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Rice Leaf Blast Disease Recognition Using Wavelet Features and Neural Network

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Abstract : Recognition of plant diseases using images is one of the most important factor to automate disease recognition process for precision farming. A new hybrid method has been proposed to identify the rice leaf blast disease. Wavelet features of the captured colored images of rice crop leaf had been extracted. These extracted features were then used to design neural network model; Back Propagation Neural Network to recognize disease infected and not infected pattern. Hybrid model is giving good recognition efficiency.

Keywords : Rice Leaf Blast Diseases, Image Processing, Wavelet Haar Features, Back Propagation Neural Network.

1. INTRODUCTION

Management philosophy for farming, to maximize crop production with minimal environmental degradation and pollution is known as Precision farming [1]. It needed site-specific, computer vision management system like remote sensing (RS), GPS, and geographical information system (GIS) [2] [3]. The core of computer vision is image analysis and processing. It provides methods for measuring specific features as per needed in various applications. In the field of precision farming; one of the important applications is; recognizing disease pattern in crop for timely and better pest management.

1.1. Rice leaf blast disease

Rice is one of the primary agricultural products of the world. There are many types of diseases the affect the rice crop. One very damaging disease known as rice leaf blast disease is distributed in 85 countries and caused production losses of millions of dollars, each year [4]. It is caused by the fungus Pyricularia grisea. Rice blast diseases infect all aerial parts of the rice plant but most infections occur on the leaf, which is known as rice leaf blast disease. On the leaves, disease form elliptical or diamond shaped spots. Present crop disease diagnosis system based on manual recognition of diseases by experience. This process cause sometime dally and mistakenly diagnosis. Image processing methods are very important for automation process to recognize crop diseases for precision farming [5][6].

1.2. Wavelet features of image

Image processing is used to recognize/classify plant and/or plant diseases in crop management system. First step of the process is to create feature database related to specific plant and/or plant diseases characteristics. These features are further used to train recognition model/ expert system. During application, newly extracted features of unknown plant and/or plant disease is passed to the recognition system and it resolves the queries, as per the need by the user [7][8][9][10].

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Diseased crop images reflect specific features as compared to the normal non-diseased images. Initially images were captured by digital media for both; leaf blast infected and leaf blast non-infected. These images reflected unique wavelet features as compared to each other. These wavelet features have been extracted to create rice leaf blast disease recognition model using neural network.

Discrete wavelet transform (DWT) is a mathematical tool to analyze images at multiple resolutions. DWT provides spatial and frequency characteristics insight of the image. The DWT uses two functions; wavelet function φ and scaling function ψ to perform simultaneously, the multi-resolution analysis (MRA) of any image (x,y) . The discrete wavelet function φ serving as a high pass filter, generated the detailed version (high-frequency components) of the decomposed signal and the scaling function ψ generated the approximated version (low-frequency components) of the image [11]. The wavelet function φ and scaling function ψ possess the properties of separability, translatebility, scalability, multiresolution compatibility and orthogonality.

In wavelet transform, input is decomposed into four lower resolution (or lower scale) components. The W_φ? coefficients are created via two lowpass filters (*i.e.* h_φ –based) and are thus called approximation coefficients; $\{W_\varphi^i$ for i = H,V,D$\}$ are horizontal, vertical and diagonal detail coefficient respectively. Output W_φ (j, m, n) can be used as a subsequent input, $W_\varphi(j + 1, m, n)$, for creating even lower resolution components; Original Image $f(x, y)$ is the highest resolution representation available and serves as the input for the first iteration.

In fast wavelet transform, both $\varphi(x)$ and $\psi(y)$ can be articulated as linear combinations of double-resolution copies of themselves. That is, via the series expansions by the following equations:

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

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

Where h_φ and h_ψ – the expansion coefficients- are called scaling and wavelet vectors, respectively. They are filter coefficient of the fast wavelet transform (FWT), an iterative computational approach to the DWT [12].

1.3. Artificial Neural Network (ANN)

ANN has been designed to emulate human brain artificially. ANN architecture consists of a large number of neurons organized in different layers. These neurons of one layer are connected to those of another layer by means of weights. ANN is trained to carry out a particular task by making proper adjustment of its architecture, connecting weights and other parameters. Training is usually done by supervised, unsupervised or reinforcement learning technique. Main steps needed to design automated leaf blast disease recognition models using ANN are:

1. Design topologies of ANN based on training input and target output.
2. Initialization of required parameter of ANN.
3. Apply learning law to update weights and other parameter during training.
4. Evaluate performance of ANN model and post processing.

Back Propagation Neural Network (BPNN) is a multi-layer forward network using extend gradient-descent based delta-learning rule. BPNN provide a computationally efficient method to update the weights with differentiable activation function units, during learning for each training set of input-output examples.

1.4. Components of rice leaf blast disease recognizer

Components of rice leaf blast disease recognizer using BPNN is given in Figure 1. Rice leaf blast infected and non infected images were captured by digital means. After preprocessing, approximation coefficient wavelet features were extracted separately for disease infected and disease non-infected images. These extracted features are divided into two data set; training and testing data sets. According to the number of input and output size of data sets, BPNN model had been created separately. After training, performance of these two models had been evaluated by testing data sets.

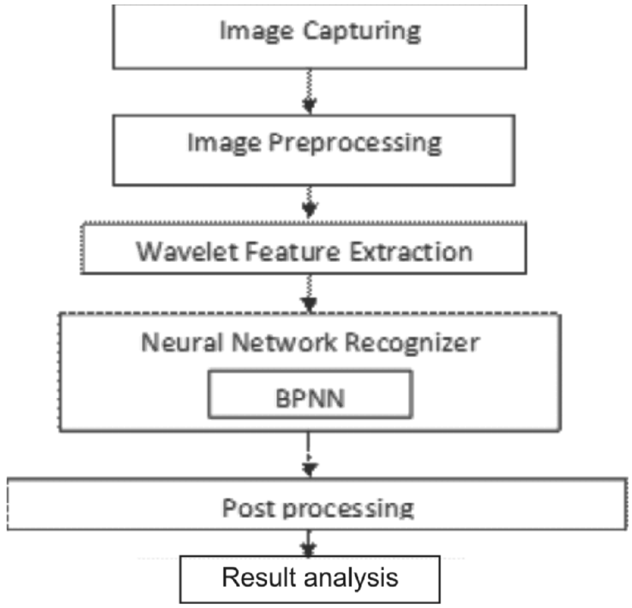

Fig. 1. Components of rice leaf blast disease recognizer using BPNN.

List of symbols used to describe methodology is given in Table 1.

Table 1. List of symbols.

Symbol	*Description*
i, j, and k	Indices of images and neurons in multilayer feed forward network
Im_i	Cropped image i; i = 1,2, … ,N – 1
Im	Set of cropped images
N	Total input images
I_i	Normalize images i
R_i, G_i, and B_i	Red, Green and Blue components of image I_i
Lo_d	Low-pass Haar decomposition filter
Hi_d	High-pass Haar decomposition filter
$Ca\_R_{i_i}$,Ca_G_i, and Ca_B_i	Approximation coefficient wavelet features of R_i, G_i, and B_i
SD	Set of tow-dimensional standard deviation of approximation coefficient wavelet features
C_j	Mean of Column j
SD_j	Standard Deviation of Column j
CC	Mean of Row
Ca_Rsd_i	Two-dimensional Standard Deviation of Ca_R_i
Ca_Gsd_i	Two-dimensional Standard Deviation of Ca_G_i
Ca_Bsd_i	Two-dimensional Standard Deviation of Ca_B_i
n	nth training pattern
$\varepsilon(n)$	Instantaneous sum of error square or error energy at iteration n
$\varepsilon_j(n)$	Error signal at the output of neuron j for iteration n
$d_j(n)$	Desired response for neuron
$y_j(n)$	Output of neuron j at iteration n

Symbol	***Description***
$w_{ji}^{(l)}$	Synaptic weight connecting the output of neuron i to the input of neuron j at iteration n at layer l of the network
$\Delta w_{ji}(n)$	Correction applied to weight at iteration n
$\vartheta_j(n)$	induced local field of neuron j at iteration n
$\varphi_j(.)$	Activation function associated with neuron j
b_j	Bias applied to neuron j
w_{j0}	Bias weight
$x_i(n)$	ith element of the input vector
$o_k(n)$	kth element of the overall output vector
η	learning rate parameter
L	Depth of the network
l	Layer of multilayer perceptron; $l = 1, 2, \ldots, L$
m_0	Size of the input layer
m_i	Size of the ith hidden layer; $i = 1, 2, \ldots, L-1$
m_L (= M)	Size of output layer
$\vartheta_j^{(l)}(n)$	Induced local field for neuron j in layer l
$w_{ji}^{(l)}(n)$	synaptic weight of neuron j in layer l
$y_i^{(l)}(n)$	Output signal of neuron i in the previous layer l at iteration n
$b_j^{(l)}(n)$	Bias to neuron j in layer l
$\Delta_{ji}(n)$	Weight update value

2. PROPOSED ALGORITHM

Outline of the system components are shown in Figure1. Processing steps are given below:

2.1. Image acquisition

Image had been captured from rice crop field by digital camera. Images were collected under two categories; first leaf blast disease infected images and another category is normal images (Images which were not infected by the disease).

2.2. Image preprocessing

In pre-processing step, cropping and resizing operation has been performed in the acquired images. Captured images are stored into two independent groups, one for normal images and another for leaf blast infected images. Independently cropping operation has been performed in both groups and manually, according to region of interest, cropped images are selected. These cropped images are resized to overcome with the limitation of memory. Normal images are directly forwarded for feature extraction, but leaf blast infected cropped images are forwarded for the segmentation using Otsu's method [12].This method assumes that entire pixels of image belong into two classes, foreground pixels and background pixels. It then calculates the optimum threshold value, separating the two classes, so that their intra-class variance is minimal, or equivalently inter-class variance is maximal.

2.3. Wavelet feature extraction

Discrete wavelet transform (DWT) is a mathematical tool to process any digital images at multiple resolutions. It provides insight into an image's spatial and frequency characteristics. Following steps have been used to extract wavelet features of normal cropped images and segmented leaf blast infected images separately.

Step 1: Select images from both group separately. Let set of images in any individual group is Im, denoted as

$$Im = \{Im_1, Im_2, Im_3, \ldots, Im_N\}$$

Step 2: Repeat step 3 for all images $i = 1, 2, 3, \ldots, N$

Step 3: Compute following steps:

(*i*) Read images Im_i

(*ii*) Resize image Im_i

(*iii*) Normalize images, $I_i = Im_i/255$

(*iv*) Extract Red component (R_i), Green component (G_i) and Blue component (B_i) of each image? I_i.

(*v*) Create decomposition, low-pass (Lo_d) and high-pass (Hi_d) Haar filters.

(*vi*) Perform single level, 2-dimensional decomposition of R_i, G_i, and B_i using Lo_d and Hi_d and compute approximation coefficient wavelet features of R_i, G_i, and B_i as Ca_R_i, Ca_G_i, and Ca_B_i.

(*vii*) Compute 2-dimensional standard deviation of Ca_R_i, Ca_G_i, and Ca_B_i of each image as $x = (x_1, x_2, \ldots, x_i, \ldots, x_N)$ of size of $N \times 3$ by computing following step for each images N.

.for $i = 1, 2, .., N$

(*a*) Compute size of Ca_R_i as m,n where m is total number of row and n is total number of column.

(*b*) Compute standard deviation (SD) of each column n by using (4) where $SD = \{SD_1, SD_2, \ldots, SD_n\}$. Ca_R_i represent 2-dimensional matrix of size $m \times n$ and (k, j) represent index number of the matrix.

for $j = 1, 2, \ldots, n$

$$C_j = \frac{1}{m}\sum_{k=1}^{m} Ca\_R_i\,(k, j) \tag{3}$$

$$SD_j = \left(\frac{1}{m}\sum_{k=1}^{m}(Ca\_R_i\,(k, j) - C_j)^2\right)^{\frac{1}{2}} \tag{4}$$

end

(*c*) Again compute the standard deviation of SD

for $j = 1, 2, \ldots, n$

$$CC = \frac{1}{n}\sum_{j=1}^{n} SD_j \tag{5}$$

$$Ca\_Rsd_i = \left(\frac{1}{n}\sum_{k=1}^{n}(SD_j - CC^2)^{1/2}\right) \tag{6}$$

end

(*d*) Repeat step *a*-*c* to compute 2-dimensional standard deviation of Ca_G_i, and Ca_B_i as Ca_Gsd_i and Ca_Bsd_i

(*e*) Return x_i where $x_i = [Ca\_Rsd_i, Ca\_Gsd_i, Ca\_Bsd_i]$

end

2.4. Back Propagation Neural Network implementation

BPNN is a multilayered feed forward neural network, where Resilient back propagation learning algorithm is used to reduce the harmful influence of the size of the partial derivatives on the weight step. Weight update depends only on the sign of the partial derivatives of the total error energy $\frac{\partial \varepsilon(n)}{\partial w_{ij}(n)}$. Individual update-value $\Delta_{ji}(n)$ determines the size of weight update $\Delta w_{ji}(n)$ according to sign of $\frac{\partial \varepsilon(n)}{\partial w_{ij}(n)}$. Steps of Resilient back-propagation algorithm cycles through the training sample $\{(x(n), d(n))\}_{n=1}^{N}$ are as follows [13]:

Step 1: Create network and initialize the synaptic weights $w_{ji}^{(l)}(n)$ and individual update-value $\Delta_{ji}(n)$ and momentum constant ?

Step 2 : Pass training examples in the network with a minimum number of epoch/ mean square error to perform the sequence of forward and backward computations.

Step 3: Apply input vector $x(n)$ to the input layer and desired response vector $d(n)$ to the output layer of computation nodes for each training example $(x(n), d(n))$ in an epoch, and perform steps from *a-f*:

(*a*) Compute the induced local fields and $\vartheta_j^{(l)}(n)$ for neuron j in layer l is of the network

$$\vartheta_j^{(l)}(n) = \sum_{i=0}^{m_0} w_{ji}^{(l)}(n)\, y_i^{(l-1)}(n) + b_j^{(l)}(n) \tag{7}$$

(*b*) Compute output signal $y_j^{(l)}$ of neuron j in layer l where

$$y_j^{(l)} = \frac{1}{1 + e^{(-\vartheta_j^{(l)}(n))}} \tag{8}$$

(*i*) If neuron j is in the first hidden layer (*i.e.* $l = 1$), set $y_j^{(0)} = x_j(n)$ where $x_j(n)$ is the jth element of the input vector $x(n)$.

(*ii*) If neuron j is in the output layer (*i.e.* l = L where L is referred to as the depth of the network), set $y_j^{(l)} = o_j(n)$

(*c*) Compute the error signal $$e_j(n) = d_j(n) - o_j(n) \tag{9}$$

(*d*) Compute $\frac{\partial \varepsilon(n)}{\partial w_{ij}(n)}$, according to the chain rule of the calculus for output layer and hidden layer

$$\frac{\partial \varepsilon(n)}{\partial w_{ij}(n)} = \frac{\partial \varepsilon(n)}{\partial e_j(n)} \frac{\partial \varepsilon_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial \vartheta_j(n)} \frac{\partial \vartheta_j(n)}{\partial w_{ji}(n)} = -\,e_j(n)\varphi_j'(\vartheta_j(n))\,y_i(n) \tag{10}$$

(*e*) Compute weight update by using following rule

$$\Delta w_{ji}(n) = \begin{cases} -\Delta_{ji}(n), & \text{if } \frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} > 0 \\ -\Delta_{ji}(n), & \text{if } \frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} < 0 \\ 0 & \text{else} \end{cases} \tag{11}$$

(*f*) Update synaptic weight according to generalized delta rule, by including a momentum term as shown below:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha[w_{ji}^{(l)}(n-1) + \Delta w_{ji}(n) \tag{12}$$

α is the momentum constant.

3. EXPERIMENT AND RESULT

3.1. Acquired images from the field

RGB images have been captured from rice crop field by digital camera (SONY DSC-H300 model) with dimensions of 5152×3864 pixels. Total 200 leaf blast infected images and 120 normal images have been captured from the field. Sample of normal images is shown in Figure 2 and leaf blast infected images are shown in Figure 3.

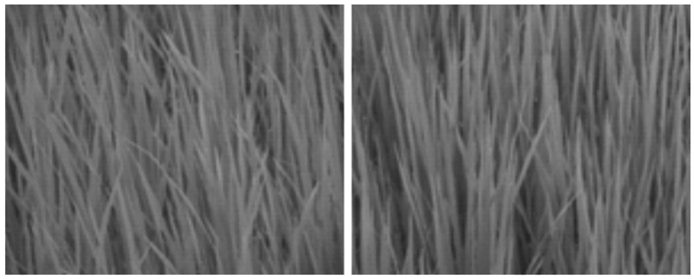

Fig. 2. Sample of acquired normal images.

Fig. 3. Sample of leaf blast infected images.

3.2. Cropped Images

Images are cropped to process on specific region of interest. Manually, 131 leaf blast infected images and 153 normal images had been selected and resized at 205×410 pixels. Sample of the cropped images are shown in Figure 4.

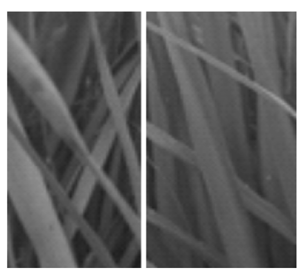

Fig. 4. Cropped images.

3.3. Extracted wavelet features

Sample of wavelet features of rice leaf blast infected images are shown in Table 2 and normal rice image features are shown in Table 3.

Table 2. Wavelet features of leaf blast infected images

Im_i/x_i	Ca_Rsd_i	Ca_Gsd_i	Ca_Bsd_i
$\mathrm{I}m_1$	0.2298	0.1311	0.1409
$\mathrm{I}m_2$	0.2724	0.1891	0.2402
$\mathrm{I}m_3$	0.2823	0.1925	0.2066
…	…	…	…

Table 3. Wavelet features of normal rice crop images.

Im_i/x_i	***Ca_Rsd_i***	***Ca_Gsd_i***	***Ca_Bsd_i***
Im_1	0.1472	0.1520	0.1026
Im_2	0.1398	0.1336	0.1168
Im_3	0.1539	0.1643	0.1108
…	…	…	…

3.4. Implementation of BPNN Model

Network size of 3-20-10-2 has been created where the number of input neuron is 3, output neuron is 2 and two hidden layer of size 20 and 10 has been created. Total 122 normal images and 105 leaf blast infected images are used to train BPNN model. Figure 5, shows learning curve of BPNN. Table 4 represents confusion matrix and Table 5 gives the performance of the proposed BPNN model. Average efficiency to recognizing rice leaf with blast disease infected and not infected, is 92% shown in confusion matrix. After training, 31 normal and 26 leaf blast infected, new images were used to test efficiency of the model. This proposed model gave 91% efficiency to recognize rice leaf which may be infected by leaf blast or not infected by leaf blast.

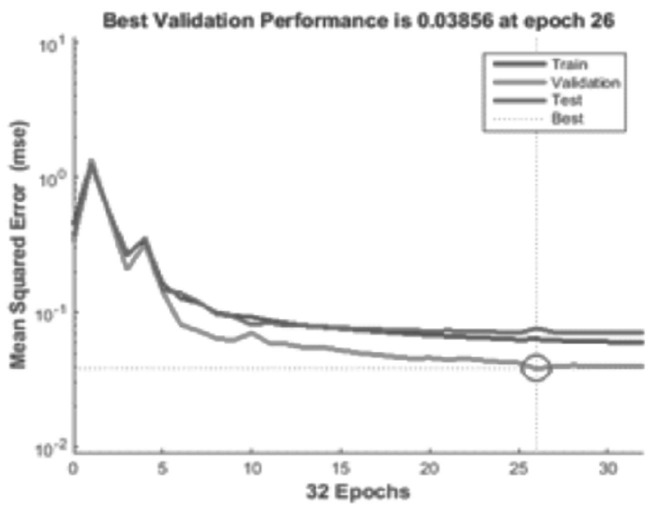

Fig. 5. Performance matrix of BPNN after testing new data.

Table 4. Confusion matrix BPNN.

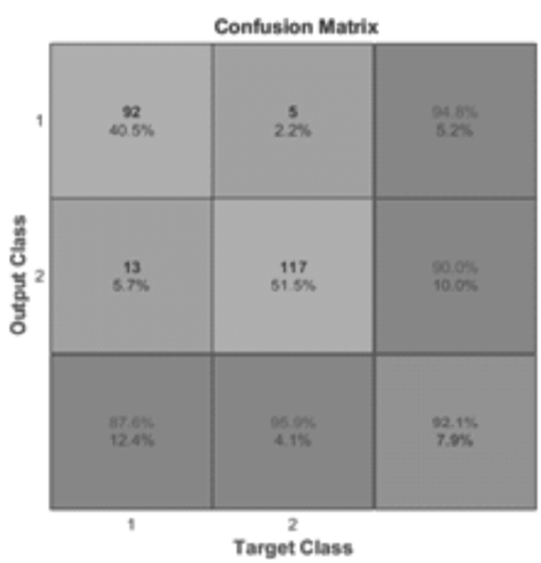

Table 5. Performance matrix of BPNN after testing new data.

Model/Efficiency	*Leaf Blast Image Recognition*	*Normal Rice Image Recognition*	*Average Image Recognition*
BPNN	88%	94%	91%

4. CONCLUSION

Crop disease pattern recognition mostly depend upon human expertise which sometime make err, cause of huge loss of crop. Proposed BPNN model give 91% accuracy to recognize leaf; infected by leaf blast disease or non infected with disease. This model can be consider as one basic step to automate disease recognition process in uncontrolled environment. This method can be extended to recognize more then one diseases.

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