International Journal of Current Advanced Research

ISSN: O: 2319-6475, ISSN: P: 2319-6505, Impact Factor: SJIF: 5.995

Available Online at www.journalijcar.org

Volume 6; Issue 10; October 2017; Page No. 6448-6452 DOI: http://dx.doi.org/10.24327/ijcar.2017.6452.0945



Researh Article

DIAGNOSIS AND CLASSIFICATION OF DISEASES IN PADDY LEAVES

Suresha M1., *Shreekanth K N1 and Thirumalesh B V2

¹Department of P.G. Studies & Research in Computer Science, Kuvempu University, Karnataka, India ²Department of P.G. Studies & Research in Applied Botany, Kuvempu University, Karnataka, India

ARTICLE INFO

Article History:

Received 13th July, 2017 Received in revised form 9th August, 2017 Accepted 25th September, 2017 Published online 28th October, 2017

Key words:

Pattern Recognition; kNN Classifier; SVM Classifier; Paddy leaves Diseases;

ABSTRACT

In Asian country paddy is the most important agricultural crop because almost human beings are depend on rice as their food, so rice is given major importance among the cereals in Asian country. There will be a yield loss due to rice plant diseases. In the proposed work, identification of Blast and Brown Spot diseases are has been done. Otus segmentation method is used to segment the image and kNN and SVM classifier used for the classification, based on extracted features for properties of gray-level co-occurrence matric. By using kNN and SVM classifier method the result obtained is 84% and 73.6% accuracy respectively.

Copyright©2017 Shreekanth K N et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

World's main staple food or crop is Rice. Nearly 2.5 billion people consume rice as a staple food. Hundreds and millions of people are investing their half of the salary on rice to feed their family. Major loss of rice yield is caused by diseases, which are fungal, bacterial and viral diseases. In this proposed work identification of fungal diseases like brown spot and blast diseases in paddy leaves has been done. The diseases destroy the plant stand, spotted kernels, lodging, smaller the grains per plant and general reduction in plant efficiency which is considered as direct losses and indirect losses like using of fungicides were more effective and also yield loss associated with cultural practices proposed by Ajay K. Gupta, (2007). In this proposed work gray level co-occurrence matrix has been constructed from an image. Then statistical features like Contrast, Correlation, Energy, and Homogeneity are extracted from GLCM. Identification of Blast and Brown Spot diseases has been done using these statistical features. kNN and SVM classifier have been used for identification of diseases.

Rice (Orvza sativa L.) suffers a number of fungal diseases and occur at times in fairly severe form and cause heavy crop loss and yield, Chakrabarti (2001). Adam Sparks et al., (2015) proposed Blast disease caused by the fungus Magnaporthe oryzae, it can affect leaf, collar, node, neck, panicle and sometimes leaf sheath. Wherever blast spores found on plant surface in that spot blast diseases can occur in any stage of the

plant growth. Initially disease symptoms are white to graygreen lesions or darker borders spots on all parts, older lesions are spindle or elliptical shape and whitish to gray with necrotic borders. Magnaporthe grisea, is a filamentous, heterothallic Ascomycotina that all things considered causes infection on numerous types of the grass (Poaceae) family. M. grisea is the teleomorph relating to the already particular anamorphs Pyricularia oryzae, tainting rice (Oryza sativa), and P. grisea, contaminating different grasses Yaegashi and Udagawa (1978).

Adam Sparks et al., (2015) proposed Brown Spot diseases also caused by fungus Bipolaris oryzae, Bipolaris oryzae belongs to class Deuteromycetes, it is the causal agent of brown spot disease of rice, Brown spot is one of the very important disease in rice, Shabana et al., (2008). The pathogen infects the coleoptiles (causing blighting), leaves and damages the photosynthetic activities, ultimately killing the leaf, Aryal et al., (2016). Symptoms of Brown spot appear initially small circular to oval spots on seedling leaves. Small spots are dark brown to reddish brown and large spots area light to reddish-brown or gray center, surrounded by margin of dark to reddish-brown and older spots are yellow halo surrounding the spot lesion. Brown spots symptoms of leaves also similar symptoms on the leaf sheath and hulls Datnoff et al., (2003). Infection causes failure of seed germination, reduces grain weight and quality it will reduce 50% of yield loss to the farmer Shabana et al., (2008); Chakrabarti et al., (2001).

LITERATURE REVIEW

Adnan et al., (2012) proposed a method to identify rubber plant leaf diseases called Corynespora Leaf spot, Bird's Eye Spot and Collectrotichum Leaf Disease. Authors used characteristics information from three different components like Red, Green and Blue and stored in MySql database. Online web application has been deployed with training data to test samples which helps farmers to identify diseases in rubber plant leaves. Phadikar et al., (2008) Proposed a method to identify Rice leaves diseases like Blast and Brown Spot. Only diseased part in the leaves is captured, then increased brightness and contrast of images and transformed HSI color model by using Entropy based bi-level thresholding method. Boundary detection algorithm is used for image segmentation. Self-organizing map neural network (SOMNN) used for classification of diseases. SOMNN has given accuracy of 92% for the features extracted from RGB color component. Author uses the gray value of spots as feature. To get a missed values author used interpolation technique on every spots and extract better gray values of every spots which are extracted from gray values of original spots, Fourier transformation of spot, Arbitrary rotation of the 50% spot and Fourier Transformation of the 50% rotation. Authors observed that transformation of the spots in frequency domain will not yield a better classification compare to original image. Orillo et al., (2013) proposed a method for identification of rice plant diseases like Bacterial leaf blight, Brown spot and Rice blast using Back Propagation Neural Network (BPNN) and proven 100% accuracy. Images were captured under controlled-light module box from green house of the International Rice Research Institute, Laguna, Philippines. Contrast adjustment and noise reduction pre-processed steps were followed and also RGB images were converted into HSV color space to represent similar to the human eye senses the color similarity. Segmentation is done by adjusting intensity of images using Otsu's segmentation method. Blob processing has been employed to reduce the noise in binary images. The segmented leaf images are converted into LAB color space. Histogram equalization method is used to classify healthy and diseased. Binary level images are used for histogram equalization to remove the healthy and diseased part of the rice leaf which helps for feature extraction like fraction covered by infected area by dividing the mask area and measured area of disease. Arithmetic mean value and standard deviation are calculated for R,G and B components of diseased part and mean values of H,S and V of diseased part. Classification is done using Back Propagation Neural Network. Asfarian et al., (2013) proposed a method to identify four major diseases in paddy crop like leaf blast, brown spot, bacterial leaf blight and tungro. The collected diseased images are cropped manually and color space is changed to HSV and saturation component is used for further process. Histogram equalization and Laplacian filters are used for image enhancement and image sharpening respectively to improve the image quality. Classification process has been carried out using Probabilistic Neural Network (PNN) classifier. Cross fold validation method was used for testing and found 83% of accuracy. Majid et al., (2013) developed a mobile application for identification of diseases in paddy leaves and found 91.46% accuracy. Authors used images of paddy leaves which are captured under open field in different location, and diseased part cropped manually. Cropped images are converted to gray images. Images are enhanced using

laplacian filter. Fuzzy entropy method is used for Feature extraction, membership function to approximate the membership of bright and dark images, membership functions parameters are used to set a threshold and Probabilistic Neural Network (PNN) Classifier is used to classify the diseases. The proposed work holds four layers like input layer, pattern layer, summation layer and output layer. Prasad et al., (2012) proposed Gabor Wavelet Transform method to detect plant leaf diseases, diseased spot is identified using histogram based segmentation. Features are extracted by using Gabor Wavelet transform and matching of features is done by SVM Classifier. In this method, classification of healthy and diseased leaf is done based color changes on the leaf surface such as healthy leaf is green in color and diseased leaves are in light yellow, brown, red or mottled on leaf surface. Diseased part of the leaves are segmented using color thresholding in RGB color model. Three individual components are selected for segmentation. Dual thresholding is used for segmentation. Texture feature extraction processes is being used on segmented disease portion by using Gabor Wavelet transform. Principle Component Analysis (PCA) has been applied on feature vectors for dimensionality reduction and classification is done using SVM classifier and found success rate of 89%. Phadikar et al., (2012) disease identification and classification methods have been proposed. Authors have proposed two methods for classification of diseased rice leaves and uninfected rice leaves. A radial features with eight direction have been extracted from the infected region of leaves. Histogram has been generated out of these features. In the first method, based on peaks of a histogram the infected and uninfected diseases have been classified. In the second method with same features comparison study has been conducted using Bayes classifier and Support Vector Machines (SVMs) classifiers and found 79.5% and 68.1% accuracy respectively.

Problem Definition

Plant also suffers from diseases same as human being by fungi, bacterial and viral infection that causes yield loss. When diseases are appears on the leaf surface it reduces the ability to produce its food. Sometime the pathogen were block the vessels in the stems which supply to leaves by attacking the roots, that will completely block the up take of water and stop nutrients to upper part of the plant which leads to death of plant Suniti Sharan et al, (2011), Hariday S. Chaube et al, (2015). Paddy crop contains different types of diseases. Most difficult task among these is diseases identification which takes time to analyze leaf evaluations of diseases are done by professionals in a naked eye based on morphological changes which is expensive. In paddy fields, machine vision technology can be employed to replace traditional human inspection. In this paper, identification of blast and brown spot diseases of paddy leaves are addressed using texture features of the diseases.

Proposed Method

Segmentation of diseased portion in the leaves is done using otsu segmentation method. GLCM is generated and statistical features like contrast, correlation, energy and homogeneity of diseased part of paddy leaves have been extracted. Classification of brown spot and blast diseases is done by kNN classifier and SVM Classifier. A typical work flow of proposed methodology is shown in Figure 1.

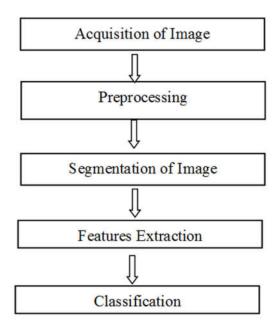


Figure 1 Typical work flow for proposed methodology

Image Acquisition

Survey has been conducted in various parts of shivamogga district, Karnataka state. Paddy images are captured using digital camera with 18.1 mega pixel resolution. The images are captured in day light such that there is clear view of leaf objects in the camera. Sample data set of paddy leaves with diseases is shown in Figure(2).

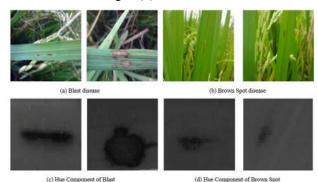


Figure 2 Sample paddy diseased leaves

Image Segmentation

Jayaraman et al., (2009) describes image segmentation is the first steps in image analysis and pattern recognition, segmentation is processes of partitioning an image into groups of pixels based on homogeneous criteria. Which helps to extract features from segmented object (images) based on the area of interest or based on the experimental objective. Extraction of region of interest is called segmentation. Preprocessing steps are involved before the segmentation process because segmentation is the major step in this process. The collected images have been resized to 256 X 256 to improve the processing time. In the next level the sample images are converted RGB color space to HSV color space. Rafael C. Gonzalez et al., (2013) explain Otus segmentation method is used for segmentation. By Histogram equalization method applied on gray images. Image histogram is obtained using equation (1)

$$p_q = n_q/n$$
 $q = 0,1,2,3,...,L$ 1 (1)

Where n denotes total number of pixels in an image, n₀ denotes the number of pixels that have intensity level q, and total number of possible intensity levels in an image is denoted by L, here intensity levels values are integers.

Consider, k is the threshold, then C_1 have the set of pixels with levels $[0, 1, 2, \ldots, k]$ and C_2 have the set of pixel with levels [k + 1,, L-1]. Threshold value k that maximizes the between class variance $\sigma_R^2(k)$, shown in equation (2)

$$\sigma_B^2(k) = p_1(k)[m_1(k) \quad m_G]^2 + p_2[m_2(k) \quad m_G]^2 \quad (2)$$
here $p_1(k)$ is the probability of occurring set C .

here, $p_1(k)$ is the probability of occurring set C_1 .

$$p_1(k) = \sum_{i=0}^{k} p_i (3)$$

If the k value set 0, the probability of set C_I having any pixels assigned to zero. Correspondingly, the probability of set C_2 is

$$p_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 \quad p_1(k)$$
 (4)

In set C_1 and C_2 , the term $m_1(k)$ and $m_2(k)$ are the mean intensities of the pixels respectively. Where m_G is the global mean shown in equation (5)

$$m_G = \sum_{i=0}^{L-1} i p_i {5}$$

And also, the mean intensity up to level k is given in equation

$$m(k) = \sum_{i=0}^{k} i p_i \tag{6}$$

expanding the expression for $\sigma_B^2(k)$, and using the fact that $p_2(k)=1-p_1(k)$, here can write the between class variance as given in equation (7).

$$\sigma_B^2(k) = [m_G p_1(k) \quad m(k)]^2 \div p_1(k)[1 \quad p_i(k)] \tag{7}$$

In the equation (7) only the parameter m and p_1 are to be commuted with the k values, so that the above said equation is comparably more efficient computation, and m_G compute only once.

Maximizing the between class variance that larger the variance, that threshold will segment the image properly. Optimality measure is obtained using image properly. Here k is an integer in the range of [0, L - I] and finding the

maximum of $\sigma_B^2(k)$ is straight forward. L possible values of k and compute the variance at each step. The k gives largest

value of $\sigma_B^2(k)$, and k is optimum threshold. If the maximum is not unique, then the threshold used is the average of all the optimum k's found. The ratio of the between class variance to the total image intensity variance given equation (8)

$$\eta(k) = \frac{\sigma_B^2(k)}{\sigma_G^2}$$
 (8)

Measure of the separability of image intensities into two classes, where k is the optimum threshold is shown in equation (9).

$$0 \le \eta(k) \le 1 \tag{9}$$

Constant images are measure its minimum value, binary images are measures maximum value.

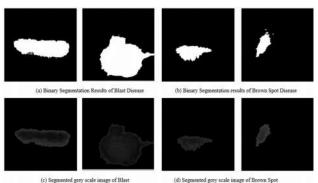


Figure 3 Sample paddy diseased leaves

Features Extraction

Important steps after segmentation process is feature extraction. The gray level co-occurrence matrix of a segmented image is generated. The properties of gray level co-occurrence matrix are extracted such as Contrast, Correlation, Energy, and Homogeneity using GLCM matrix. Suresha et al., (2014) proposed a method to classify healthy and diseased arecanut by collecting a sample images of arecanut seeds from different region. Author transformed RGB images to HSI and YCbCr color space, and segmentation processes are carried out using saturation component of HSI component, segmented binary image multiplied with all component of HIS and YCbCr color component individually. By using GLCM, Haar Wavelets and Gabor features are extracted from each color component and using subset of texture features kNN classifier are used to classify the healthy and diseased arecanut.

Contrast: Local variations are measured by contrast attribute in gray level co-occurrence matrix.

$$\sum_{i,j} |i - j|^2 \ p(i,j) \tag{10}$$

Correlation: Joint probability occurrence of specified pixel pairs are measured by correlation

$$\sum_{i,j} \frac{(i - \mu i)(j - \mu j)p(i,j)}{\sigma_i \sigma_j} \tag{11}$$

Energy: Angular second moment or uniformity is called as energy which provides sum of squared elements in gray level co-occurrence matrix

$$\sum_{i,j} p(i,j)^2 \tag{12}$$

Homogeneity: closeness of the distribution of elements in gray level co-occurrence matrix to gray level co-occurrence diagonal matrix is measured.

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{13}$$

Classification

In the proposed method, Support Vector Machine (SVM) and kNN classification are used, for classification of Brown spot and Blast diseases.

SVM Classification: SVM technique is used in many practical applications like handwritten digit recognition to text category data, and also it works for high dimensional data to avoid the dimensionality problem. The main unique aspect of SVM approach is representing the decision boundary using a subset of the training data called it as support vectors. SVM classifier uses the features mentioned from equation (10) – (13). Classification result are plotted in cartesian coordinate system using SVM Classifier is shown in the Figure 4.

kNN Classification: Training data set has a pair of order set of features and corresponding labels. Let say h_x is the feature vector and y_i is the corresponding label vector. In training data set label is known where as in testing set label in unknown. kNN classifier determines k nearest neighbors and then determines labels for the sample based on neighbor weight. Let us say a training set D has x_i training samples. The training samples are labeled with the class label y_o . The objective is to classify testing sample q for each $x_i \in D$ and the distance between q and x_i is calculated using equation (14).

$$d(q, x_i) = \sum_{f \in F} w_f \delta(q_f, x_{if})$$
(14)

The equation for finding k nearest neighbors is selected for continuous and discrete attributes is given below.

$$\delta(q_i, xi_f) = \begin{cases} 0 & f \text{ discrete and } q_f = x_{if} \\ 1 & \text{discrete and } q_f \neq x_{if} \\ |q_f \quad x_{if}| & f \text{ Continuous} \end{cases}$$
(15)

These are variety of methods for identifying k nearest neighbors to determine the class. The most popular method is majority rule for assigning a label to unknown sample.

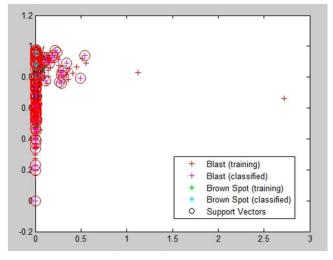


Figure 4 Result of SVM classification

EXPERIMENTAL RESULTS

Collected paddy leaves images are resized to 255 X 255 size to improve the algorithm accuracy. 60% of images have been used for training and 40% of images have been used for testing out of 330 images. In this proposed methodology kNN and SVM classifier have given 84% and 73.6% of accuracy respectively in the proposed methodology. SVM classifier has been used for radial features within the result of 68.1% by S. Pradikar *et al*,. in 2012. Bayes classifications have been given accuracy of 79.5%. Where Bayes classification have been got certain limitations which works only for offline data. Our

work shows better result using kNN and SVM classifier. In this proposed work the nearest neighbors are considered.

CONCLUSION

Classification of Brown Spot and Blast diseases of paddy leaves are carried out in the proposed work. In this proposed work GLCM features are extracted for both training and testing sample, by using kNN and SVM classifier classification have been done. Fungal diseases have been considered in this proposed work. In future work, other types of diseases like will be addressed.

References

- Adam Sparks, NP Castilla & CM Vera Cruz. Blast (leaf and collar). International Rice Research Institute (IRRI). Retrieved February 07 2015 from http://www.knowledgebank.irri.org/training/fact-sheets/pest-management/diseases/item/blast-leaf-collar
- Adam Sparks, NP Castilla & CM Vera Cruz. Brown spot. *International Rice Research Institute (IRRI)*. Retrieved February 07 2015 from http://www.knowledgebank.irri.org/training/fact-sheets/pest-anagement/diseasesitem/brown-spot
- Adnan, S. F. S., Abdullah, N. E., Hashim, H., Yusof, Y. W. M., & Malim, M. Y. S. (2012, December). A development of online database system for rubber tree leaf diseases. In Computer Applications and Industrial Electronics (ISCAIE), 2012 IEEE Symposium on (pp. 312-317). IEEE.
- Ajay K. Gupta. (2007). "Hand books on Rice cultivation processing", NPCS Board Consultants and Engineers.
- Aryal L , Bhattarai G , Subedi A , Subedi M, Subedi B & Sah G.K. 2016. Response of Rice Varieties to Brown Spot Disease of Rice at Paklihawa, Rupandehi. Global Journal of biology, Agriculture and Health sciences, 5(2): 50-54.
- Asfarian, A., Herdiyeni, Y., Rauf, A., & Mutaqin, K. H. (2013, November). Paddy diseases identification with texture analysis using fractal descriptors based on fourier spectrum. In Computer, Control, Informatics and Its Applications (IC3INA), 2013 International Conference on (pp. 77-81). IEEE.
- Chakrabarti, N. K. (2001). Epidemiology and disease management of brown spot of rice in India. In *Major Fungal Diseases of Rice* (pp. 293-306). Springer Netherlands.
- Datnoff, L.E. and Lentini. R.S. (2003). Brown Spot in Florida Rice. *University of Florida IFAS extension, Document PP128*. http://ipm.ifas. ufl.edu/pdfs/RH00700.pdf

- Hariday S. Chaube & Ramji Singh. (2015). *Introductory Plant Pathology*. CBS Publishers and Distributors ISBN: 978-81-239-2670-4.
- Jayaraman, S., Esakkirajan, S., & Veerakima, T. (2009). Digital image processing, ed iii.
- Majid, K., Herdiyeni, Y., & Rauf, A. (2013, September). I-PEDIA: Mobile application for paddy disease identification using fuzzy entropy and probabilistic neural network. In *Advanced Computer Science and Information Systems (ICACSIS)*, 2013 International Conference on (pp. 403-406). IEEE.
- Orillo, J. W., Cruz, J. D., Agapito, L., Satimbre, P. J., & Valenzuela, I. (2014, November). Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network. In *Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2014 International Conference on (pp. 1-6).* IEEE.
- Phadikar, S., & Sil, J. (2008, December). Rice disease identification using pattern recognition techniques. In *Computer and Information Technology, 2008. ICCIT 2008. 11th International Conference on* (pp. 420-423). IEEE.
- Phadikar, S., Sil, J., & Das, A. K. (2012). Classification of Rice Leaf Diseases Based on Morphological Changes. *International Journal of Information and Electronics Engineering*, 2(3), 460.
- Prasad, S., Kumar, P., Hazra, R., & Kumar, A. (2012, December). Plant Leaf Disease Detection Using Gabor Wavelet Transform. In *SEMCCO* (pp. 372-379).
- Rafael C. Gonzalez, Richard E. Woods & Steven L. Eddins. (2013 ninth reprint). *Digital Image Processing Using MATLAB*. McGraw Hill Eduction (India) Private Limited, ISBN 978-0-07-070262-2.
- Shabana, Y. M., Abdel-Fattah, G. M., Ismail, A. E., & Rashad, Y. M. (2008). Control of brown spot pathogen of rice (*Bipolaris oryzae*) using some phenolic antioxidants. *Brazilian Journal of Microbiology*, 39(3), 438-444
- Suniti Sharan. (2011). *Plant Diseases*. Pacific Book International, ISBN 978-93-80472-38-6.
- Suresha, M., Danti, A., & Narasimhamurthy, S. K. (2014). Classification of Diseased Arecanut based on Texture Features.
- Yaegashi, H., & Udagawa, S. (1978). The taxonomical identity of the perfect state of Pyricularia grisea and its allies. *Canadian Journal of Botany*, 56(2), 180-183.

How to cite this article:

Suresha M et al (2017) 'Diagnosis and Classification of diseases in Paddy Leaves', *International Journal of Current Advanced Research*, 06(10), pp. 6448-6452. DOI: http://dx.doi.org/10.24327/ijcar.2017.6452.0945
