Mathematical Biosciences and Engineering

MBE, 16(6): 7719–7733.
DOI: 10.3934/mbe.2019387
Received: 04 May 2019
Accepted: 28 July 2019
Published: 23 August 2019

http://www.aimspress.com/journal/MBE

Research article

Web enabled paddy disease detection using Compressed Sensing

T. Gayathri Devi[1,*], A. Srinivasan[1], S. Sudha[1] and D. Narasimhan[2]

[1] Department of ECE, Srinivasan Ramanujan Centre, SASTRA Deemed University, Kumbakonam 612001, India

[2] Department of Mathematics, Srinivasan Ramanujan Centre, SASTRA Deemed University, Kumbakonam 612001, India

* **Correspondence:** Email: devigayathri77@src.sastra.edu.

Abstract: In agricultural industry, paddy diseases play a vital role to cause economic losses. Hence, the detection of diseases of paddy plants and give suggestions to the peasants is beneficial to increase the yield quantity of rice. In this paper, a novel web-based paddy disease detection using Compressed Sensing is proposed to detect and classify paddy diseases. First, the diseased leaf is pre-processed using contrast enhancement, and then LAB color space is applied. The segmentation is done using K-Means clustering. The storage complexity is reduced using the Compressed Sensing technique. The segmented leaf images are compressed and then uploaded to the cloud. In the transmitter section, the Compressed Sensing recovery algorithm is used to reconstruct the segmented image. Then Statistical Gray Level Co-occurrence Matrix (GLCM) method is used to extract the features from the segmented image. Support Vector Machine classifier is used to classify the diseases. The performance of the proposed method is compared with other existing techniques. The proposed system is also experimentally tested with Arduino board. The proposed system achieves the disease recognition rate of 98.38%.

Keywords: K-Means clustering; Compressed Sensing; Statistical Gray Level Co-occurrence Matrix; Support Vector Machine; Arduino

1. Introduction

In India, agriculture is the significant contribution of the life of people. The quality of food and huge production at lower expenditure is the consideration for the agricultural field. The most vital source of crop management is the exact detection and giving a timely solution to the problem. Detection of a problem in manually is a very complex task against numerous parameters. The advancement of image processing techniques provides an easier solution to these problems. Rice (Oryzae Sativa) is the main food commodity over 75% of the world. There are several rice plant diseases like Leaf Blast, Bacterial Blight, Brown Spot, sheath Blight, leaf streak, Sheath rot, false Smut, etc., occur in the rice-growing fields. Out of these, the proposed method takes into account of five diseases, namely Bacterial Blight, Rice Blast, Brown Spot, Bacterial Leaf Streak, and false Smut. This proposed method recognizes and classifies the disease type of the paddy plant and notifies the stage of the disease to the farmers.

Paddy plant diseases significantly reduce the quality and yield quantity of the rice. These diseases origins are mainly viruses, fungi, and Bacteria. These diseases can cause in parts like leaf, stem, and root. The most common paddy diseases are Leaf Blast, Brown Spot, Bacterial Leaf Blight, Leaf Streak, False Smut, etc. In this work, focus the following four conditions.

(a) Leaf Blast

Leaf Blast is formed by the Magnaporthe Oryzae fungus. It infects all the parts above the ground of the rice plant. It occurs in low soil moisture areas, frequent rain shower areas, and chill temperature in the daytime. Initial symptoms of this disease appear as white to gray-green lesions or spots, with dark green borders. In the developing stage, the lesions on the leaves are elliptical or spindle-shaped and whitish to gray centers with red to brownish or necrotic border. Lesions can first appear in a diamond shape and expand to grow up, which destroys the entire leaf.

(b) Brown Spot

Brown Spot is caused by Cochliobolus Miyabeanus fungus. Brown spot is one of the most common rice diseases which causes huge damaging in the rice plant. This disease affects the coleoptiles, leaves, leaf sheath, panicle branches, glumes, and spikelet. When the infection started in the seed, the discolored seeds are formed especially with a round to oval, dark-brown lesions with a yellow or gold halo.

(c) Bacterial Leaf Blight

Bacterial Leaf Blight is formed by Xanthomonas Oryzae pv. Oryzae fungus. It causes flopping of seedlings and yellowing and drying of leaves. The diseases develop in the weed areas and stubbles. In both temperate and tropical environments, these diseases are highly designed specifically an irrigated and lowland rained areas.

(d) False Smut

False Smut created by grains silkiness, which tends to decrease the grain weight. It also minimizes the germination of seeds. The false Smut is developed in the areas of Rain, high humidity, and high nitrogen soils. Wind also spread the disease spores from one plant to other plants. It is visible only after panicle exertion. It affects the plant at the flowering stage.

2. Literature review

The authors [1] proposed a plant disease detection system using statistical based thresholding segmentation. The authors also developed a Raspberry pi-3+ board. They achieved an overall detection accuracy of 98.5%. The authors [2] have made a survey on major technologies using the Internet of Things. They have also reviewed the various applications giving significance to all people. The authors [3] have described the Wireless Moisture Sensor Network (WMSN) and IoT based system for a greenhouse environment. They investigated and observed that the moisture level was reached at the predefined threshold while the plants were watered. And, it is also observed that the fertilizer and the water optimize the described method. The authors [4] presented an algorithm for image segmentation technique for automatic detection and classification of plant leaf diseases. In which, they surveyed different disease classification techniques used for plant leaf disease detection. Image segmentation is performed using a genetic algorithm.

The authors [5] have presented the studies the image processing technologies deployed in paddy domain. They also proposed the architecture for identifying the early stage of the leaf diseases and finding the weed species. This system reduces the risk of diseases and to increase the yield of paddy. The authors [6] have proposed a new technique to diagnose and classify rice diseases. Four rice diseases have identified and classified using minimum distance classifier and K Nearest Neighbor classifier (KNN). By using this different algorithm, features like shape, the color of a diseased portion of the leaf has extracted. The authors got the overall accuracy rated of 87.02% using K Nearest Neighbor classifier (KNN) and 89.2% by using Minimum Distance Classifier (MDC).

The authors [7] developed a three layer IoT architecture used for precision agriculture applications. It collects the required data and relays it to a cloud-based back-end. There it is processed and analyzed. They also developed a prototype of proposed architecture to show its performance advantages. The authors [8] presented the detection and classification of leaf diseases of grape using Support Vector Machine (SVM) classification technique to detect the type of leaf disease. This system detected the diseases with an accuracy of 88.89%. The authors [9] developed an Android based detecting stem diseases on the plant by using image analysis. Hue-based segmentation is used to segment the image and feature values are extracted from the segmented portion for texture analysis using color co-occurrence method.

The authors [10] discussed the methods used for the detection of plant diseases using their leaves images. And also they discussed some segmentation and feature extraction algorithm used in plant disease detection. The authors [11] presented a study on the image processing techniques used to identify and classify fungal disease symptoms affected by different agriculture/horticulture crops. The authors [12] described the different image segmentation algorithms and compared the diseased portion of the rice plant leaves.

The authors [13] proposed a cloud deployment model “Agri-Assistant" to provide agriculture related information assistance to Indian farmers living in rural areas, facing financial and connectivity constraints. This model leverages the existing Government services and mobile service to provide a solution to the existing scenario with minimum burden on farmer's pocket. The authors [14] presented the survey methods to detect, quantify and classify plant diseases from digital images in the visible spectrum using image processing techniques. The authors [15] described a pest disease detection system of different plant leaves. They proposed an automatic detection and calculation of the infected area of leaves in the early stage.

The authors [16] presented an effective method for disease detection in Malus Domestica using techniques like K-Mean clustering, color, and texture analysis. The authors [17] introduced the review of rapid, cost-effective, and reliable health-monitoring sensor which facilitate advancements in agriculture. They also described the modern technologies used for developing a ground-based sensor system to assist in monitoring health and diseases in plants under field conditions. These technologies include spectroscopic and imaging-based, and volatile profiling-based plant disease detection method.

The authors [18] developed an image recognition system to recognize paddy diseases. Images were acquired under laboratory condition using a digital camera. They selected three major diseases Rice Blast (Magnaporthe grisea), Rice sheath blight (Rhizoctonia solani) and Brown Spot (Cochiobolus miyabeanus) for their work. Agriculture work made comfort by the advancement of web based technologies. A digital system for agriculture is developed to increase the crop quality with the help of the Internet of Things (IoT). And, also by developing a website, to help farmers make decisions in advance about his farm, in case they detect any disease. An image processing algorithm based on the pattern recognition methods has been developed for leaf disease detection and classification, and thereby eliminates conventional protruding and time consuming techniques.

3. Proposed system

A novel Web Enabled Paddy Disease Detection using Compressed Sensing is proposed to detect and classify Paddy diseases. This proposed system will upload the acquired and segmented image to the cloud using Compressed Sensing. This system is useful to minimize the complexity of manual monitoring in the big farms and easily identify the diseases at a very early stage. The Figure shows the web enabled paddy disease detection system.

Images are captured using a digital camera. The segmentation methods are used to perform segmentation for infected area. Then for further classification, the segmented image is uploaded to the cloud. The storage complexity of the cloud is reduced using the Compressed Sensing technique. At the monitor side, the segmented image is reconstructed from the cloud using Compressed Sensing recovery algorithm. Then the features are extracted using statistical Gray Level Co-occurrence Matrix (GLCM) method.

Further using Support Vector Machine (SVM) classifier is used to classify the diseases and give suggestions to the farmers.

The Proposed System consists of Image capturing, Pre-processing, Segmentation by Compressed Sensing in the transmitter section and feature extraction and classification is at the receiver side.

3.1. Image acquisition

The images of leaves are captured using a digital camera and then applied to the segmentation process to separate the diseased area. The image quality is enhanced using the pre-processing, which is done before the segmentation.

3.2. Image pre-processing

In the pre-processing stage, first contrast enhancement of the image is performed. Then the RGB to L*a*b* transformation is performed. Then the pre-processed image is segmented using K-Means clustering algorithm. Figure 2 shows the input image, Contrast enhancement, and LAB image. Figure 3 shows the LAB color space result.

3.3. *Image segmentation*

In the segmentation part, the proposed system uses the K-Means clustering method to segment the diseased part of the leaves. Then the segmented image performs the process of Compressed Sensing algorithm to reduce the storage complexity of the segmented images which are transmitted to the cloud through a wireless medium. The segmented image is shown in Figure 4.

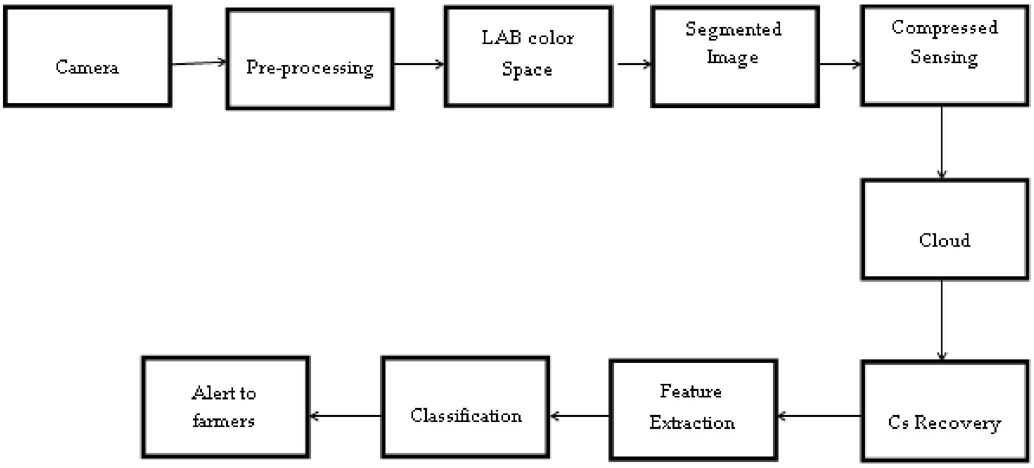

Figure 1. Web based Paddy Disease Detection System.

(a) (b) (c)

Figure 2. (a) Input image. (b) Contrast Enhancement. (c) LAB image.

Figure 3. LAB color space result.

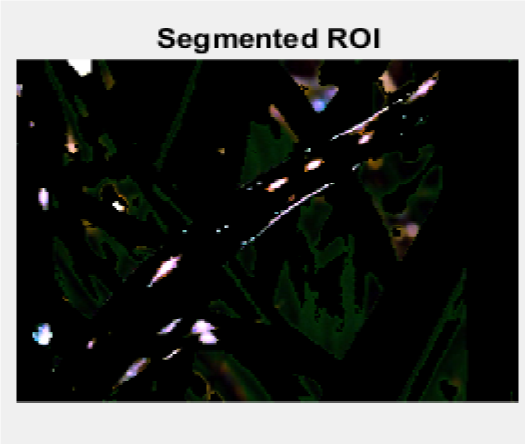

Figure 4. Segmented image.

3.3.1. K-Means clustering

K-Means clustering technique used for segmentation partitions the images into K number of clusters depends on their features. The classification is performed using Euclidean distance is given below.

$$(\mathrm{E.d})^2 = \min(\mu_1 - \mu_k) \sum_{i=1}^{i=n} \sum_{j=1}^{j=n} |X(i,j) - \mu^2| \tag{1}$$

$$\mu_k = \frac{\sum_{i=1}^{i=n} P(i) + i}{\sum_{i=1}^{i=n} P(i)} \tag{2}$$

The first step in K-Means clustering algorithm is getting input image. Using the output of K means, labeling of each pixel is done. Image is segmented based on color. Then the infected part of the image is selected. Figure 5 shows the K-Means clustering output.

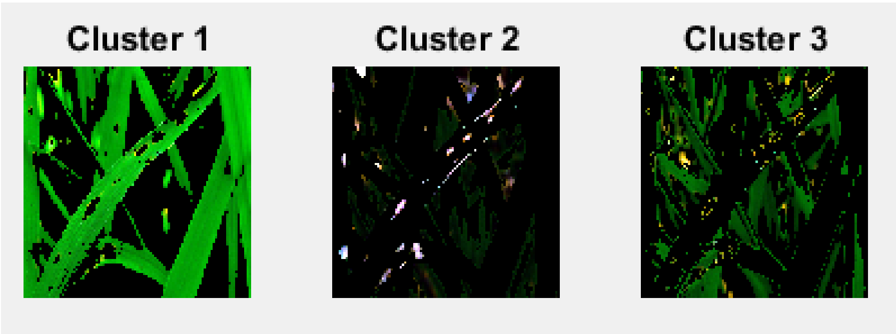

Figure 5. K-Means clustering output.

3.4. Compressed Sensing

The segmented image extracts the measurements using Compressed Sensing. The Discrete Cosine Transform is used to transform the segmented image to the sparse image. Compressed Sensing is applied only to sparse signals. In this proposed method, Block Based Compressed Sensing (BBCS) approach is employed to minimize the computational complexity of the process of Compressed Sensing. The Eqs 3 and 4 gives the blocks corresponding to the disease infected areas which undergoes a Compressed Sensing and to transmit the measurements to the cloud.

$$St^{1/4}Wr_{St} \tag{3}$$

$$Y_{St}^{1/4}U_{St} \tag{4}$$

Where r_{st} the sparse vector of the segmented blocks, t = 0, 1,…,T the blocks, w the basis matrix, y_{st} the measurement vector of the segmented block and U the hybrid measurement matrix.

After getting all the measurements, it is uploaded to the cloud. Figure 6 shows the segmented image uploaded into the cloud.

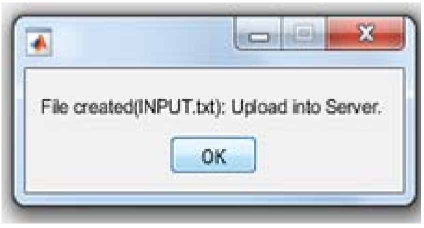

Figure 6. Cloud image.

3.5 Feature extraction

Using the Orthogonal Matching point Pursuit (OMP) algorithm, the segmented images are reconstructed after all the measurements are retrieved from the cloud. This method is an easy and simple method to estimate the sparse signals using the iteration process. Then the segmented image is reconstructed using inverse Discrete Cosine Transform (DCT).

Figure 7 shows the Compressed Sensing (CS) reconstructed segmented image.

Feature extraction is used to extract statistical texture features. These features are obtained using the Gray Level Co-occurrence Matrix (GLCM). The Gray Level Co-occurrence Matrix (GLCM) extracts the first order features such as mean, standard Deviation, Kurtosis, and Skewness and second order features namely contrast, correlation, entropy, energy, homogeneity, variance, and Root Mean Square (RMS).

3.6 Classification

The extracted features are applied to the classification algorithm. The Support Vector Machine

(SVM) classifier is used for the classification which gives high accuracy with the texture features. SVM uses the linear kernel function to classify the healthy and diseased leaves.

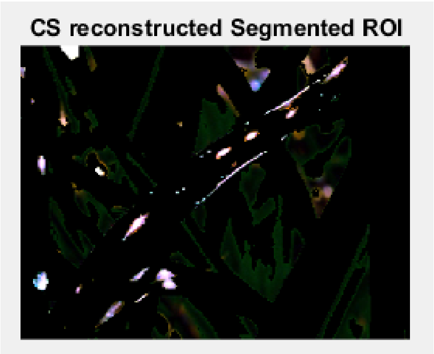

Figure 7. Compressed Sensing (CS) reconstructed image.

The Support Vector Machine (SVM) is a binary classifier which uses the hyper-plane. It is also called the decision boundary between two of the classes. The Figure shows the concept of Support Vector Machine. Different kernels are used to divide the classes. SVM is a binary classifier which examines the hyper-plane dividing into two categories. The boundary is maximized between the hyperplane and the two classes. The samples that are nearest to the margin will be selected in determining the hyperplane are called as support vectors.

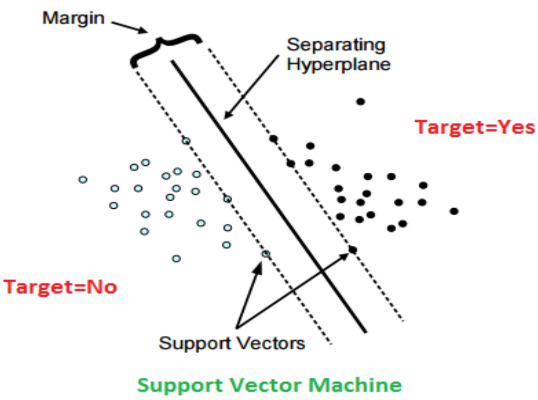

Figure 8. Support Vector Machine.

Multiclass classification is also possible either by using one-to-one or one-to-many. The highest output function will be determined as the winning class. Classification is performed by considering a larger number of support vectors of the training samples. The standard form of SVM was intended for two-class problems. However, in real life situations, it is often necessary to separate more than two classes at the same time.

After classification, the results are analyzed by the experts, and the information is sent to the farmers. This disease detection makes the farmers take decisions and increases the yield cultivation. Figure 9 shows the classifier output.

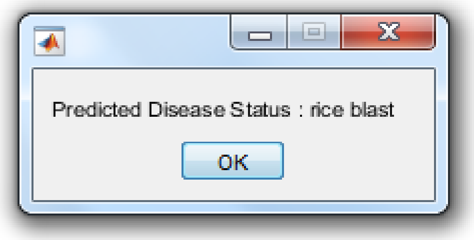

Figure 9. Classifier output.

4. Results and discussions

The proposed web enabled paddy disease detection is analyzed using simulation and experimental method. The Paddy images are taken from the internet and Indian Rice Research Institute website. There are 1140 images used for this work, 840 images used for training and 400 images taken for testing, and the same images are classified using K Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifiers.

The diseases considered for this work are Leaf Blast, Bacterial Blight, Brown Spot, and False Smut. The performance evaluation of the proposed system is done in terms of accuracy, sensitivity, and specificity.

4.1. Simulation results and analysis

The proposed web enabled paddy disease detection is simulated using MATLAB R2016 in Windows 10 PC. The input samples of Paddy with the disease symptoms of Leaf Blast, Bacterial Blight, Brown Spot, False Smut, and Healthy paddy are considered as the input data. The Table 1 shows the percentage of reduction in data for different leaf diseases proportional to the number of the blocks corresponding to the segmented image.

Figures 2, 3, 4 and 7 show the input images, pre-processed images, segmented images, and reconstructed segmented images from cloud after CS recovery of Paddy plant diseases.

Table 1. Analysis of percentage of reduction in data in paddy diseases.

Leaf diseases	Affected area (%)	Number of Blocks corresponding to the affected area□	Percentage of reduction in data (%)
Leaf Blast	16.23	205	89.1
Bacterial Blight	15.6	514	72.8
Brown Spot	17.5	640	67.4
False Smut	16	587	74.6
Healthy	15	629	63.3

Table 2 describes the number of leaves disease samples classified into four categories of leaves disease using the proposed algorithm.

Table 2. The number of Leaf samples for training and testing.

Disease category	Leaf mages used for training	Leaf images used for testing
Healthy	250	100
Blast	150	75
Bacterial Blight	130	75
Brown Spot	110	70
False Smut	100	80

Table 3. Confusion Matrix for Disease Detection.

Accuracy = 98.38%		Predicted class				
		Healthy	Blast	Bacterial Blight	Brown Spot	False Smut
Actual class	Healthy	98	0	0	1	1
	Blast	0	73	1	0	1
	Bacterial Blight	1	0	74	0	0
	Brown Spot	1	1	0	68	0
	False Smut	0	1	0	1	78

From Table 3, it can be seen that only two leaves from Blast, Brown Spot, and False Smut leaves are misclassified. Only one leaf with Bacterial Blight disease is classified as healthy, and two Blast diseases are classified as Bacterial Blight and False Smut. Similarly, two Brown Spot leaves are classified as Blast and Healthy leaf. False Smut leaf is classified as Blast and Brown Spot.

From the experimental results, it is observed that the proposed method can identify and classify the leaf diseases in their initial stages with a less computational effort. The disease recognition rate is assessed using the K Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifier. Table 3 shows the disease recognition rate of K Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifier.

Table 4. The disease recognition rate for K Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifiers.

Classifiers	Disease recognition rate				
	Healthy (%)	Blast (%)	Bacterial Blight (%)	Brown Spot (%)	False Smut (%)
KNN	96.77	95.6	96	96.77	96.77
Multi class SVM	98	97.33	97.14	98.38	98.66

Table 4 gives the recognition rate of various diseases and healthy leaf. The KNN classifier produces the accuracy rate of 95.6% for Bacterial Blast, 96% for Bacterial Blight, 96.77% for

False Smut, Brown Spot, and healthy leaf. The Multiclass SVM gives the recognition rate of 97.33% for leaf blast, 98.38% for Brown Spot, 98.66% for False Smut, 97.14% for Bacterial Blight and for healthy leaf the recognition rate is 98%. From the results, it is clear that the Multiclass SVM classifier achieves the highest accuracy than other classifiers used in this work.

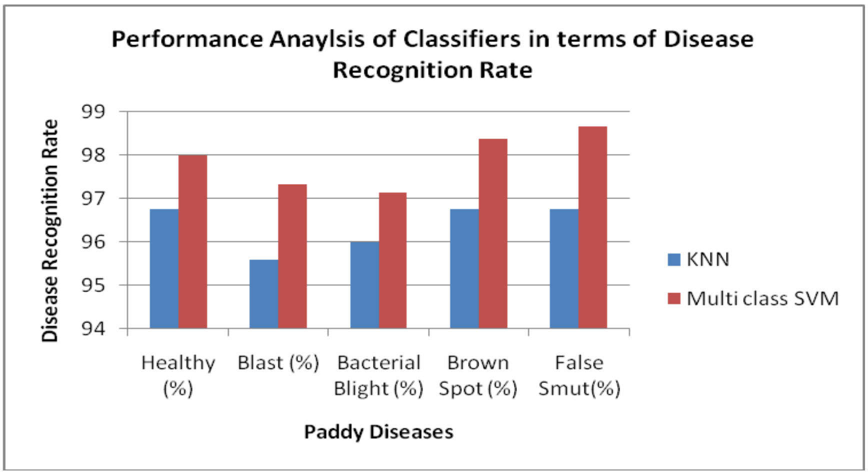

Figure 10. Performance analysis in terms of recognition rate.

The classification of diseased and healthy leaves is done effectively using multiclass SVM classifier, which is shown in the illustrated in the above graph. The Multiclass SVM classifier achieves the best performance with an accuracy of 98.38%, i.e., out of 400 leaves, 391 leaves were correctly classified, while 9 were not. The KNN has produced the accuracy at 96%. In addition to the overall accuracy, the performance of the proposed system is also assessed by the performance measures of sensitivity, specificity, precision, FP rate and kappa, etc.

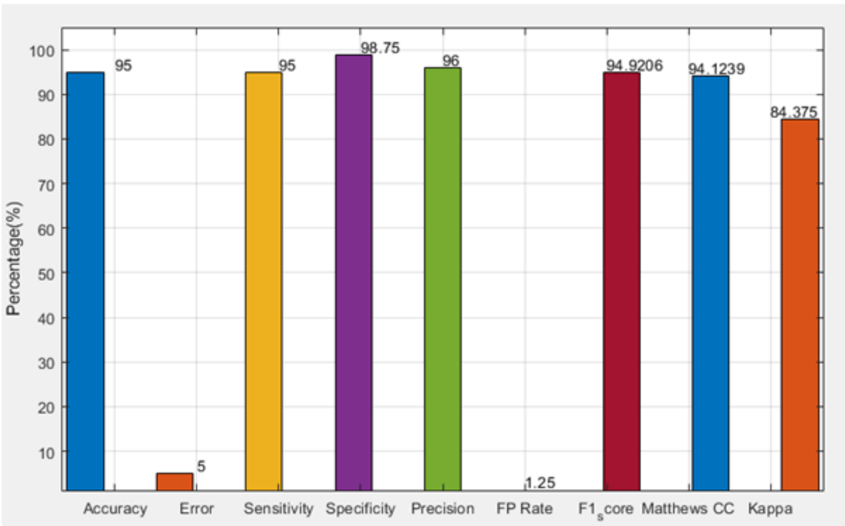

Figure 11. Performance measures of the Rice Blast Image.

The Figure 11 depicts the performance measures of the rice blast image. The classification accuracy of proposed method is compared with other existing method which are shown in Table 5. The classification accuracy of 98.38% is achieved using the proposed method.

Table 5. Comparison of classification accuracy of proposed method with existing method.

Classifier	Classification accuracy (%)		
	Thresholding	K-Means clustering	K-Means clustering with CS
Support Vector Machine	98.44	94.4	98.37
K-Nearest Neighborhood	93.4	94.4	96.77

4.2. Experimental analysis

The experimental evaluation performed using Arduino is shown in Figure 12. Which is operated using MATLAB software.

Figure 12. Arduino Board.

The Paddy Disease detection and classification is implemented using Arduino board. Arduino Board is interfacing with MATLAB using Thingspeak Platform. The segmentation measurements are obtained using CS algorithm. The CS measurements are uploaded to the cloud from Arduino board using the inbuilt Wi-Fi.

Figure 13 shows the Block diagram of IoT system.

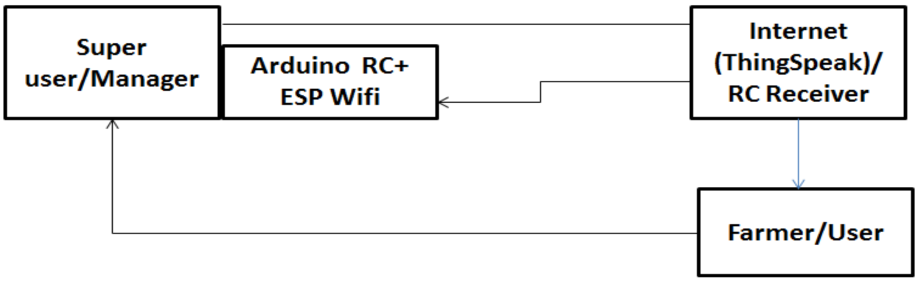

Figure 13. IoT Architecture.

The Manager/Superuser performs the task of detecting the diseases present in the leaf image. It is interfaced to a platform called ThingSpeak where a user can check his/her result. Thingspeak is the IoT platform which is used to collect the data privately from the sensor. Thingspeak has both private and public channels to upload the data, and each channel is assigned with an ID. The disease output obtained by hardware is shown in Figure 14.

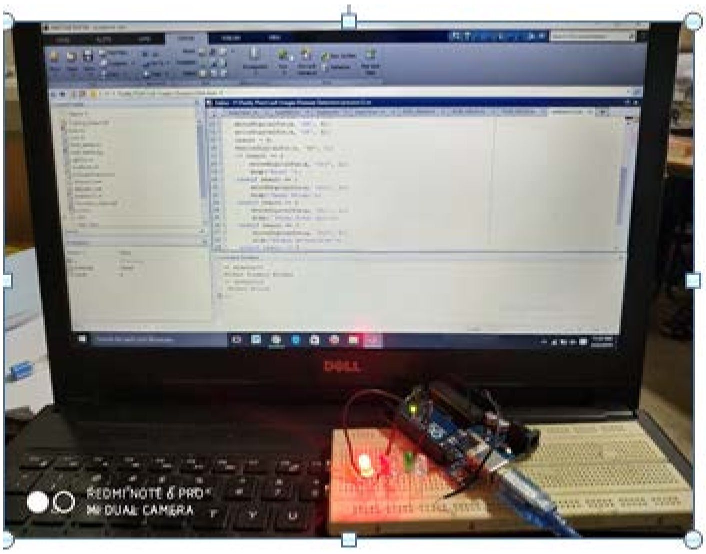

Figure 14. Disease detection output using Arduino.

5. Conclusion

Paddy disease detection is the most noteworthy for agricultural applications to increase the yield. In this paper the digital camera is used to capture the diseased leaves and analyse using image processing techniques. An efficient web based system using Compressed Sensing is proposed for automatic detection and classification of the Paddy diseases namely Leaf Blast, Brown Spot, Bacterial Blight and False Smut and furthermore gives the auspicious notice to agriculturists utilizing web based tool.

The captured images are segmented using K-Means clustering and then the segmented images are uploaded to the cloud using Compressed Sensing algorithm. Then at the monitoring side the segmented images are reconstructed using the compressing sensing recovery algorithm. This method extracts the features using statistical Gray Level Co-occurrence Matrix (GLCM) algorithm. It is trained and tested using the K Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifiers. The proposed system is also experimentally tested using Arduino, and the CS measurements are transmitted to the Thingspeak IoT platform in real time. The experiment is implemented using MATLAB and measurements are uploaded to the cloud using Thingspeak channels.

This proposed system pertaining only for paddy plants and it can also be applied to other plants by including more diseases and a large number of samples in the input database. It will increase the accuracy rate of disease identification. The proposed and implemented methods have given better performance in terms of accuracy using Support Vector Machine (SVM) classifier than the K Nearest Neighbor (KNN) classifiers.

References

1. S. A. Nanduini, R. Hemalatha, S. Radha, et al., Web enabled Plant Disease detection for Agricultural Application using WMSN, *Wireless Pers. Commun.*, **102** (2018), 725–740.
2. P. Sethi and S. R. Sarangi, Internet of Things: Architectures, protocols and applications, *J. Electr. Comput. Eng.*, **2017** (2017), 1–25.
3. I. Mat, M. R. M. Kassim, A. N. Harun, et al., *IoT in Precision Agriculture applications using Wireless Moisture Sensor Network*, IEEE conference on open systems (ICOS), 2016. Available from: https://ieeexplore.ieee.org/abstract/document/7881983.
4. V. Singh and A. K. Misra, Detection of plant leaf diseases using image segmentation and soft computing techniques, *Inf. Process. Agric.*, **4** (2017), 41–49.
5. S. Mutalib, M. H. Abdullah, S. Abdul-Rahman, et al., *A brief study on paddy applications with image processing and proposed architecture*, IEEE Conference on Systems, Process and Control (ICSPC), 2016, 124–129. Available from: https://ieeexplore.ieee.org/abstract/document/7920716.
6. A. A. Joshi and B. D. Jadhav, *Monitoring and controlling rice diseases using Image processing techniques*, International Conference on Computing, Analytics and Security Trends (CAST), 2016, 471–476. Available from: https://ieeexplore.ieee.org/abstract/document/7915015.
7. A. Khattab, A. Abdelgawad and K. Yelmarthi, *Design and implementation of a cloud-based IoT scheme for precision agriculture*, 28th International Conference on Microelectronics (ICM), 2016, 201–204. Available from: https://ieeexplore.ieee.org/abstract/document/7847850.
8. P. B. Padol and A. A. Yadav, *SVM Classifier Based Grape Leaf Disease Detection*, Conference on Advances in Signal Processing (CAPS), 2016, 9–11. Available from: https://ieeexplore.ieee.org/abstract/document/7746160.
9. Z. N. Reza, F. Nuzhat, N. A. Mahsa, et al., *Detecting jute plant disease using image processing and machine learning*, 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 2016, 22–26. Available from: https://ieeexplore.ieee.org/abstract/document/7873147.
10. S. D. Khirade and A. B. Patil, *Plant disease detection using image processing*, International conference on computing communication control and automation (ICCUBEA), 2015, 768–771. Available from: https://ieeexplore.ieee.org/abstract/document/7155951.
11. J. D. Pujari, R. Yakkundimath and A. S. Byadgi, Image Processing Based Detection of Fungal Diseases in Plants, *Proc. Comput. Sci.*, **46** (2015), 1802–1808.
12. D. A. Devi and K. Muthukannan, *Analysis of segmentation scheme for diseased rice leaves*, IEEE International Conference on Advanced Communications, Control and Computing Technologies, 2014, 1374–1378. Available from: https://ieeexplore.ieee.org/abstract/document/7019325.
13. A. Tuli, N. Hasteer, M. Sharma, et al., *Framework to leverage cloud for the modernization of the Indian agriculture system,* IEEE International Conference on Electro/Information Technology, 2014, 109–115. Available from: https://ieeexplore.ieee.org/abstract/document/6871748.
14. J. G. A. Barbedo, Digital image processing techniques for detecting, quantifying and classifying plant disease, *Springer Plus*, **2** (2013), 660–672.

15. G. Bhadane, S. Sharma and V. B. Nerkar, Early Pest Identification in Agricultural Crops using Image Processing Techniques, *Int. J. Electr. Electron. Comput. Eng.*, **2** (2013), 77–82.
16. S. Bashir and N. Sharma, Remote Area Plant Disease Detection Using Image Processing, *IOSR J. Electron. Commun. Eng.*, **2** (2012), 2278–2834.
17. S. Sankarana, A. Mishra, R. Ehsani, et al., A review of advanced techniques for detecting plant diseases, *Comput. Electron. Agric.*, **72** (2010), 1–13.
18. G. Anthonys and N. Wickramarachchi, *An image recognition system for crop disease identification of paddy fields in Sri Lanka*, International Conference on Industrial and Information Systems, 2009, 403–407. Available from: https://ieeexplore.ieee.org/abstract/document/5429828.