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Detection of Disease Onset in Rice Plant Leaves in Monochrome Light

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ABSTRACT

Rice is one of the most important crops in the world because of its vast usage irrespective of age and gender. Machine vision and image processing techniques are widely used to detect diseases in plant leaves. In this paper, a prototype system is developed for rice disease onset detection from images in monochrome light. Initially, images of leaves of rice plant are acquired in controlled environment. After preprocessing, local binary patterns and local ternary patterns are extracted as features of the image. Support vector machine and k-nearest neighbors are applied as classifier to identify the healthy and diseased image. Training is completed on 70% of the images while testing is done on the remaining 30% images. Experimental values of the results are 0.94, 0.93, 0.98 and 0.93 for Precision, Sensitivity, Specificity and F1 Score respectively. Overall accuracy of the method is 93.55%. The results show encouraging performance of the proposed method.

1. Introduction

Our life mostly depends on the plants [1] for food, oxygen in the air, clothing, etc. Plants are vulnerable to the diseases, if they get any disease, they cannot do anything by their own [2]; we have to take care of the plants. Rice is the most important food crop in the world, it is a staple food for over half of the world's population [3]. Healthy plants produce healthy and better crops. An expert with relevant knowledge can detect diseases in the plant by inspecting the leaves. The symptoms are observed with naked eyes so this process is highly subjective and depends mostly on the personal experience. Onset of disease detection is often difficult even for experienced agricultural experts. To detect the diseases from the crops we need to have some mechanism, which should observe the leaves of the plants and inform us about the health of the plants in objective manners without personal bias. As early, a disease is noticed within a crop, we can try to take some counter measures, before it damages the product/crop. Early detection of disease is important to obtain good yields from the crops. In Southeast Asia, rice diseases potentially loss the productivity up to 50% [4].

Therefore, in order to achieve high productivity, a system is proposed that detects the disease in rice plant leaves early using red light spectrum image. Proposed method takes input as image of leaf of a rice plant and gives output about its health. Most of the existent methods find the disease when it is visible to our eyes but the proposed method is able to find the disease on its onset even when it is not visible to our naked eyes. Bacterial blight, brown spot and blast are important bacterial and fungal diseases at various rice growing areas of Pakistan. Healthy and diseased plants are shown in Fig. 1. It is evident from both leaf photos that leaves are very distinct in colour when disease occurs in the plants.

Several efforts have been carried out to detect the diseases using leaves images of different plants in last two decades. Many researchers are working on image processing techniques in this field to achieve high classification between healthy and diseased plants.

(a) (b)

Fig. 1: (a) Healthy plants (b) Diseased plants.

Bindushree and Givasankari [5] proposed a technique to classify green foliage of plant disease in three steps. In first step, region of interest containing disease affected area is segmented, while in second step gray level co-occurrence matrix (GLCM) is calculated as features and finally support vector machine (SVM) is applied as classifier. Anand et al. [6] presented a method to detect disease in brinjal leaf images using k-mean clustering for segmentation and neural networks are applied for classification. Lukic et al. [7] proposed an approach based on uniform LBP and Hu's invariant moments as features and SVM as classifier to recognize the plant species. Narayan and Subbarayan [8] proposed the optimal feature set for leaf analysis. They extracted color, shape and texture features of leaf images using genetic algorithm and kernel based principal component

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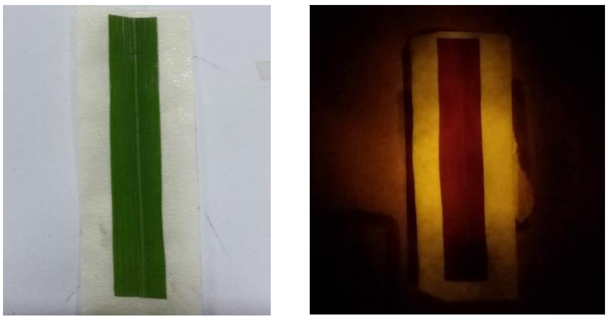
analysis (PCA). SVM is applied as classifier to classify different plants with 88% accuracy.

Mangala et al. [9] described a method to detect disease in paddy leaves by thresholding based segmentation technique and classification of the disease is performed by SVM. Oo and Htun [10] proposed a method to detect and classify different plant diseases using three classifiers, i.e., SVM, k-nearest neighbours (KNN) and ensemble. Sethy et al. [11] described a technique to detect healthy and diseased parts of rice plant leaf by using K-Means clustering or 3-Means clustering with best area accuracy of 29.69% that is related to healthy area. Yao et al. [12] proposed image processing technique for detecting rice disease. They extracted shape and texture features of the diseased spot from the leaf and applied SVM for classification with disease spots accuracy of 97.2%. Plant leaves were classified and disease was recognized using SVM by Mahapatra et al. [13]. In their method, different features like shape, colour and texture were extracted to apply SVM for the identification of disease. Plant name is also used as an attribute in the training to achieve accuracy of 91%.

Xiao et al. [14] proposed a method based on PCA and back propagation neural network for rice blast recognition. They processed image lesion and extracted different color, morphological and texture features. PCA was applied to reduce the dimensions and NN for classification to achieve 95.83% accuracy but they only used image of the lesion part of the leaf.

2. Materials

Nursery of rice plants of disease susceptible variety "Super Basmati" was raised in the trays and at 2-3 leaf stage, seedlings were transplanted into pots, approximately ten plants per pot. At tillering stage the rice plants were inoculated with Bacterial Leaf Blight (BLB), a common disease in rice plants. This process was conducted at National Agricultural Research Centre, Islamabad, Pakistan. The diseased and healthy leaves were collected randomly at 4^{th}, 7^{th}, and 32^{nd} days after inoculation of disease. These leaves were pasted on a paper and then images were acquired using a DLSR camera. All images were collected in (red spectrum) monochrome light. A (ready to take photo) plant leaf is shown in Fig. 2(a) and image of the same plant leaf is acquired in control environment is shown in Fig. 2(b).



(a) (b)

Fig. 2: (a) Rice plant leaf is ready for imaging (b) Image of rice leaf in monochrome light spectrum.

Classes of plant leaves images were named as (a) Healthy, (b) BLB4, (c) BLB7 and (d) BLB32. Here the prefix number represents the leaf image acquired after these number of days. A total of 420 images were used in this study.

3. Proposed Method

Following steps are applied to detect healthy and unhealthy rice plant leaf from the image. After image acquisition first step is pre-processing in which image is cropped and converted to gray scale image. Next is feature extraction followed by classification of the leaf. Block diagram of the proposed method is shown in Fig. 3. Detail of each block is as follows.

3.1 Image acquisition

In order to acquire the image of rice leaf a setup is designed based on DSLR camera, red emitting light diod, a chamber in which plant leaf is placed and a slit is formed in the chamber from which monochrome light bounce on the leaf. Before image acquisition, leaf is cut into a small piece and is pasted on a white paper.

Image of this leaf is acquired in monochrome light while camera setting are 18-55mm lens, ISO speed 125, focal length 4mm and no flash. Initially, healthy plant leaves gone through this process and after disease inoculation of 4^{th}, 7^{th} and 32^{nd} days, the diseased plant leaves images are acquired that make four classes of images as discussed in Materials section. Original image in red spectrum light is shown in Fig. 2(b).

3.2 Preprocessing

After acquisition of images, pre-processing is applied so that noise, like extra part of the image and paper on which leaf is pasted, is removed from the images and features of same dimension are extracted. To remove unwanted part of the leaf, images are cropped manually of the same size as 64×128 pixels. Cropped images are then converted to grayscale images for faster processing of feature extraction. Preprocessed image is shown in Fig. 4.

3.3 Feature extraction

Feature extraction is an important step towards classification; highly distinctive features make the training model better to create wide class separation distance. Leaves have many features that can be useful for plant classification based on shape, color and texture [1, 7, 15–18]. However, pre-processed leaves have same shape and color so texture based features are extracted. Two types of local texture features: Local binary pattern (LBP) and local ternary pattern (LTP) are extracted, followed by histogram of the LBP image. In this research work, normalized LBP are extracted that has 59 bins histogram, i.e., 0-58. Details of these local features descriptions are as follows:

3.3.1 Local binary patterns (LBP)

LBP is a simple but efficient texture extractor which threshold the neighboring pixels based on the value of central pixel. Thresholded neighboring values are converted to decimal number which represent the LBP feature [19] of

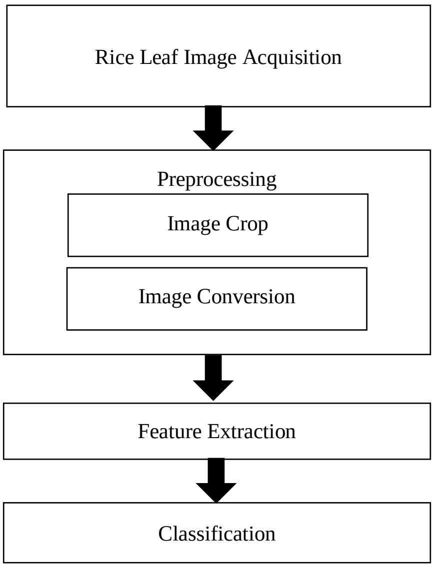


Fig. 3: Block diagram of proposed method.

(a) (b)

Fig. 4: Image after (a) cropping (b) conversion to gray scale.

that pixel. Image containing LBP features is used for histogram processing. For a pixel in the image, LBP is calculated using following mathematical Eq (1):

$$LBP = \sum_{n=0}^{7} t(p_n - p_c)2^n \quad (1)$$

Where p_n is the pixel value of neighbours of the central pixel, p_c is the pixel value of central pixel and t is the threshold function defined as:

$$t(m) = \begin{cases} 1, & if\ m \geq 0 \\ 0, & if\ m < 0 \end{cases} \quad (2)$$

This process is elaborated for a sample pixel and its neighbors in Fig. 5.

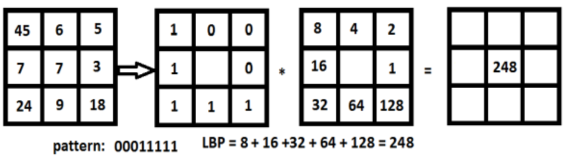


Fig. 5: Local Binary Patterns extraction process.

Most commonly used variant of LBP is Uniform LBP in which patterns that contains more than two transitions from 0 to 1 (or 1 to 0) are considered as same pattern which reduced the total number of patterns from 256 to 59 [15, 18, 20]. After obtaining LBP features of the pre-processed image, histogram of occurrence frequencies in the image is created to represent the feature of the image.

$$\mathrm{H(k)} = \sum_{i=1}^{I}\sum_{j=1}^{J} f(\mathrm{LBP(i,j),k}) \qquad \mathrm{k} \in [0, \mathrm{K}] \quad (3)$$

such that

$$f(x,y) = \begin{cases} 1, & if\ x = y \\ 0, & otherwise \end{cases} \quad (4)$$

where K, I and J are the maximum value, number of rows and number of columns of LBP image, respectively.

3.3.2 Local Ternary Patterns (LTP)

LBP are invariant to monotonic gray level transformation, i.e., they works well for lighting effects, they are sensitive to noise. In LBP, neighbors are thresholded by central pixel value, where as LTP [21] used a small value as threshold "t" to define a zone with width 2t+1, i.e., [p-t p+t], neighbor pixel values in this zone are converted to zero where as positive values are converted to 1 and remaining values are converted to -1. This change of neighbors pixel values into three different values are based on the equation below [20].

$$f(p_n, p_c, t) = \begin{cases} 1, & if\ \ p_n \geq p_c + t \\ 0, & if\ |p_n - p_c| < t \\ -1, & if\ \ p_n \leq p_c - t \end{cases} \quad (5)$$

Where t is threshold, p_c is central pixel value and p_n are neighbor pixel value. This patterns with negative numbers is changed into two LBPs: upper binary pattern and lower binary pattern. Upper binary pattern is obtained by converting all -1 values to 0, i.e., considering the mentioned zone similar to smaller values while in lower binary pattern all positive 1s are converted 0 and "-1s" are changed to 1, i.e., considering the mentioned zone similar to higher values. After that, LTP are calculated similar to LBP.

$$LTP = \sum_{n=0}^{7} \check{f}(p_n, p_c, t)2^n \quad (6)$$

where $\check{f}$ is the pattern after conversion of described method. Further details can be found in an article by Liao [21]. Pictorilly the process is shown in Fig. 6 in which threshold of 5 is used to obtain the pattern by using Eq (5). Details are discussed above.

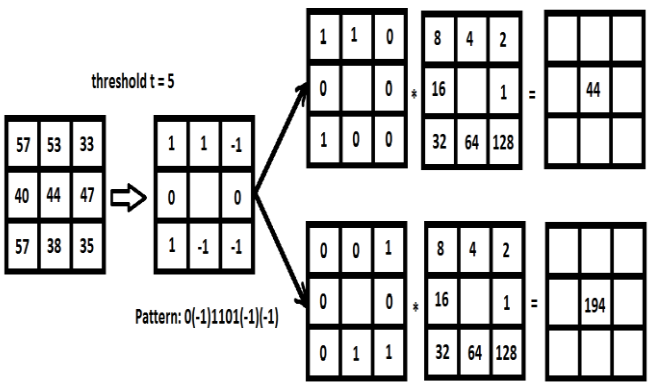


Fig. 6: Calculation of Local Ternary Patterns.

3.4 Classification

Support Vector Machine (SVM) is a popular classifier, which separate the data by finding a hyperplane between the different training classes. This hyperplane classifies the new data points. SVM is a supervised machine learning classification method. In case of two dimensional feature vectors, hyperplane is a line in the plane that classify each class in either side. Let training labeled sample set be $T = \{(x_i, l_i), i = 1, 2, \dots, L\}$, where x_i is the feature vector of class i and l_i is the class label and a new feature vector x can be classified based on the sign of Eq. (7).

$$f(x) = sign \sum_{i=1}^{L} w_i . x_i + b \quad (7)$$

where "w" is a weight vector and "b" is the bias (threshold value). Quadratic optimization problem is solved to maximize the margin w to minimize the function $\min_{w,b} \frac{1}{2} \|w\|^2$ such that $y_i(w.x_i) + b \geq 1$ sign of the function f(x) classify the leaf.

K-nearest neighbor (KNN) is a classification method based on distance among the input features vectors of the leaves. The number "K" represent the number of nearest neighbors of the test feature space to search for classification. A test sample is assigned a class based on the majority of votes for that class among the "K" neighbors. If K = 1, then the test sample is assigned to the class of that single nearest neighbor whereas in this research work its value is 3.

4. Results and Discussion

Experiments are carried out to test the proposed method where MATLAB 9.2.0 is used as development tool on a windows 10 platform with Intel Core i7 processor with 16 GB ram.

Results of the proposed method are evaluated under the following quantities. Precision, sensitivity, specificity, F1 score and accuracy. Precision is overall percentage of the result, sensitivity is the probability of correctly identifying the healthy and diseased leaf. Specificity is the ability of the method to designate the leaves that do not have disease. F1 score also known as dice similarity coefficient is another important quantity that measures the test's accuracy. It balances the use of precision and sensitivity by taking weighted harmonic mean of them. It provides a more realistic measure. Accuracy is also an important measure that provides overall result of a proposed method. If TP is true positive, TN is true negative, FP is false positive and FN is false negative then mentioned performance quantities are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$F1\ Score = \frac{2TP}{2TP + FP + FN}$$

In the present study, true positive means leaf is diseased and our method predicts it is diseased, false positives means leaf is healthy but proposed method classify it as diseased. Similarly, true negative means leaf is healthy and predicted results is also healthy; whereas false negative means that leaf is diseased but it is classified as healthy. Values of TP, FP, FN and TN are shown in Table 1.

Table 1. Evaluatoin measure of proposed method with knn and svm.

Leaf classes	Evaluation measure values for							
	SVM				kNN			
	TP	FP	FN	TN	TP	FP	FN	TN
Healthy	31	0	0	93	31	0	0	93
BLB4	21	7	10	86	23	0	8	93
BLB7	24	10	7	83	31	5	0	88
BLB32	31	0	0	93	31	3	0	90

Results of accuracy, precision, sensitivity, specificity and F1 score of the experiments using KNN and SVM classifier are given in Table 2.

Table 2. Values of evaluation quantities of proposed method.

Sr. No	Quantities	SVM	KNN
	Accuracy	86.29%	93.55%
	Precision	0.86	0.94
	Sensitivity	0.86	0.93
	Specificity	0.95	0.98
	F1 Score	0.86	0.93

Proposed method achieved accuracy of 86.29% and 93.55% with SVM and KNN, respectively. Since we are finding the diseased and heathy plant so accuracy of individual classes is also important specially accuracy to detect healthy plant. Fig. 7 represents the result of accuracy of individual classes with respect to SVM and KNN. It is pertinent to know that achieved accuracy for healthy class is 100%, i.e., if a plant leaf is healthy then resulted prediction by the proposed method is healthy. If the system has input a diseased leaf just after four days, i.e., class BLB4 then the system predicts it as a diseased plant. Most of the incorrect cases of BLB4 are classified as BLB7, i.e., plant having disease after seven days. If the system classifies early diseased leaf as later diseased (i.e., severe diseased) then it is fine because the later we detect the disease, the more is the spread of disease. So early detection of disease is significantly well to alarm the farmers to take precautionary measures for the safety of the crop. When the disease in the plant reaches to 32^{nd} day then the proposed system classifies the plant as diseased with 100% accuracy. In these experiments, KNN performed better than SVM, which implies that data cannot be conveniently segregated using the decision planes calculated by SVM; whereas KNN provides highly convoluted decision boundary as it is driven by the training data. The accuracy of the different algorithms for various plant leaf diseases is shown in Table 3 which depicts encouraging performance of the proposed method.

Table 3: Comparison with other techniques.

Sr. No	Method	Accuracy
	Senan et al. [22]	93.0%
	Mahapatra et al. [13]	91.0%
	Xiao et al. [14]	95.83%
	Shrivastava et al.[23]	91.37%
	Mohan et al. [24]	93.33%
	Sulistyaningrum et al. [25]	86.10%
	Kakade and Ahire [27]	92.94%
	Phadikar et al. [26]	79.5%
	Proposed	**93.55%**

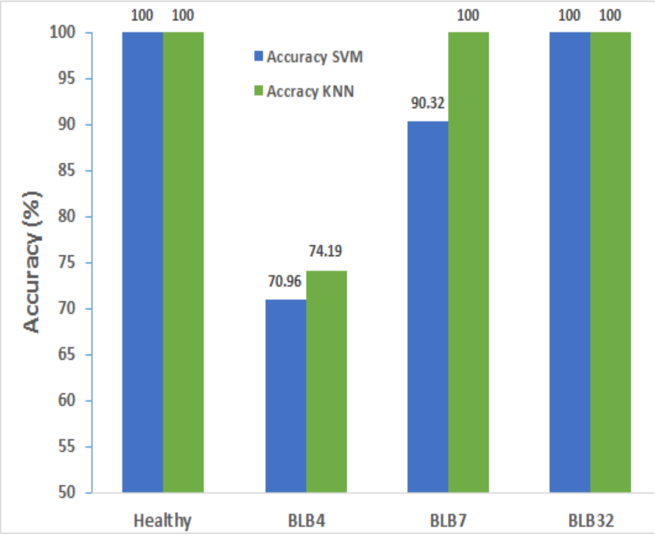


Fig. 7: Results of the proposed method.

5. Conclusions

Rice crop plants are one of the high production resources for agricultural counties and loss in its production is mainly due to diseases on it. Many methods have been applied to detect disease from rice plant leaves using image processing techniques. In this paper, an approach is proposed to detect early, disease from the rice plant leaf images acquired in monochrome light. After acquisition of images in controlled environment and preprocessing, local binary patterns and ternary local patterns are extracted as features for further classification based on SVM and KNN. 70% of the images are used in training, whereas proposed method is tested on remaining 30% images. Experimental results show that the proposed approach has achieved classification accuracy of 86.29% and 93.55% using SVM and KNN respectively.

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