

## **Crop Diseases Recognition Using Hybrid Features and Linear Vector Quantization**

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### **Abstract**

Pattern recognition using image processing has found great promises in various rice crop diseases recognition. Accurate crop disease recognition is very important for conducting integrated pest management, to control and minimize the damages caused by the diseases. Diseased conditions in rice crop are observed by localized structural change in the lesion, mainly discoloration and spots, caused by parasitic and/or non-parasitic agents. Discoloration may reflect change in the color of whole rice plant or one or more its parts which vary according to the intensity of the disease. Spots are other important symptoms of rice crop diseases commonly produced by fungal and bacterial infections which vary in size, shape and color.

This paper introduces rice crop disease recognition using statistical and signal features of acquired images. Initially leaf blast and brown spot disease infected images of rice crop have been captured from the field with the help of digital camera. Image processing has been done to segment disease infected part from the images. Color, texture and wavelet features of spots and discolored part of segmented rice crop images have been extracted, after pre processing of captured images. These image features has been used to design linear vector quantization neural network model to recognize leaf blast and brown spot disease. Model with hybrid features show better recognition efficiency as comparison to individual features used neural network model.

**Keywords:** Pattern Recognition, Rice Blast Disease, Image Processing, Features Extraction, Linear Vector Quantization

## I. INTRODUCTION

Blast and brown spot is the most important fungal disease of rice and occurs in all the rice-growing regions. Some time, these diseases have been responsible for complete destruction of the rice crop. The symptoms of rice blast and brown spot infection can be seen on the leaves as characteristic spindle-shaped spots, with ashy center, and on the leaf-sheaths and at the juncture as irregular oval discolorations. In the absence of a regular rice disease recognition model, it is difficult to conduct integrated pest management to minimize the damages caused by the diseases [1] [2].

Present day applications require automation of process to interpret and analyze the information. These applications require various kinds of images and pictures as source of information for interpretation and analysis. The major application areas of image processing are: improve quality of pictorial information for better interpretation by human; and process image data for machine perception [3].

Designing of pattern recognition model needed features of acquired images. These features may be color, shape, texture or wavelet features. Some features extracted directly from the digital image components like color, shape and texture. Wavelet features give information about spatial and frequency components of any images. Discrete Wavelet Transform (DWT) helps to analyze images at multiple resolutions level [3][7].

DWT process uses decomposition and reconstruction low pass and high pass filters. These filters are applied to extract specific discrete features. In this proposed methodology,

‘haar’ filters are used to extract approximation features of segmented images.

Pattern recognition can be defined as a process of identifying structure in data by comparisons to known structure; the known structure is developed through methods of classification. In pattern recognition system, data is usually divided into two categories: training data and test data. Training data are used to compute parameter used in the algorithmic of the pattern recognition system. Test data are used to evaluate the overall performance of the pattern recognition system [4][5].

System components of rice’s, leaf blast and brown spot disease pattern recognizer using linear vector quantization are shown in Figure 1. Color and texture statistical features of segmented images passed into learning vector quantization (LVQ) neural network model. LVQ work on competitive learning, where single winning neuron active during learning process.

Learning law for supervised learning vector quantization (LVQ1) is given below:

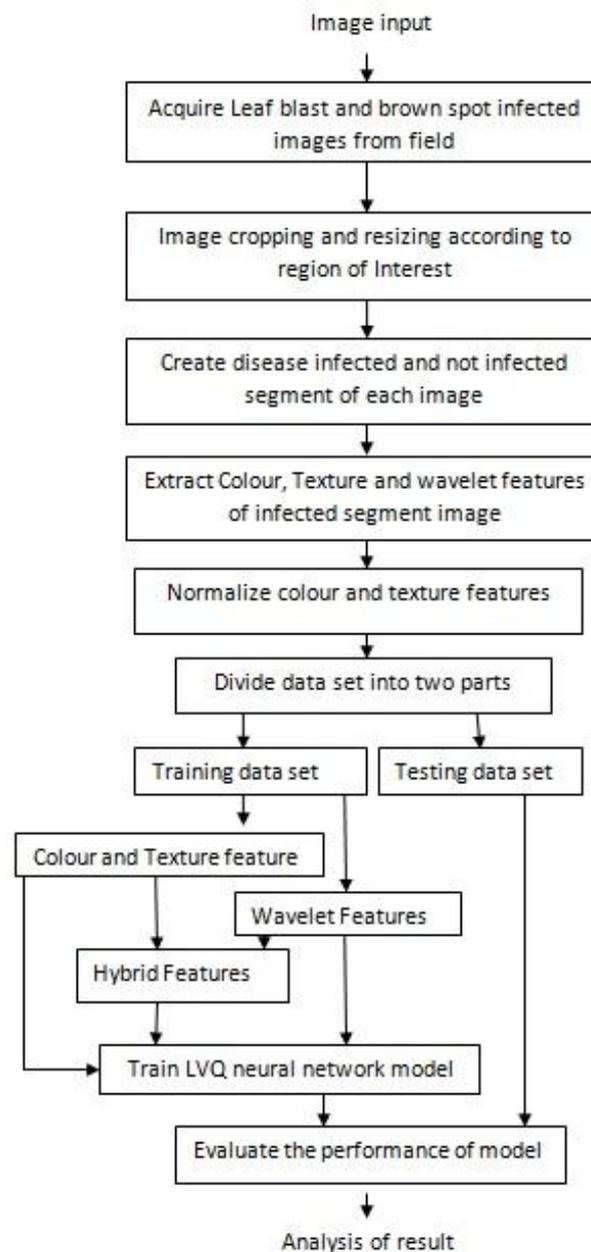
If the class of the input vector  $\mathbf{x}$  is given, then

$$\Delta w_{kj} = \begin{cases} \eta(x_j - w_{kj}) & \text{if } x_j \text{ is classified correctly} \\ -\eta(x_j - w_{kj}) & \text{if } x_j \text{ is classified incorrectly} \end{cases}$$

Where  $\eta$  is learning- rate parameter,  $\mathbf{x}$  is input pattern,  $\mathbf{w}_k$  is synaptic weight vector,  $k$  is neuron number [6].

Components of rice disease recognition model are shown in Figure 1. Captured images of leaf blast and brown spot infected rice crop has been preprocessed and

forwarded for color image segmentation using Otsu's method. Statistical color and texture features, and wavelet signal features of segmented diseased part has been extracted. These extracted features have been used to train and test LVQ neural network model.



**Figure 1.** Components of disease recognition model

## II. METHODOLOGY

Outline of the system components are shown in Figure.1. Processing steps are given below:

### A. Image Acquisition

Image has been captured from rice crop field by digital camera. Images are collected under two categories; leaf blast disease infected images and brown spot infected images.

### B. Image Preprocessing and Segmentation

In pre-processing step, cropping and resizing operation has been performed in 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 [3]. 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. Image pre processing and segmentation steps are given below:

Step 1: Separate  $R, G$  and  $B$  component from image  $I_i$  where  $i = 1, 2, \dots, m$  and  $m$  is total number of cropped images.

Step 2: Create device independent colour space  $r, g$  and  $b$  for each machine dependent images with colour space  $R, G$  and  $B$  by using following equation:

$$r_i = \frac{R_i}{R_i + G_i + B_i}$$

$$g_i = \frac{G_i}{R_i + G_i + B_i}$$

$$b_i = \frac{B_i}{R_i + G_i + B_i}$$

Where  $i = 1, 2, \dots, m$ .

Step 3: Apply multi level threshold using Otsu's method, to create two segments, disease affected segment as  $S_i$  and disease non affected segment as  $S_j$  where  $i, j = 1, 2, \dots, m$ .

### C. Color and Texture Feature Extraction

The color and texture, statistical features of segmented images have been extracted to make classification model. Color feature extraction process is given below:

*for all segmented images  $S_i, i = 1, 2, \dots, m$  do*

*Step 1: Convert  $S_i$  to  $Lab_i$  images*

*Step 2: Sepereate components  $L_i, a_i$  and  $b_i$*

*from  $Lab_i$  image*

*Step 3: Extract following features:*

$x_{i1}$  = Standard deviation of  $a_i$

$x_{i2}$  = Standard deviation of  $b_i$

$x_{i3}$  = Correlation factor between ( $a_i, b_i$ )

$x_{i4}$  = Kurtosis of  $a_i$

$x_{i5}$  = Kurtosis of  $b_i$

$x_{i6}$  = Skewness of  $a_i$

$x_{i7}$  = Skewness of  $b_i$

*Step 4: Combine total extracted colour features  $X_i$*

$= (x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, x_{i6}, x_{i7})$

*end*

Texture feature extraction process is given below:

*for all segmented images  $S_i, i = 1, 2, \dots, m$  do*

*Step 1: Convert  $S_i$  image to gray image  $G_i$*

*Step 2: Create covariance matrix  $B_i$  of gray image  $G_i$*

*Step 3: Extract following features:*

$x_{i8}$  = Contrast( $B_i$ )

$x_{i9}$  = Correlation( $B_i$ )

$x_{i10}$  = Energy( $B_i$ )

$x_{i11}$  = Homogeneity( $B_i$ )

*Step 4: Combine all extrcted texture feture  $Y_i = (x_{i8}, x_{i9}, x_{i10}, x_{i11})$*

*end*

### D. Discrete Wavelet Feature Extraction

Approximation features of disease infected segmented images has been extracted to design neural network model. Wavelet feature extraction process is given below:

*for all segmented images  $S_i, i = 1, 2, \dots, m$  do*

Step 1: Normalize the  $S_i$  image .

$$S_i = \frac{S_i}{255}$$

Step 2: Seperate  $R_i, G_i$  and  $B_i$  components of  $S_i$ .

Step 3 : Initialize low – dimension and high  
– dimension decomposition haar filters

Step 4: Extract approximation features of  $R_i, G_i$  and  
 $B_i$  components:

$x_{i12} = \text{Approximation Features}(R_i)$

$x_{i13} = \text{Approximation Features}(G_i)$

$x_{i14} = \text{Approximation Features}(B_i)$

Step 4: Combine all extrcted wavelet fetures  $W = W_i = (x_{i12}, x_{i13}, x_{i14})$   
end

E. Normalize color and texture extracted features Extraction

Processing steps to normalize extracted features are given below:

for  $i = 1$  to  $m$  do

Step 1: Concatenate extracted colour and texture  
features as  $Z_i = X_i Y_i$

Step 2: Compute  $c = \text{mean of } (Z_i)$

Step 3: Compute  $\sigma = \text{Standard deviation of } (Z_i)$

stpe 4: Apply Gaussian function to normalize  $Z_i$ .

Normlized value

$$CT = CT_i = e^{-\frac{(Z_i - c)^2}{2\sigma^2}}$$

end

F. Disease Recognition Using Linear Vector Quantization (LVQ) Extraction

The algorithm for LVQ net is to find the output unit that has a matching pattern with the input vector. In LVQ, winner unit is identified. Winner unit index is compared with the target, and based upon its comparison result, the weight updating is performed. Colour and texture features  $CT$  and wavelet features  $W$  passed in LVQ. Initially, separate neural network model has been implemented by considering Colour-texture features,  $CT$  and wavelet features,  $W$  separately. Later this two features has been concatenated as  $CTW$  to design hybrid rice disease recognition model using LVQ neural network. In the following algorithm, for all input sequence  $(CT, W, CTW)$ , symbolic representation  $N = N_i$  has been used.

The steps of LVQ algorithm is given below:

Step 1: Read features vector  $N = N_i$  where ,  $i = 1, 2, \dots, m$ .

Step 2: Initialize weight (reference) vectors and learning rate, target class  $t = 1, 2$ .

Step 3: Repeat step 3-7 until stopping is false

Step 4: For each training input  $N_i$ , do steps 4-5

Step 5: Compute  $J$  using squared Euclidean distance.

$$D(j) = \sum (w_{ij} - N_i)^2, j = 1, 2 \text{ (Number of Target Class, } t)$$

Step 6: Find  $J$  when  $D(j)$  is minimum.

Step 7: Update  $w_j$  as follows:

If  $t = C_j$  then

$$w_j(\text{new}) = w_j(\text{old}) + \eta (N_i - w_j(\text{old}))$$

If  $t \neq C_j$  then

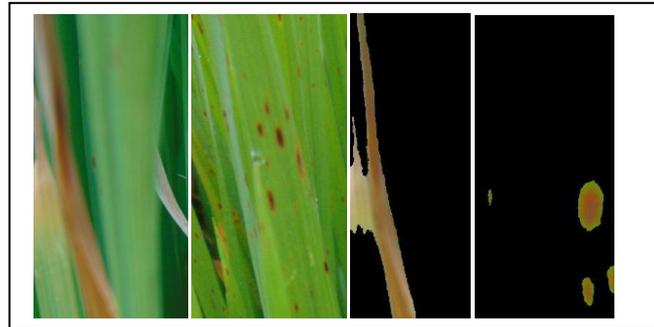
$$w_j(\text{new}) = w_j(\text{old}) - \eta (N_i - w_j(\text{old}))$$

Step 6: Decrease the learning rate.

Step 7: Test for the stopping condition.

### III. EXPERIMENTAL SETUP AND RESULTS

Digitally captured images are cropped according to region of interest. These images are forwarded for segmentation. Samples of original cropped leaf blast and brown spot images are shown in Figure 1 and segmented images are shown in Figure 2.



**Figure 1:** Sample of leaf blast and brown spot infected rice crop images and segmented images

Total 105 leaf blast infected images and 92 brown spot infected images are segmented. Total 7 colors, 4 textures and 3 wavelet features of segmented part of infected images have been used to design LVQ neural network model. Samples of segmented features are shown in Table I, Table II and Table III.

**TABLE I: SAMPLES OF COLOR FEATURES**

S.No./Features	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$
1	2.8	6.57	5.81	7.09	2.14	-2.12	-0.89
2	3.11	9.61	24.83	11.53	0.31	-0.40	-0.44
3	1.88	6.56	3.45	4.34	0.91	-1.13	-0.68
...	...	...	...	...	...	...	...

**TABLE II: SAMPLES OF TEXTURE FEATURES**

S.No./Features	$x_8$	$x_9$	$x_{10}$	$x_{11}$
1	2.80	6.57	5.81	2.14
2	3.11	9.61	24.83	0.31
3	1.88	6.56	3.45	0.91
...	...	...	...	...

**TABLE III: SAMPLES OF WAVELET FEATURES**

S.No./Features	$x_{12}$	$x_{13}$	$x_{14}$
1	0.18	0.19	0.10
2	0.19	0.17	0.03
3	0.16	0.15	0.06
...	...	...	...

To create LVQ using color and texture features, 11-20-2 size neural network has been created where 11 is the number of inputs, 20 is total number of hidden layer and 2 is the number of recognized classes. LVQ has been initialized with 50 iteration and learning rate 0.01. Training performance graph is shown in figure 2 and confusion matrix is shown in Table IV. According to confusion matrix, recognition efficiency of leaf blast disease infected images is 69.6% and brown spot disease infected images are 85.7%. Average performance is 78.2%. It gives minimum error 0.22 at iteration 4.

**TABLE IV: CONFUSION MATRIX OF LVQ WITH COLOR-TEXTURE FEATURE**

		Confusion Matrix		
Output Class	n	1	2	
		1	2	Target Class
1	64	15	81.0%	32.5%
		7.6%	19.0%	
2	28	90	76.3%	14.2%
		45.7%	23.7%	
1	69.6%	85.7%	78.2%	30.4%
		14.3%	21.8%	

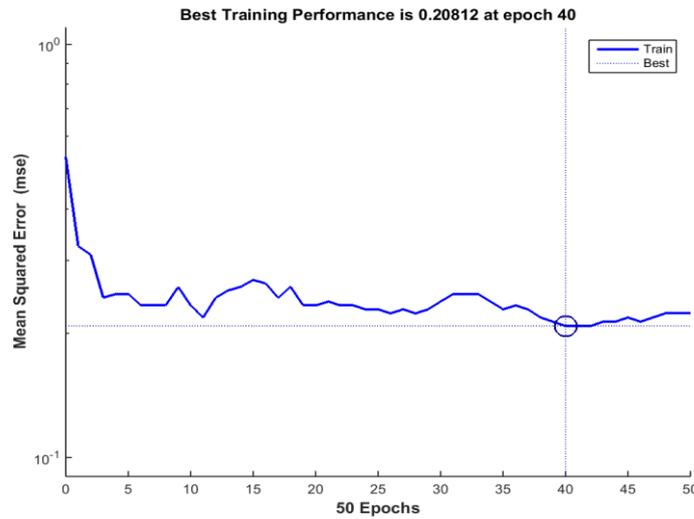


**Figure 3:** Performance graph of LVQ with color and Texture features

LVQ neural network with size of 3-20-2 s has been created for 3 input wavelet features for each image, where 3 is the number of inputs, 20 is total number of hidden layer and 2 is the number of recognized classes. Training performance graph is shown in figure 2 and confusion matrix is shown in Table 4. According to confusion matrix, recognition efficiency of leaf blast disease infected images is 88.0% and brown spot disease infected images are 71.4%. Average performance is 79.2%. It gives minimum error 0.21 at iteration 40.

TABLE V: CONFUSION MATRIX OF LVQ WITH WAVELET FEATURE

		Confusion Matrix		
		1	2	Average
Output Class	1	81 41.1%	30 15.2%	73.0% 27.0%
	2	11 5.6%	75 38.1%	87.2% 12.8%
	Average	88.0% 12.0%	71.4% 28.6%	79.2% 20.8%
		1	2	
		Target Class		

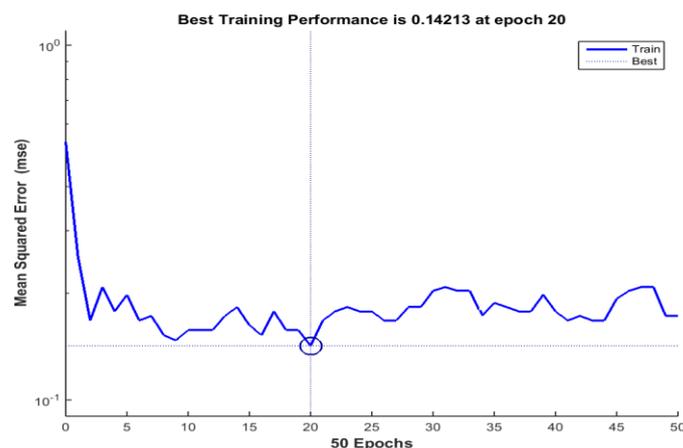


**Figure 4:** Performance graph of LVQ with wavelet features

LVQ neural network with size of 14-20-2 s has been created for 14 hybrid input features for each image. Here 14 is the number of inputs, 20 is total number of hidden layer and 2 is the number of recognized classes. Training performance graph is shown in figure 2 and confusion matrix is shown in Table 4. According to confusion matrix, recognition efficiency of leaf blast disease infected images are 84.8% and brown spot disease infected images are 86.7%. Average performance is 85.8%. It gives minimum error 0.14 at iteration 20.

**TABLE VI:** CONFUSION MATRIX OF LVQ WITH HYBRID FEATURE

		Confusion Matrix		
		1	2	
Output Class	1	78 39.6%	14 7.1%	84.8% 15.2%
	2	14 7.1%	91 46.2%	86.7% 13.3%
		84.8% 15.2%	86.7% 13.3%	85.8% 14.2%
		1	2	Target Class



**Figure 5:** Performance graph of LVQ with hybrid features

Summary of the overall performance of the LVQ neural network is given in Table VII.

**TABLE VI:** SUMMARY OF OVERALL PERFORMANCE OF LVQ

Features/ LVQ Performance	Leaf Blast Recognition Efficiency	Brown Spot Recognition Efficiency	Average Performance	Minimum Performance Error
Color+ Texture	69.6%	85.7%	78.2%	0.22
Wavelet	88.0%	71.4%	79.2%	0.21
Color+ Texture +Wavelet	84.8%	86.7%	85.8%	0.14

#### IV. CONCLUSION AND FUTURE SCOPE OF WORK

It has been observed that LVQ neural network recognition model for rice leaf blast and brown spot recognition disease, give better performance when hybrid statistical and signal features passed for training. In case of only statistical or signal features, model can recognize single disease only but not able to recognize another disease. LVQ performance with hybrid features is 85.8%.

In future, multiple rice disease pattern recognition system can be designed with the help of this technique. Various optimization techniques can be implemented to optimize number of input features required for enhancing recognition performance.

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