

Detection and Classification of Rice Diseases: An Automated Approach Using Textural Features

KOMAL BASHIR*, MARIAM REHMAN*, AND MEHWISH BARI**

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ABSTRACT

Image processing techniques are widely used for the detection and classification of diseases for various plants. The structure of the plant and appearance of the disease on the plant pose a challenge for image processing. This research implements SVM (Support Vector Machine) based image-processing approach to analyze and classify three of the rice crop diseases. The process consists of two phases, i.e. training phase and disease prediction phase. The approach identifies disease on the leaf using trained classifier. The proposed research work optimizes SVM parameters (gamma, nu) for maximum efficiency. The results show that the proposed approach achieved 94.16% accuracy with 5.83% misclassification rate, 91.6% recall rate and 90.9% precision. These findings were compared with image processing techniques discussed in review of literature. The results of comparison conclude that the proposed methodology yields high accuracy percentage as compared to the other techniques. The results obtained can help the development of an effective software solution by incorporating image processing and collaboration features. This may facilitate the farmers and other bodies in effective decision making to efficiently protect the rice crops from substantial damage. While considering the findings of this research, the presented technique may be considered as a potential solution for adding image processing techniques to KM (Knowledge Management) systems.

Key Words: Rice Disease, Image Acquisition, Image Pre-Processing, Segmentation, Feature Extraction, Disease Diagnosis.

1. INTRODUCTION

Pakistan is an eminent agricultural country with agriculture being the largest sector in its economy. According to Pakistan Bureau of Statistics, agriculture adds approximately 24% to GDP (Gross Domestic Product) [1-2]. Pakistan is the fourth largest rice crop producer [3-4]. Rice (*Oryza Sativa*) is

considered as a main crop in this region, efforts are being carried out at government and private sector level to increase production and hazard prevention [5]. Due to lack of formal education and training, farmers struggle to prevent and cure crops from diseases such as brown spot, bacterial leaf blast, false smut, and stem rot [6]. Rice

Authors E-Mail: (komal.bashir@gmail.com, dr.mrehman13@gmail.com, mehwishbari@yahoo.com, mehwishbari@gmail.com)

* Department of Computer Science, Lahore College for Women University, Lahore, Pakistan.

** National College of Business Administration & Economics, Bahawalpur, Pakistan.

production is substantially affected by diseases at any stage of plant growth [5]. Different parts of plant such as seed, root, stem, and leaf may get affected [7]. The major causes of diseases are fungi, bacteria, virus and nematode [7-8]. Timely detection and classification of disease is important for cure recommendation [8]. Government departments guide cures and precautionary measures but still there is a room for improvement because farmers have to wait for the extension agents' visit [9].

1.1 Selected Diseases

Rice crops in Pakistan are effected by a number of diseases. However, this research detects and classifies three of frequently occurring diseases named as, Brown Spot, False Smut, and Bacterial Leaf Blight [4]. Next section briefly describes the characteristics of these diseases.

1.1.1 Brown Spot

Brown Spot disease as shown in Fig. 1 is rife in rice crops and is recorded in all parts of Pakistan. At early stage,



FIG. 1. BROWN SPOT [12]



FIG. 2. FALSE SMUT [15]

small, light colored, circular or oval shaped spots appear on plant leaves. Later these spots increase in size and merge with each other to form linear spots in darker tones of brown color followed by withering and yellowing of leaves. This disease also causes sterility and poor germination. Affected seeds, plant debris and soil is contaminated by fungus which is further transmitted to other healthy plants by air or irrigation water [2,10-11].

1.1.2 False Smut

False smut is another common rice crop disease which causes chalkiness of grains as shown in Fig. 2. It affects the rice grain germination that results in weak grains. Areas with 90% humidity, 25-35°C temperature, and high nitrogen content in soil provide optimum condition for this disease. Fungal spores from infected plants travel with air flow and affect healthy plants [13-14].

1.1.3 Bacterial Leaf Blight

Bacterial Leaf Blight as shown in Fig. 3, effects the rice planted along the leaf margins. At advance stage, it may

cover the entire leaf and change its appearance to yellow. This disease is also spread through air flow and irrigation water [8,11,13].

1.2 Image Processing for Rice Leaf Disease Identification

Nowadays, research in the field of plant disease detection is gaining pace [14]. Image processing techniques are used for disease identification and classification. Moreover, computer vision applications are making their importance in the field of agriculture [16]. Image processing provides tools and techniques for improvement and analysis of images from microscopic to telescopic level [14].

The aim of this research paper is to use image processing techniques for the detection and classification of rice leaf diseases. This section discusses the techniques used in this research work.

1.2.1 Scale-Invariant Feature Transform

SIFT (Scale-Invariant Feature Transform) is used to extract key points and calculate their descriptors. It is responsible for the detection and description of the local features of images [17]. These key points are stored for

further referencing. For the recognition of a new object, SIFT detects key features of the new image and then compares each feature individually to the ones stored in the database based on Euclidean distance of their feature vectors. After matching the new key points to the stored ones, good matches are filtered out based on the matching of location, orientation and scaling parameters. Clusters are formed for three or more features that matches object and its position, probability is computed for set of features against indication of existence of an object which gives the percentage count of true and false matches [18-19].

1.2.2 Bag of Words

BoW (Bag of Words) converts the features identified by SIFT to words for image classification. It gives count of occurrence of words for an image [19]. It is the most commonly used methodology for categorizing the object features. The main principle of BoW is to quantize each extracted feature key point as one of visually created words, later representing each image by a histogram of these words. Clustering is done for similar words making them a single group, mostly K-means clustering algorithm is used for this purpose [20].



FIG. 3. BACTERIAL LEAF BLIGHT [10]

1.2.3 K-Means Clustering

K-means clustering algorithm is used to form groups or categories of data depicting similar behavior. ‘K’ represents the number of groups to be formed in given data; the aim of this algorithm is to locate all the features with common properties. Iterative approach is used to locate group for each key point feature or word which forms groups or clusters of data based on the similar features. Each cluster has a centroid holding feature values for that group [21-23].

1.2.4 Brute-Force Matcher

BF (Brute-Force) matcher is a modest matching technique. The input to BF matcher is the descriptor of a feature of the first set. This input is matched with all other features of the second set using distance calculation. The function returns the closest one which locates the closest descriptor in the set by matching with each feature descriptor [24-25].

1.2.5 Support Vector Machine

SVM is a technique for the analysis and recognition of data. It is used to carry out regression analysis and classification tasks. SVM takes a group of input data and estimates classes for each input [21,26-27]. SVM is linear model based trainer which creates a hyper plane that groups the data into separation between the hyper plane and the nearest training points based on extracted features [27-28].

2. RELATED WORK

The research work is conducted at various levels for the improvement of agriculture sector like seed selection, soil analysis, weed cure and water management. This section

gives overview of the research carried out by using image processing techniques for identification of plant leaf diseases.

Morphological changes were used by researchers to distinguish diseased area of rice leaf. It addressed two rice leaf diseases and developed a system for their identification. Normal and affected leaves were classified based on peaks in the histogram. Bayes’ classifier and SVM were applied to classify the leaf diseases. The accuracy for Bayes’ method was stated as 79.5% and that for SVM classification was 68.1% [28].

Fermi energy based region extraction technique was used to detect the rice leaf diseases. Color based features were extracted by calculating mean and standard deviation of the diseased region with the background region, color variation was also considered. Test data was compared with the trained data. Its accuracy was stated to be 75% [27].

An algorithm has been designed to detect and classify grape leaf disease. The process involved following steps i.e. image acquisition, image pre-processing, features extraction and classification based on neural network. Extracted images were further stored in the database, the feature comparison was made for the healthy leaf and the one having disease. The researcher claimed it to be 92.94% accurate [14].

Image processing techniques based on color segmentation were used to detect pomegranate leaf diseases. K-means clustering along with fuzzy classifier is used [29]. The accuracy of the proposed technique was not stated.

Rice leaf disease detection and classification was performed using Haar-like features and AdaBoost

classifier. The detection accuracy rate was 83.33%. In disease recognition, the disease type was recognized using SIFT feature and classifiers namely kNN (k-Nearest Neighbor) and SVM. The stated disease recognition accuracy rate was 91.10%. Moreover, no database was designed to store the images for future referencing [8].

3. MATERIALS AND METHOD

This research validates the proposed approach on three rice crop diseases. The dataset of 400 images was gathered from various sources. These sources include RKB (Rice Knowledge Bank), APS (American Phytopathological Society), SS (Shutterstock) and RRI

(Rice Research Institute) Kala Shah Kaku, Punjab, Pakistan [10,12,15,30]. Table 1 shows the list of rice plant diseases along with their pathogen (infection causing agent) and the number of images taken for each disease. Initially image data for three diseases has been collected, 150 images for Brown Spot, 150 for Bacterial Leaf Blight and 100 images were gathered for false smut disease.

The proposed approach comprises of two phases i.e. training and disease prediction phase as shown in Fig. 4. Training phase encapsulates proposed steps for analysis of training dataset and training SVM, whereas, disease detection phase detects and predicts disease from image that was not used in training phase.

TABLE 1. LIST OF RICE DISEASES WITH PATHOGEN AND SELECTED SAMPLE SIZE [4,34]

No.	Disease	Pathogen	Sample Size
1.	Brown Spot	Bipolarisoryzae	150
2.	Bacterial Leaf Blight	Xanthomonasoryzaepv. Oryzae	150
3.	False Smut	Ustilaginoideavirens	100



FIG. 4. IMAGE CONVERTED TO GREYSCALE

3.1 Training Phase

The training phase consists of following five steps:

- (i) Image acquisition included the process of gathering infected rice leaf images for implementing the proposed work flow.
- (ii) Image pre-processing was performed to convert leaves images to greyscale using EM GUI functions as shown in **Fig. 4**. The reason for this conversion is to make uniform color of all images, although all leaves are green yet there are variations in color levels [14].

Feature detection and description was carried out using SIFT algorithm. SIFT was used to detect and extract a number of regions from an image, these regions were grouped in the next phase. SIFT associated a signature to regions by adding description to it.

Vocabulary Building was based on the features extracted and described in the previous step. These were clustered in this phase by using k-means clustering algorithm and a visual word (a represented member of each cluster) was calculated for each cluster. BoW k-means trainer performed this task, resulting in visual BoW. At the end of this phase, clusters were formed each having set of common features.

The K-means clustering algorithm was used for this purpose, cluster count was set to 80 for current work and “pp centers” was used as k-mean clustering type. The grouping of features was carried out by reducing the sum of the squares of the distance between the object and the corresponding cluster [31]. Fig. 5 shows the results of K means clustering on an infected rice leaf.

BF matcher was used for matching the features which finds the closest descriptor in the set by trying each one [23]. L1 was used as parameter to reflect SIFT as descriptor (Fig. 6).

Next, for every image to be learnt, image descriptor was made by making the histogram of clusters for that image, forming numeric descriptor for all the images. Image regions were grouped as BoW along with their vocabulary.

Training Normalized Histograms were provided for classification process. Classification task was performed using SVM. Classification is considered as a vital part of image analyzed digitally [23]. A classifier is capable of classifying an unknown image but it must be trained before. It has a number of parameters including C, gamma and nu. Nu is related to the ratio of SVM and the ratio of training error, this



FIG. 5. RESULT OF K-MEAN CLUSTERING

research work performed parameter optimization for SVM in order to get maximum efficiency out of it. Two parameters i.e. gamma and nu were tested with multiple values to generate more effective results. The factor C allows to trade off training error verses model complexity. A small value for C increases the number of training errors, whereas a large C leads to a behavior similar to that of a hard-margin SVM. Gamma is a kernel parameter, it defines how far the influence of a single training example reaches, with low values meaning ‘far’ and high values meaning ‘close’. The parameter ‘nu’ is an upper bound in the fraction of training points outside the estimated region whose value directly influenced the value of C parameter. Various pairs of (C, gamma) values were tested and it was found that using exponentially growing sequences of C and gamma gave a practical method to identify good parameters i.e., $C = 2^{15}, 2^{13}, \dots, 2^3$, $\text{gamma} = 2^{-15}, 2^{-13}, \dots, 2^{-3}$ [32]. Kernel type for SVM was selected to be RBF (Radial Basis Function). This phase ends with provision of a trained system.

3.2 Disease Prediction Phase

Used previous phase results for disease detection. Its steps were as follows:

- (i) Image acquisition took new image for testing purpose, this image was not used to train the system.
- (ii) Image pre-processing was performed at first phase to convert leaves images to greyscale.
- (iii) Feature detection and description was carried out similar to first phase, extracted local SIFT features. Determined all the local features of the new image in order to guess the cluster to which they belong.
- (iv) Classification/Disease Prediction involved making a histogram of the new image and comparing of new histogram to the histograms of the already learnt images. SVM performed prediction of the disease class for the new image which helps the system to suggest the appropriate cure.

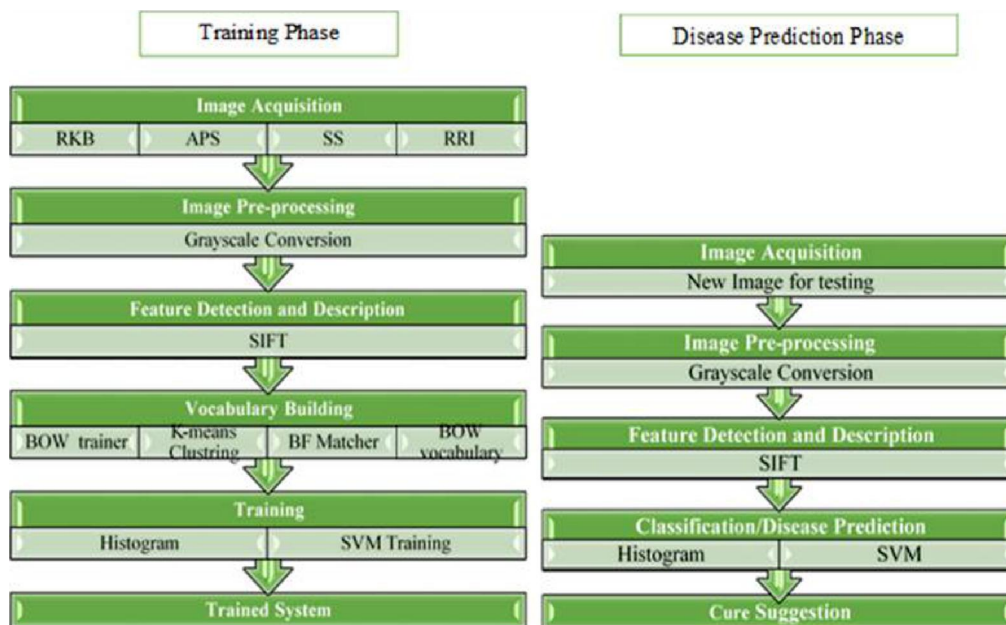


FIG. 6. FLOW OF PROPOSED WORK

- (v) Cure Suggestions were made by the system based on the identified disease. Precautionary and cure measures were gathered from experts of agriculture domain. Fig. 7 showed infected leaf, disease identified and suggested cure.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Image Distribution

Total of 400 diseased rice leaf images were used to validate the stated approach of disease identification. Out of these

400 images, 280 (70%) were used to train the system and 120 (30%) for testing. Testing images were again categorized into two groups, 60 (15%) images were used for parameter optimization in order to get optimal values of SVM parameters, and 60 (15%) images were used for identification of diseases. **Table 2** indicates the image distribution.

4.2 Parameter Optimization

Parameter optimization was performed on 15% of the testing sample images for two SVM parameters. The concluded optimal values for the parameters are shown in Table 3.

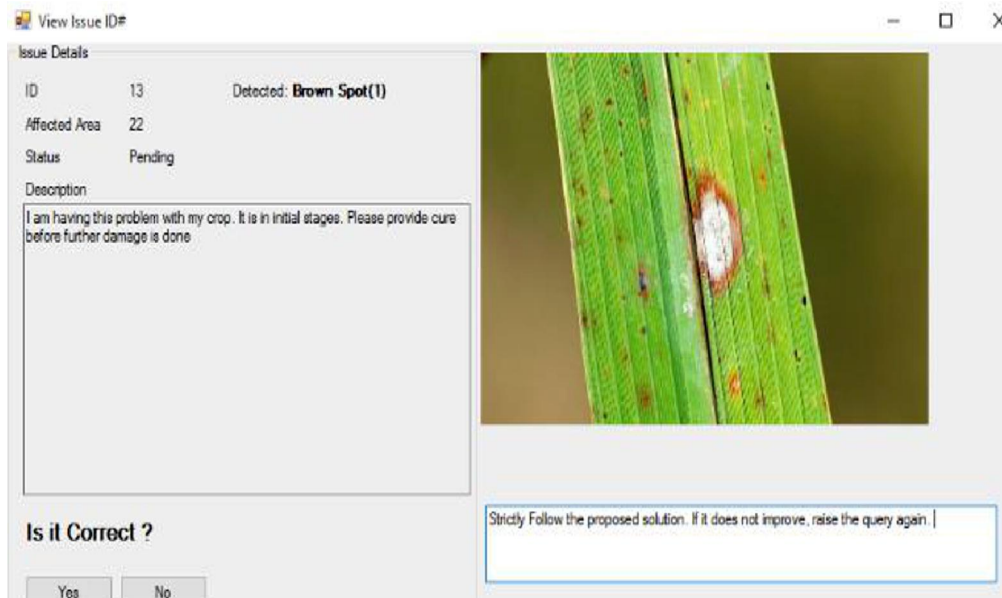


FIG. 7. SYSTEM VIEW

TABLE 2. IMAGES DISTRIBUTION

Disease	Images	Training Sample	Testing Sample	
			Parameter Optimization	Identification
Brown Spot	150	106	22	22
Bacterial Leaf Blight	150	106	22	22
False Smut	100	68	16	16
Total	400	280	60	60
Percentage	100%	70%	15%	15%

4.3 Evaluation

The proposed approach was evaluated using precision and recall method. Confusion matrix presented in Table 4 indicates the evaluation process. Images are grouped according to the results generated, 60 images were used for testing purpose.

These images were classified as TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) based on results generated by the system.

True Positive: The image was infected and its disease was predicted truly.

True Negative: The image was not infected by a certain disease and the system predicted it as negative.

False Positive: The image lacked a certain disease but the system predicted it positive.

False Negative: The image had a certain disease but the system predicted absence of it.

The summary of the results is given in Table 5, which depicted 113 TN, 51 TP, 9 FN and 7 FP cases.

The proposed methodology was evaluated based on features estimated in Table 6 using the results of Tables 4-5. Following parameters were estimated:

TABLE 3. OPTIMAL VALUES FOR SVM PARAMETERS

Parameter	Optimal Value
Gamma	10
Nu	0.8

TABLE 4. CONFUSION MATRIX

Disease	Images	TP	TN	FP	FN
Brown Spot	44	43	71	5	1
Bacterial Leaf Blight	44	38	72	4	6
False Smut	32	29	86	2	3
Total	120	110	229	11	10

TABLE 5. SUMMARY OF RESULTS

	Predicted Negative	Predicted Positive
Negative Cases	TN: 229	FP: 11
Positive Cases	FN: 10	TP: 110

TABLE 6. EVALUATION OF THE PROPOSED METHODOLOGY BASED ON FEATURE ESTIMATION

Feature	Formula	Resulted Value	Accuracy (%)
GT	Actual Positive Images	120	
TC	TP+TN+FP+FN	360	
RM	FP + TP	121	
Accuracy	$(TN+TP) / TC$	0.9416	94.16
Misclassification	$(FP+FN) / TC$	0.0583	5.83
Recall	TP / GT	0.916	91.6
Precision	TP / RM	0.909	90.9

GT (Ground Truth): It represents the number of images containing diseases.

TC (Total Cases): Count of total comparisons carried out during testing process.

RM (Result of Method): Indicates the sum of all false positive and true positive predictions.

Accuracy: Gives percentages of correct predictions made by the system.

Misclassification: Indicate the percentage of wrong predictions made by the system.

Recall: It is percentage of positive cases identified by the system.

Precision: It shows percentage of positive predictions made by the system.

The evaluation results shows that proposed approach gave 94.16% accuracy with 5.83% misclassification rate. Moreover, recall rate was 91.6% and precision was 90.9%. These results were compared with those of existing research work studied in literature. It was found

that the proposed methodology give high accuracy percentage as compared to the other techniques. Moreover, most of the existing systems were developed in Matlab, the proposed system suggest use of C# along with EM GUI- 3.0 wrapper of Open CV for ease of extension as software module. Table 7 gave the comparison of existing techniques studied and the proposed one.

Fig. 8 shows the comparison of rice leaf identification techniques.

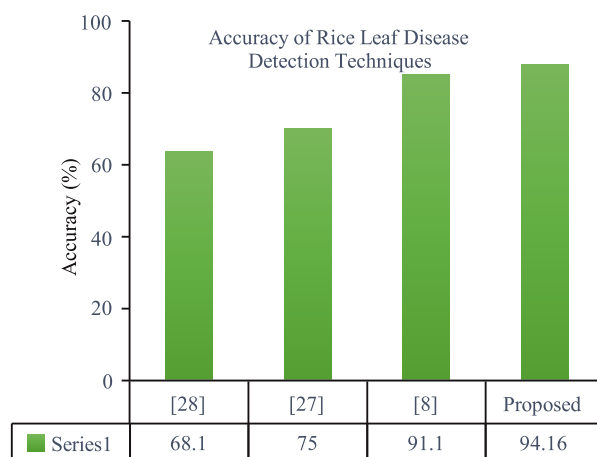


FIG. 8. COMPARISON OF RICE LEAF DETECTION TECHNIQUES

TABLE 7. COMPARISON OF EXISTING AND PROPOSED METHODOLOGY

Technique	Crop	Accuracy
Phadikar et. al. [28]	Rice	79.5% (Bayes') 68.1% (SVM)
Charliepaul [27]	Rice	75%
Kakadeand Dnyaneswar [14]	Grape	92.94%
Sannakki and Rajpurohit [29]	Pomegranate	Not Given
Mohan [8]	Rice	91.1% (SVM) 93.33% (KNN)
Proposed Methodology	Rice	94.16%

5. CONCLUSION

The presented image processing approach aimed to detect and suggest cure for rice leaf diseases. Treatment measures were suggested against the disease type identified by the presented approach which effectively processed the input leaf image followed by detection and identification of disease using SIFT. Later, BoW were formed based on features identified and were clustered using K-means clustering approach. The system was trained by using Brute force matcher histograms and SVM classifier. It accurately detect the diseased spots present if any and classified the type of the disease being affected and cure suggestions were provided against identified disease. The system was evaluated using precision and recall method and found to be 94.16% accurate. The results obtained can help the farmers in effective decision making which can efficiently protect their rice crops from substantial damage.

6. FUTURE ENHANCEMENTS

The presented approach focused three diseases for a specific crop, in future more diseases could be added. Moreover, researcher may adopt the stated approach for prediction of diseases for other cereal crops. The presented methodology can help in precision agriculture by forming bases for rice disease KM.

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