the rules

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad (11)$$

Layer 4:
This layer consists of the adaptive nodes that execute the consequent part of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}\left(p_i x + q_i y + r_i\right) \qquad (12)$$

where parameters p_i, q_i, r_i are consequent parameters.

Layer 5
It consists of a single node that determines the overall output:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (13)$$

The network is trained by using forward and backward pass. The input vector gets propagated through the network layer by layer in the forward pass. In the backward pass the error is sent back through the network similar to the backpropagation algorithm.

The Sugeno –type fuzzy inference system is used as FIS. The FIS using fuzzy subtractive clustering is generated using genfis2. The combination of least square method and gradient method is applied for training of membership function. An optional checking data set for over fitting model validations used. All the 192 CLD's derived are used for training purpose.

IX. DISCUSSION AND CONCLUSION

The sample images of the three diseases under study are divided into two sets for training and testing purpose. The graph shown in Figure 11 summarizes the success rate of classification of the proposed model.

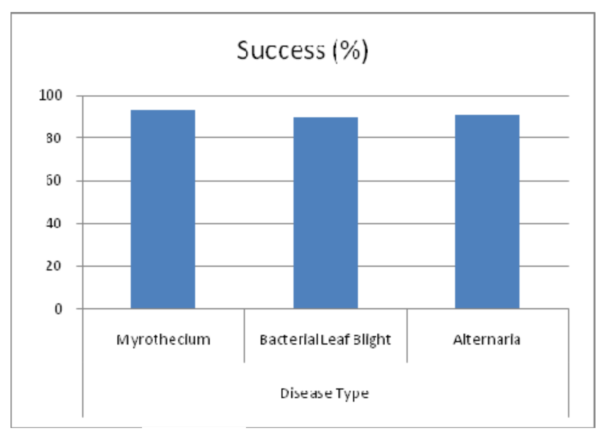


Figure 11 Performance of the system

Digital image analysis combined with neural network has proven to be a feasible approach to the identification of cotton leaf disease. The results obtained have shown that the identification of Bacterial Blight, Myrothecium and Alternaria is feasible using color layout descriptors as features for training the anfis model.

This work can be extended for identification of Rhizoctonia, Powdery mildew, leaf curl and other leaf diseaseson cotton. This work may be extended for identifiction ofdiseaseson other plants. The same work may be repeated with different features and classifier.

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