ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, *Vol 10(46), DOI: 10.17485/ijst/2017/v10i46/116025, December 2017*

Paddy Disease Recognition using Image Processing and Radial basis Function Network

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Abstract

Objectives: To automate paddy disease recognition process by statistical pattern recognition model. **Methods/ Statistical Analysis:** This paper presents, designing of a radial basis function network model to automate paddy diseases pattern recognition. Total 5 categories of diseased infected paddy images along with non infected images had been captured by the digital camera in an uncontrolled environment in day lighting. The captured images had been cropped to select aregion of interest and resized to reduce space/time complexity of the system. These preprocessed images had been segmented using multi-level of thethreshold. The discrete wavelet features of red, blue and green components of highest inensity level segmented images had been extracted. The 80% of the extracted features had been used to train the model and remaing 20% had been used to test the performance of the model. **Findings**: The results of the study show the advantages of the proposed method compared to some other existing methods in terms of recognition efficiency and generalization. The average diseased/non-diseased pattern recognition using radial basis function network model is 97.9% for training data sets and 95.5% for testing data sets. The method is implemented in an uncontrolled environment instead of laboratory setup give advantages of easy generalization. **Application/Improvements:** The method can be used to design aplant diseases monitoring system for farmers to inspect and asses threats of diseases and make on-location decision to cure and/or control the spread of diseases. The government agencies can also use this monitoring system to generate periodical reports/warnings from acomputer database for high threat potential diseases.

Keywords: Color Image Processing, Diseases Pattern Recognition, Discrete Wavelet Feature, Paddy Diseases, Radial basis Function Network

1. Introduction

The present day applications in agriculture require automation of process to interprets and analyze the observed information and make effective decision to control the spread of disease and losses. These applications require various kinds of images and pictures as a source of information in the form of digital signal for interpretation and analysis of disease infected crops to recognize and take corrective actions to diagnosis. The diseases in the plant are induced by a pathogen or a biotic factors which compromised; plant's performance to produce or survive[1]. The visual effect of these diseases can be seen on the leaves as characteristic spindle-shaped spots, with the ashy center, and on the leaf-sheaths and at the juncture as irregular oval discolorations. The major diseases of Cereals are Blast, Brown Spot, Bacterial Blight, Foot and Stem Rot, Sheath Blight, False Smut, Virus Diseases etc[2].

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1.1 Rice or Paddy Diseases

Total 5 different rice crop diseases have been considered in this research. Each disease has a specific symptom which reflects on the rice plant. The leaves of plants are affected in leaf blast. Symptoms on the leaves originate as small specks which subsequently enlarge into the centre of the well developed spot is whitish grey with a brown margin. The neck of the panicles is affected in panicle blast. Panicle blast symptoms appear by blackening on the Culm, Culm nodes and glumes. The observed symptoms of Brown spot are leaf spotting with leaf sheaths are brown, round to oval. In Sheath blight, spots or lesions appear on the leaf sheath, extending to the leaf blade with greenish grey color and ellipsoid or ovoid shape. Later stage, they enlarge and become grayish white with brown margins and somewhat irregular lines. The observed symptom due to Stem borers are; in the young stage, center leaves of the damaged tillers turn brown and die. If the damage occurs after the panicle form, then the panicles turn white[15].

1.2 Image Processing

The images are mainly used to present pictorial information for human perception. The image processing is done for storage, transmission, and representation for machine learning. An image is defined as a two-dimensional function, $f(x,y)$. In digital image; x,y and the intensity value of f are all finite with discrete quantities. The intensity value f is mainly manipulated for feature extraction of the image after acquisition by digital media[3].

1.3 Discrete Wavelet Transform (DWT)

The DWT is a powerful mathematical tool which provides insight into a digital image's spatial and frequency characteristics at multiple resolutions. An iterative computational approach of DWT is Fast Wavelet Transform (FWT). The properties of wavelet; 1. and 1. can be expressed as linear combinations of double-resolution copies of themselves as (1) and (2); via the series expansions

1. $$\varphi(x) = \sum_n h_\varphi(n)\sqrt{2}\varphi(2x-n)$$

1. $$\psi(x) = \sum_n h_\psi(n)\sqrt{2}\varphi(2x-n$$

Where 1. and 1. - are the filter coefficient of the FWT. In wavelet transform, the input is decomposed into four lower resolution (or lower scale) components. The approximation coefficients 1. are created via 1. based two low pass filters and 1. $\{W_\psi^i \mathbf{for} i = 1$ are horizontal, vertical and diagonal detail coefficient respectively. Output 1. $W_\varphi($ can be used as a subsequent input, 1. $W_\varphi(j+1$ for creating even lower resolution components; 1. is the highest resolution representation available and serves as the input for the first iteration[4].

1.4 Pattern Recognition

The pattern recognition system rests on mathematical models. It can be defined as a process of structure identification in data using classification methods. Pattern recognition is a two step process. In the first step; training phase, a recognizer is built by describing a predetermined set of feature vector classes. Different input observations are assigned to the same class if with similar features and to different classes with dissimilar features. In this phase, parameters of classification algorithm build. In the second step; testing phase, identification of a class of unknown feature vector is done[5,6].

1.5 Radial basis Function Network

RBFN take the design of a neural network as a curve fitting (approximation) problem. The RBFN find a surface in a multidimensional space for the training data with the best fit criterion. These multidimensional surfaces are used to interpolate the test data during generalization process. The basic form radial-basis function (RBF) network consists of three layers with different roles. An input layer is a sensory unit that connects the networks to its environment. The second layer, the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space. The output layer is a linear, supplying the response of the network to the activation pattern applied to the input layer[7].

1.6 Plant Disease Recognition using Image Processing

The plant disease affects a wide range of commercial crops, and can result in a significant yield loss. Timely diagnosis by accurate recognition of plant diseases saves the quantitative and qualitative loss of the production. Therefore, detection and recognition of diseases is a very important task. Still in major places, diseases are recognized by visual observation of diseases symptoms. Each disease has unique symptom pattern. The naked eye observation makes error causes great loss of production. To automate this process, Image processing techniques have used by some researchers for detection and classification of plant diseases. Major application area of image processing for plant diseases is recognition and classification[8-12], quality inspection[13,14]. Image processing techniques are used to extract color, shape, and texture features. These extracted features are used to train and create recognition model by a neural network[15,16], fuzzy logic, neuro-fuzzy[17] and more on. Radial basis function network is used in many application areas as a classifier[18-20].

2. Materials and Method

The major components of RBFN based pattern recognizer are shown in Figure 1. The descriptions of the components are given below:

2.1 Image Capturing and Pre-Processing

Many color images in JPEG (JPG) format with default size 5152×3864 had been captured from rice crop field by digital camera SONY/DSC-H300 in an uncontrolled environment. The images had collected under 6 categories; leaf blast, Brown spot, Panicle Blast, Sheath Blight, Stem Borer disease infected images and non infected images. Some images were replicated due to lack of data sets. In a pre-processing step, the image had been cropped and resized at 205×410 and manually selected images which carry disease infected region in each category. These collected images had been forwarded for segmentation.

2.2 Image Segmentation

The cropped images had been segmented in the size of 200×250 using global thresholding method; Otsu's method. Each image is segmented into three parts. These segmented parts are stored in three groups $\boldsymbol{ISeg_1}, \boldsymbol{ISeg_2}, and \boldsymbol{ISeg_3}$. Each group carries the segmented images according to predefined 6 categories. In this research, the images stored in $\boldsymbol{ISeg_3}$ are used for feature extraction. The pseudo-code of image segmentation process is given below:

Pseudo code

for all categories of images: $g = 1,2, \dots ,6 do$

for all images $i = 1,2, \dots , m$ in each category g do

Read JPG image (Ig_i) and resize image (Ig_i)

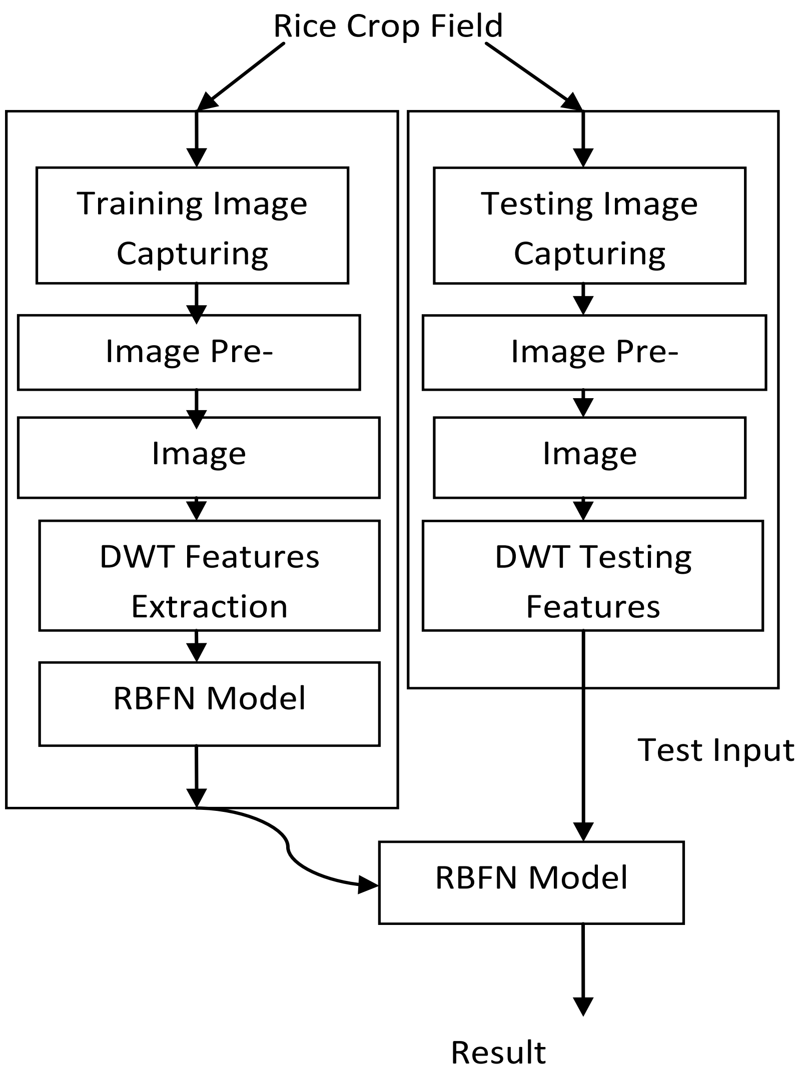


Figure 1. Components of RBFN based paddy disease recognition model.

Convert RGB color model image Ig_i to *Lab* color model image Lab_i

Extract component a_i from Lab_i

Apply multilevel thresholding using Otsu's method to find 3 threshold levels in component a_i.

Quantize a_i into three threshold level

Create three binary images: b_{i1}, b_{i2}, b_{i3}, according to three quantized level of a_i where $b_{i1} \wedge b_{i2} \wedge b_{i3} = 0$.

Separate Red, Green and Blue components of Ig_i as R_i, G_i, B_i

Multiply R_i, G_i, B_i with all three binary components b_{i1}, b_{i2}, b_{i3} as

$$Rb_{i1} = multiply(R_i, b_{i1}), Rb_{i2} = multiply(R_i, b_{i2}) and Rb_{i3} = multiply(R_i, b_{i3})$$

$$Gb_{i1} = multiply(G_i, b_{i1}), Gb_{i2} = multiply(G_i, b_{i2}) and Gb_{i3} = multiply(G_i, b_{i3})$$

$$Bb_{i1} = multiply(B_i, b_{i1}), Bb_{i2} = multiply(B_i, b_{i2}) and Bb_{i3} = multiply(B, b_{i3})$$

Concatenate these components to find three segments $ISeg_{i1}, ISeg_{i2}, and ISeg_{i3}$ of image Ig_i by implementing

$$ISeg_{i1} = concatenate(Rb_{i1}, Gb_{i1}, Bb_{i1})$$

$$ISeg_{i2} = concatenate(Rb_{i2}, Gb_{i2}, Bb_{i2})$$

$$ISeg_{i3} = concatenate(Rb_{i3}, Gb_{i3}, Bb_{i3})$$

Save $ISeg_{i1}, ISeg_{i2}, and ISeg_{i3}$ for further processing.

$endofforloop$ // $i = 1,2,\ldots,m$

$endofforloop$ // $g = 1,2,\ldots,6$

2.3 DWT Feature Extraction

In this step, haar filter has been used to extract approximation wavelet features of each image stored in $\boldsymbol{ISeg_3}$ for 6 categories. The psuedo-code for approximation feature extraction with haar filter is given below:

Pseudo code

$forallcategoryimagesISeg_{3g}, g = 1,2,\ldots,6\ do$

$forallsegmentedimagesISeg_{3ig} ineachcategory, i = 1,2,\ldots,mdo$

$Step\ 1: NormalizetheISeg_{3ig} image\ by$

$$S_i = \frac{ISeg_{3ig}}{255}$$

$Step\ 2: SeperateR_i, G_i andB_i componentsofS_i.$

$Step\ 3:\ Initializelowdimensionandhighdimension$

$decompositionhaarfiltersinR_i, G_i andB_i components$

$Step\ 4: Extractapproximationfeaturesof R_i, G_i andB_i componentsandcombinethereult$

$$Out_1 = ApproximationFeatures(R_i)$$

$$Out_2 = ApproximationFeatures(G_i)$$

$$Out_3 = ApproximationFeatures(B_i)$$

$$x_{i1} = Std2(Out_1)$$

$$x_{i2} = Std2(Out_2)$$

$$x_{i3} = Std2(Out_3)$$

$$W_{gi} = (x_{i1}, x_{i2}, x_{i3})$$

$Step\ 4: Combineallextrctedwaveletfeturesofeachcategory$

$seperatlyas$

$$W_g = \{W_{gi}\}_{i=1}^{m}$$

$endofforloopendofforloop$ // $i = 1,2, \dots, mi = 1,2, \dots, m$

$endofforloopendofforloop$ // $g = 1,2, \dots ,6g = 1,2, \dots ,6$

2.4 Radial basis Function Network Implementation

The approximation wavelet features are used to create and generalize RBFN. The pseudo code of entire process is given below:

Pseudo code

Step 1: Separate extracted features $W_g = \{W_{gi}\}_{i=1}^{m}, g = 1,2,\ldots,6$

category wise as$W_1, W_2, W_3, W_4, W_5\, and W_6$.

Step 2: Create training and testing data sets for RBFN and also initialize desired response according to a number of training inputs. The 90% extracted features of each category had been used for the training of RBFN and remaining 10% had used for the testing purpose.

$xBS_{train} = W_1 \times 0.9$, $xBS_{test} = W_1 - xBS_{train}$,$dBS_{desired} = [1\ 0\ 0\ 0\ 0\ 0]$

$xLB_{train} = W_2 \times 0.9$, $xLB_{test} = W_2 - xBS_{train} xLB_{test} = W_2 - xBS_{train}$,
$dLB_{desired} = [0\ 1\ 0\ 0\ 0\ 0]\ dLB_{desired} = [0\ 1\ 0\ 0\ 0\ 0]$

$xPB_{train} = W_3 \times 0.9\ xPB_{train} = W_3 \times 0.9$, $xPB_{test} = W_3 - xBS_{train} xPB_{test} = W_3 - xBS_{train}$,
$dPB_{desired} = [0\ 0\ 1\ 0\ 0\ 0] dPB_{desired} = [0\ 0\ 1\ 0\ 0\ 0]$

$xSB_{train} = W_4 \times 0.9\ xSB_{train} = W_4 \times 0.9$, $xSB_{test} = W_4 - xBS_{train} xSB_{test} = W_4 - xBS_{train}$,
$dSB_{desired} = [0\ 0\ 0\ 1\ 0\ 0] dSB_{desired} = [0\ 0\ 0\ 1\ 0\ 0]$

$xSTB_{train} = W_5 \times 0.9\ xSTB_{train} = W_5 \times 0.9$, $xSTB_{test} = W_5 - xBS_{train}$
$xSTB_{test} = W_5 - xBS_{train}$, $dSTB_{desired} = [0\ 0\ 0\ 0\ 1\ 0] dSTB_{desired} = [0\ 0\ 0\ 0\ 1\ 0]$

$xNI_{train} = W_6 \times 0.9\ xNI_{train} = W_6 \times 0.9$, $xNI_{test} = W_6 - xBS_{train} xNI_{test} = W_6 - xBS_{train}$,
$dNI_{desired} = [0\ 0\ 0\ 0\ 0\ 1] dNI_{desired} = [0\ 0\ 0\ 0\ 0\ 1]$

Training input data set: $\mathbf{x}= x_j = \begin{bmatrix} xBS_{train} \\ xLB_{train} \\ xPB_{train} \\ xSB_{train} \\ xSTB_{train} \\ xNI_{train} \end{bmatrix}, j = 1,2, \dots, N_1$

Desired response: $\mathbf{d}=d_i = \begin{bmatrix} dBS_{desired} \\ dLB_{desired} \\ dPB_{desired} \\ dSB_{desired} \\ dSTB_{desired} \\ dNI_{desired} \end{bmatrix}, i = 1,2, \dots, N_1$

Step 3: Choose a set of centers randomly from training data set $\mathbf{x}$: $t_i,\ i = 1,2, \dots, m_1$ where $(t_i \subseteq \mathbf{x} \text{and} m_1 \leq N_1)$

Step 4: Evaluate maximum distance between chosen centers t_i: d_{max}

Step 5: Define radial-basis function G for hidden layer and evaluate $\mathbf{G}$

$for j = 1,2, \dots, N_1 do$

$for i = 1,2, \dots, m_1 do$

$$\mathbf{G} = G\left(\left|\left|\mathbf{x} - t_i\right|\right|^2\right) = G\left(\left|\left|x_j - t_i\right|\right|^2\right) = \exp\left(-\frac{m_1}{d_{max}^2}\left|\left|x_j - t_i\right|\right|^2\right),$$

$endofforloop$ // $i = 1,2, \dots, m_1$

$endofforloop$ // $j = 1,2, \dots, N_1$

Step 6: Evaluate Pseudoinverse $\mathbf{G}^+$ of $\mathbf{G}$ (Haykin S. , 2009)

Step 7: Evaluate linear weight associated with the output unit(s) of the network by

$\mathbf{w} = \mathbf{G}^+\mathbf{d}$

$$y(\mathbf{x}) = \mathbf{wG} + b = \sum_{i=1}^{m_1} \mathbf{w}\, G\left(\left\|\mathbf{x} - t_i\right\|^2\right) + b$$

2.5 Analysis of Results

In this step, result analysis has been done to find the recognition efficiency of RBFN model.

Pseudo code

Step 1: Initialize test data set

$$\mathbf{x}_{Test} = \begin{bmatrix} xBS_{test} \\ xLB_{test} \\ xPB_{test} \\ xSB_{test} \\ xSTB_{test} \\ xNI_{test} \end{bmatrix}$$

Step 2: Calculate the output of the neural network for the test input

$$y(\mathbf{x}_{Test}) = \mathbf{wG} + b = \sum_{i=1}^{m_1} \mathbf{w}\, G\left(\left\|\mathbf{x}_{Test} - t_i\right\|^2\right) + b$$

Step 3: Match output value or generated response $y(\mathbf{x}_{Test})$, with desired response $C_{Recognized}$ with each testing category sample T_{sample}.

$RecognitionAccuracy(\%) = \dfrac{C_{Recognized}}{T_{sample}} \times 100$ test data sets as

3. Result and Discussion

The entire process is implemented in MATLAB version 8.4. Total 150 cropped images of each category had been considered for image pre-processing and segmentation. A sample of the result of pre-processed and segmented images is shown in Figure 2, Figure 3-7 for all the categories. The wavelet features for Red, Blue and Green components of each image had been extracted. The sample of the first five features of extracted images for all 6 categories are shown in Table 1. Total 1. 1, feature pattern had been extracted for all six categories of images. In these extracted features, 90%

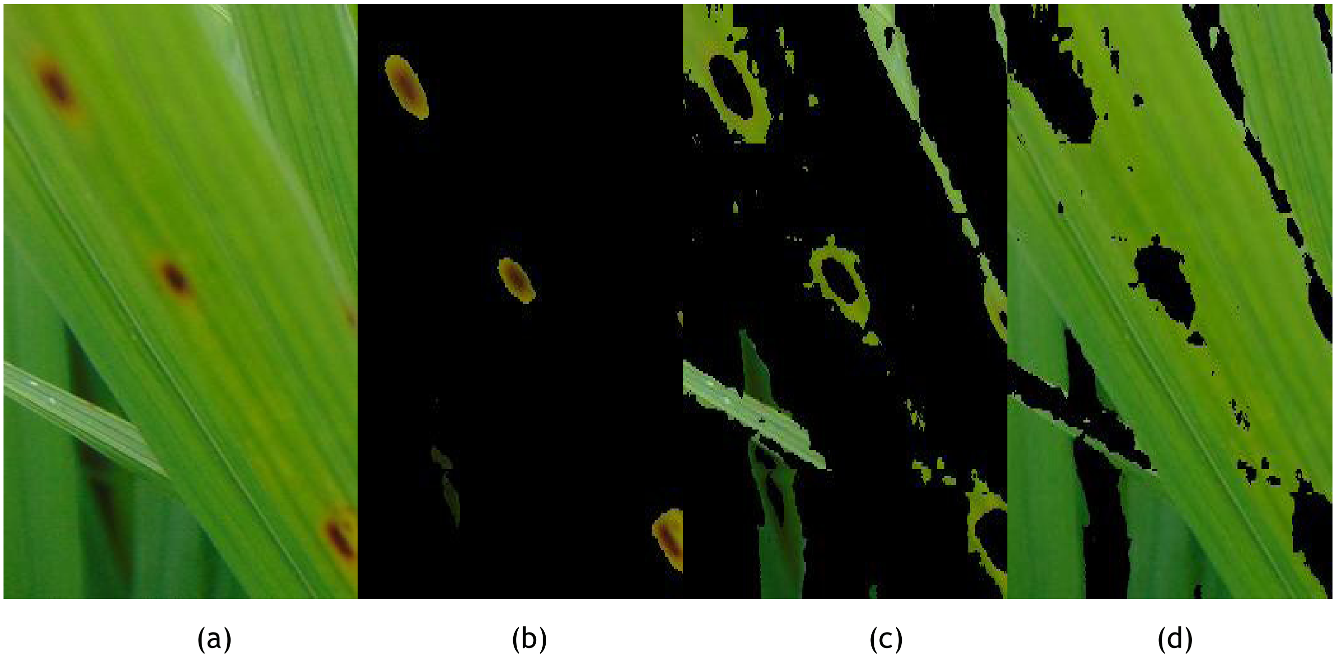


Figure 2. Brown spot images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.

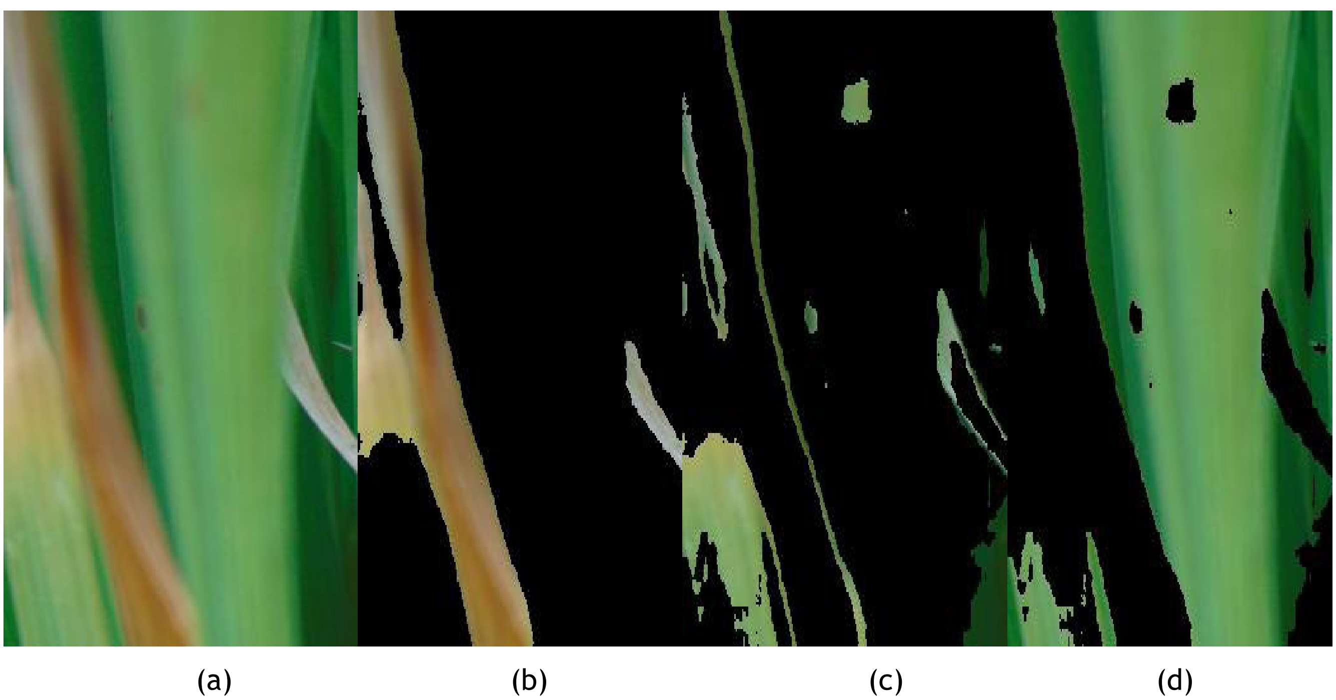


Figure 3. Leaf Blast images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.

(a) (b) (c) (d)

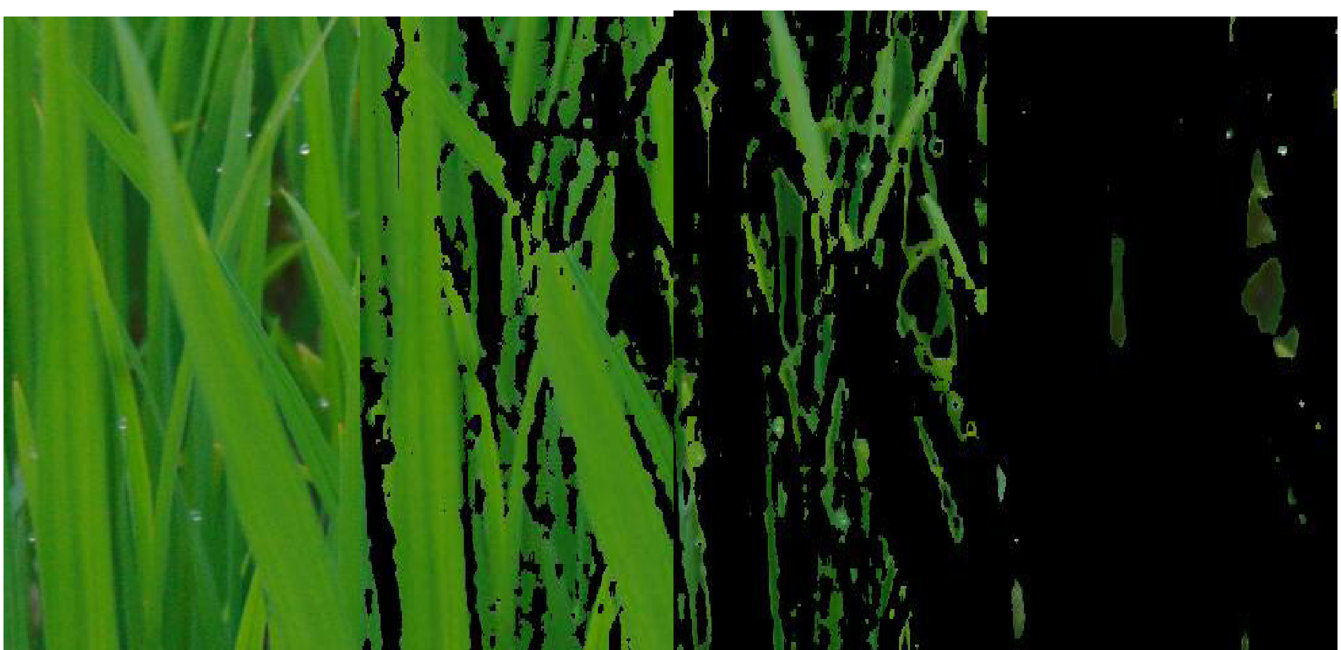
Figure 4. Panicle Blast images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.

(a) (b) (c) (d)

Figure 5. Sheath Blight images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.

(a) (b) (c) (d)

Figure 6. Stem Borer images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.



(a) (b) (c) (d)

Figure 7. Non-Infected images with (a) Cropped (b) segmented images with high intensity level threshold (c) segmented images with low intensity level threshold (d) segmented images with mid intensity level threshold.

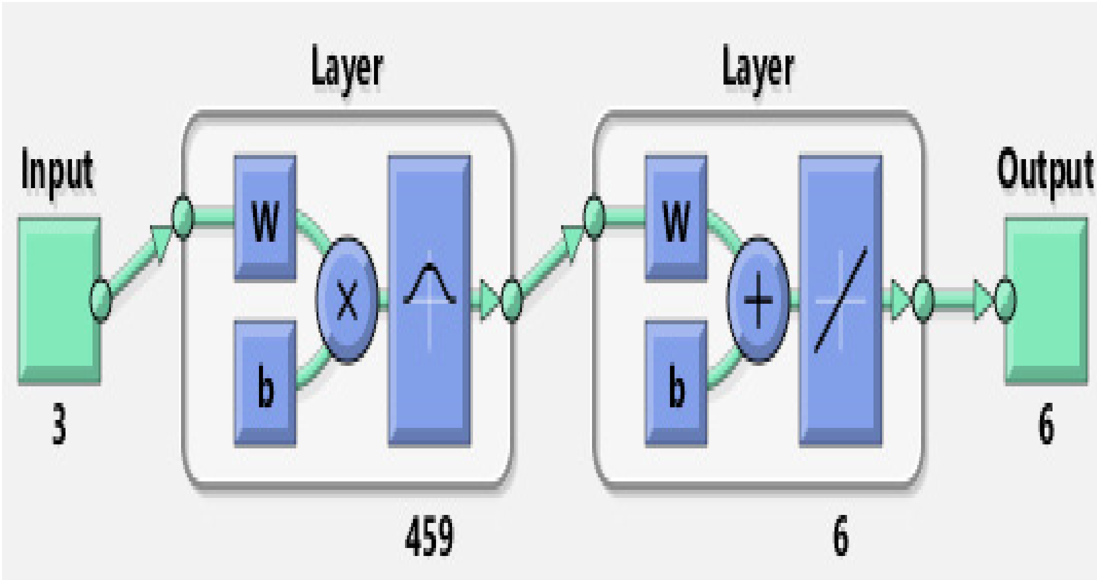


Figure 8. RBFN architecture for paddy disease pattern recognizer.

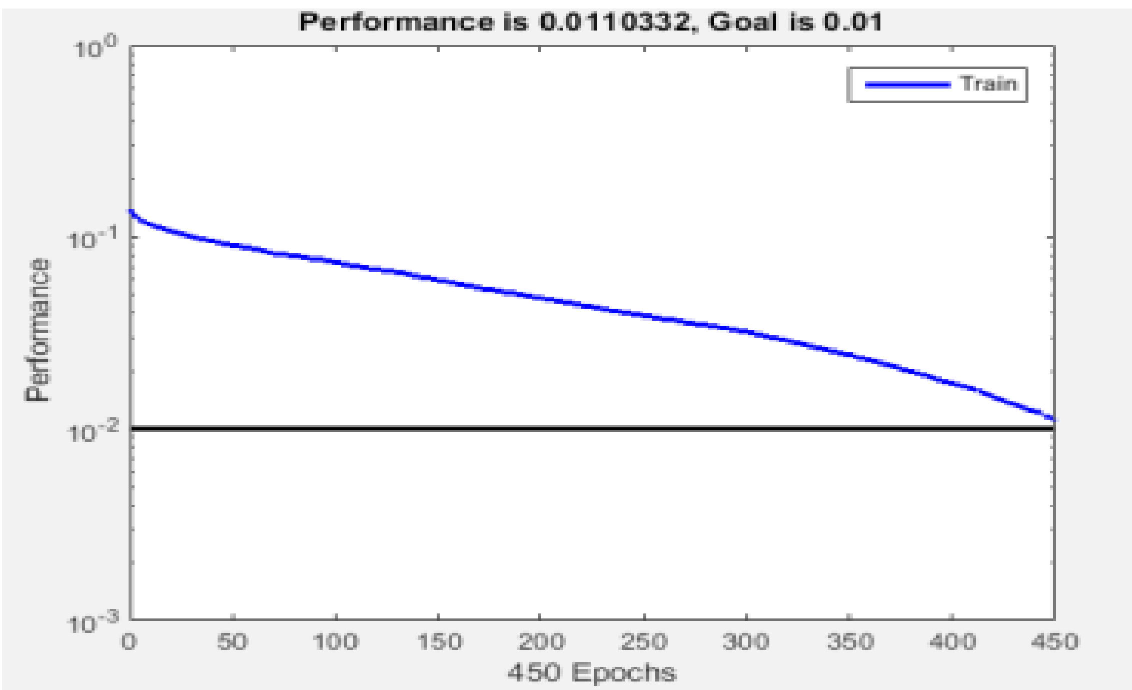


Figure 9. Performance Graph.

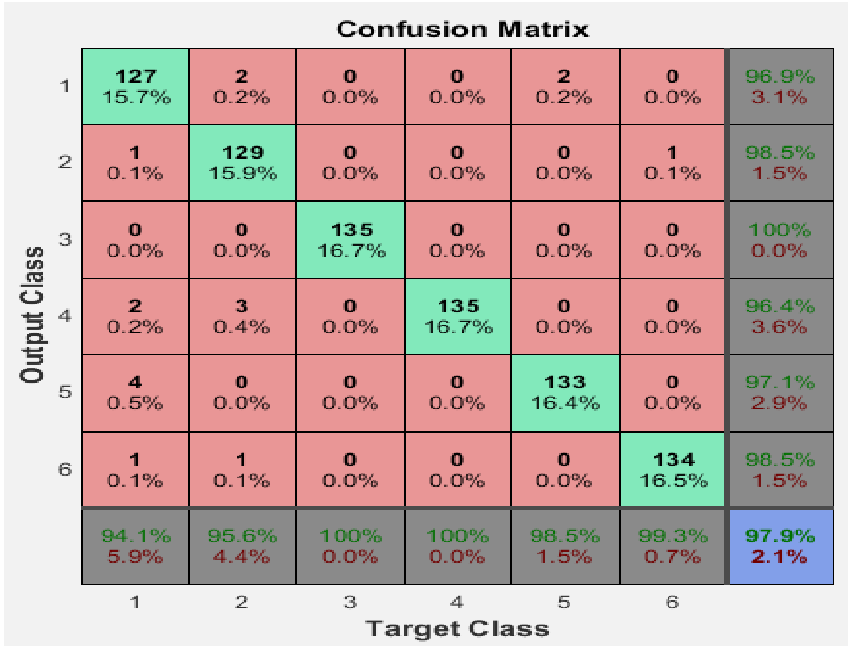


Figure 10. Confusion Matrix.

Name	Value
TestDWTRBFNPerf1	80
TestDWTRBFNPerf2	100
TestDWTRBFNPerf3	100
TestDWTRBFNPerf4	100
TestDWTRBFNPerf5	100
TestDWTRBFNPerf6	93.3300

Figure 11. Test result on RBFN Model.

of features are used to train RBFN rice plant diseases pattern recognizer. The created architecture for RBFN model is shown in Figure 8. During designing of RBFN model, error goal is set to 0.01. The training process of RBFN model is complete after 450 epochs as shown in Figure 9. Total 459 hidden neurons created for nonlinear transformation from the input space to the hidden space. The confusion matrix shown in Figure 10 represents the training accuracy of 97.9% for the same input pattern. Average recognition efficiency of test patterns is 95%. The individ-

Table 1. Sample extracted wavelet approximation features of Brown spot, Leaf blast, Panicle blast, Sheath blight, Stem borer and Non-infected segmented images wavelet features of red (r), green (g) and blue (b) components.

S.No	Brown spot	Leaf Blast	Sheath Blight
1	0.1923, 0.2006, 0.1468	10.2515, 0.2361, 0.1082	0.0865, 0.1061, 0.0656
2	0.1212, 0.1046, 0.0265	0.3132, 0.3001, 0.1744	0.082, 0.0956, 0.0609
3	0.1244, 0.1149, 0.0613	0.3041, 0.302, 0.164	0.0814, 0.1027, 0.0629
4	0.1566, 0.1231, 0.0717	0.2123, 0.1952, 0.1142	0.0985, 0.1213, 0.074
5	0.0719, 0.118, 0.0378	0.3196, 0.3281, 0.1745	0.128, 0.1536, 0.0612
S.No.	**Non-infected**	**Panicle Blast**	**Stem Borer**
1	0.2139, 0.41, 0.100	0.3203, 0.2942, 0.2545	0.2776, 0.2968, 0.2728
2	0.1816, 0.3954, 0.1888	0.3647, 0.3652, 0.2108	0.3849, 0.4207, 0.399
3	0.1733, 0.4338, 0.1392	0.3104, 0.3441, 0.2768	0.3846, 0.4267, 0.3829
4	0.2008, 0.2204, 0.2032	0.2204, 0.4538, 0.2095	0.3132, 0.296, 0.244
5	0.1485, 0.3829, 0.1427	0.2214, 0.2184, 0.1566	0.4495, 0.4388, 0.3909

ual recognition efficiency for each categories are 80% for Brown Spot, 100% for Leaf Blast, 100% for Panicle Blast, 100% for Sheath Blight, 100% for Stem Borer and 93.3% for non infected images as shown in Figure 11.

4. Conclusion

Individual diseased and non-diseased plants reflect observable feature patterns in the form of color shape and texture features. We had segmented infected part of the rice plant of each category using multi-level thresholding. The unique observable statistical features are extracted in the form of discrete wavelet approximation features which carry spatial and frequency features of the image bit pattern. These extracted features are used to design RBFN rice plant diseases recognition model; gives 95.5% average recognition efficiency. Some diseases are 100% recognized. Most importantly, entire images were captured in an uncontrolled environment for the process, which will, help to generalize this approach for other plant diseases easily. The image resizing of cropped or segmented images are applied to overcome the limitation of the system in terms of required memory and execution time. The DWT features represent spatial and frequency (energy) information about an image. The observed pattern of plant diseases appears in the form of different colour, shape and textures features also. Some of these features can be combined with DWT features to make robust plant diseases recognition system. In the presence of vague data sets, fuzzy inference system can be designed for the recognition process. Various optimization techniques can be used before learning or after learning the process of recognition model to enhance the quality of input pattern and efficiency.

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