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# Hybrid Embedded System Design For Real Time Monitoring The Growth and Detection Of Diseases in Oryza Sativa L and Triticum Aestivum

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**Abstract-** In recent days, world population is incredibly growing, so it is an essential need to develop the agriculture. *Oryza sativa L (Paddy)* and *Triticum aestivum (Wheat)* are the most important food crops in India. This proposed research work introduces a new technology for paddy and wheat cultivation in agriculture. The objectives of proposed research are to monitor and control the plant soil moisture sensor and water level sensor and also to identify the diseases are occurred in Paddy and Wheat. The values detected by sensors and it are transmitted through Wireless Sensor Network (WSN) for further controlling process. Plant cultivation is always under surveillance using wireless IP camera. The diseases are identified using LabVIEW image processing techniques such as preprocessing, feature extraction and classification. In this paper, texture features are extracted using GLCM and Mean, Standard deviation, Kurtosis and Skewness. K- Nearest Neighbor (KNN) and Support Vector Machine (GRBF) are used for classifications. The results obtained by WSN and identified diseases from SVM (GRBF) and KNN are sent to the concerned person using GSM and E-MAIL using Ethernet techniques. This idea saves a lot of man power, increase quality with quantity and feasible for application in precision agriculture.

**Keywords:** LabVIEW, Image Processing, WSN, GSM and Precision agriculture

## I INTRODUCTION

Advancing in Electronics and Instrumentation have made possible of precision agriculture, plant disease detection automatically, quality and quantity loss plays a significant economic in the whole country. Paddy and Wheat are the most important food in the world, India is the second largest producer of Paddy and third largest of wheat in the world [1]. Paddy is the staple food for approximately semi of the world population. Tamil Nadu is mostly contributed to Paddy cultivation in India. Paddy crop growing duration time for short duration varieties (90 – 120 days), medium duration varieties (120 – 140 days) and long duration varieties (140 – 180 days). Spring wheat crop growing period ranges from 100 – 135 days and winter wheat crop growing period ranges from 185 – 230. Ultra Pradesh is the largest wheat producer in India.

Today water management system is very important for Paddy and wheat cultivation [2]. The Wireless Sensor Network is a wireless network consisting of spatially distributed autonomous device using sensors to monitor physical or environmental conditions. Water level sensor indicates the presence of water in the cultivated field. Soil moisture sensor has more contributed for Paddy and wheat use less water to grow a crop to increase yield and quality. The data collected from the Water level sensor and soil moisture sensors are sent to LabVIEW software through wireless sensor network. If the data across the limit range, without any delay a message can be send to concern person by GSM modem. We must prevent Paddy and wheat diseases for increasing the quantity and quality. The diseases which often affect the Paddy are Zinc deficiency and *Mycorellosiellaoryzae*, in wheat, stripe rust and Barley yellow dwarf virus. The symptoms of Zinc deficiency diseases are small round, dark spots to oval sopts with gray or white center.

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Mycorellosiellaoryzae symptoms are long narrow lesions with white center and brown borders. Stripe rust of wheat disease symptoms are rust pustules are yellow and arranged into long conspicuous stripes. Barley yellow dwarf virus disease symptoms are stunted, poorly tillered across a field. The diseased images of paddy and wheat are acquired by wireless IP camera. The acquired image is having some kind of noise namely salt and pepper noise. Median filter is the most popular method for removing salt and pepper noise [3]. After preprocessing statistical features are extracted using GLCM and mean, standard deviation, kurtosis and skewness. The results of the feature extraction are given as an input to the classifiers. In this paper, Support Vector Machine (GRBF) and K- Nearest Neighbor (KNN) is employed to detect the diseases.

The rest of this paper is structured as follows section. In Section 2 Related work, Section 3 describes the materials and methods in brief. Experimental results and discussion are given in Section 4. Section 5 outlines the conclusion obtained from the study.

## II RELATED WORK

Santanu Phadikar et al. [4] proposed a rice diseases classification using feature selection and rule generation techniques. This paper focused on classifying from the infected regions in the rice plant image. Symptoms of the diseases colour, shape and position of the infected portion and extracted by developing novel algorithms. Mohammad Ashiklqbal Khan et al. [5] proposed a neck blast disease influences grain yield and quality traits of aromatic rice. The neck blast disease increased grain sterility percentages, reduced grain size, yield and quality traits at seeds. The transmission of a blast pathogen from the branches to the seed is very poor. Mitsuro Hyakumachi et al. [6] proposed a novel method for controlling rice blast disease using fan – forced wind on paddy fields. Rice blast disease is one obstacle of rice producing countries. The effects of fan – forced wind on the incidence of rice blast disease were studied in two successive seasons. Electric fan and wind fan set on the ridge of paddy field.

Veera Rabhavulu Bitra et al. [7] proposed an effect of wheat grass powder on aluminium induced Alzheimer's disease in Wistar rats. This paper out of the effect of wheat grass on an aluminium induced Alzheimer's disease. This study clearly demonstrated the beneficial effects of wheat grass the shows good antioxidant properties. Stefano Sforza et al., [8] proposed a genetic and environmental factors affecting pathogenicity of wheat as related to celiac disease. This paper explains the gluten proteins are the basis of the theological properties of wheat derived products such as bread and pasta. The results demonstrated a very high variability in the amount of pathogenic peptides producer of different lines. Jose A. Lopez et al. [9] proposed the economics of foliar fungicide applications in winter wheat in Northeast Texas. This paper among plant pathogenic organisms, fungi are a major reason for crop losses around the world and have a significant impact on yield and quality.

Francisco G. Montoya et al., [10] proposed an a monitoring system for intensive agriculture based on mesh networks and the android system. One of the most important changes in the southeast Spanish lands is the switch from traditional agriculture to agriculture based on the exploitation of intensive farmlands. For this type of farming it is important to use techniques that improve plantation. Web applications, database and advanced mobile system to facilitate real time data acquisition for effective monitoring. Deqin Xiao et al. [11] integrated soil moisture and depth sensor for paddy fields. This paper reports the development of a wireless, integrated, frequency domain soil moisture sensor for paddy fields. This soil sensor is able to measure soil moisture content and water depth at the same time and transmit the collect data wirelessly to target receiver.

Changying Li et al. [12] proposed a development of software for spectral imaging data acquisition using LabVIEW. This paper presents the design and implementation of a data acquisition program using LabVIEW for a liquid crystal tunable filter based spectral imaging system (900-1700nm). The image acquisition process, modeled by a finite state machine was implemented in the LabVIEW to control the spectral imaging system to collect hyperspectral of multispectral images. This program is a useful data acquisition tool for the filter – based spectral imaging system.

Antonio-Javier Garcia-sanchez et al., [13] proposed a wireless sensor network deployment for integrating video-surveillance and data-monitoring in precision agriculture over distributed crops. Crop monitoring in precision agriculture may be achieved by a multiplicity of technologies, however the use of wireless sensor network result in low-cost and low-power consumption deployments by intruders (human or animals) and insufficient control of the production process. The only cost-effective technology employed is IEEE 802.15.4, and it efficiently integrates crop data acquisition, data transmission to the end-user and video-surveillance tasks. M. Mohammad El-Basioni et al., [14] proposed a precision farming solution in Egypt using the wireless sensor network technology. This paper gives an overview of the wireless sensor network and its application in precision farming, and its importance for improving the agriculture in Egypt.

YAO Qing et al. [16] proposed an Automated Counting of Rice Planthoppers in Paddy Fields Based on Image Processing. This paper describes a handheld device for easily capturing plant hopper images on rice stems and an automatic method for counting rice plant hoppers based on image processing. The handheld device consists of a digital camera with WiFi, a smartphone and an extendable pole. For the counting of plant hoppers on rice stems of detection is a Support Vector Machine (SVM) classifier based on the histogram of oriented gradient features.

A nearest neighbour approach to the simulation of spread of barley yellow dwarf has been proposed by T.J. Chausalet et al. [18]. In this paper, virus spread is described by the probability of a plant becoming infected conditioned on the number of infected plants neighbouring it. This has the advantage that the influence of aphid movement can be incorporated into the definition of the probability of a neighbour becoming infected.

### III MATERIALS AND METHOD

#### A Soil moisture and Water level sensor

Soil moisture sensor consists of probe, sensor acquisition module, communication module, processor module and power supply module. This soil sensor sensing soil moisture [1]. At the same time water level sensor senses the water in the field. These two sensors are placed at the paddy and wheat field, sensor output is connected to WSN node. Several WSN nodes connected one WSN gateway using Wireless Sensor Network (mesh network topology). This WSN gateway connected to LabVIEW through serial communication. The main advantages WSN modules are low power consumption, low cost and long distance data communication. In LabVIEW, serial communication can be done using VISA tool. To initialize the program, we have to set the baud rate, data bit, parity, and stop bit.

#### Leaf sample collection

The Paddy samples are used in this research were collected from a Uppupalayam, Namakkal district in Tamil Nadu, India. Moreover 200 samples collected for investigation in this research. (100 Zinc deficiency and 100 Mycorellosiellaoryzae), 110 training samples and 90 testing samples. The wheat samples used in this research were collected from a Indur, Maharashtra in India. More the 150 samples collected for stripe rust of wheat and barley yellow dwarf virus diseases. The complete detection methodology is shown in the figure 1 and it is described in the following subsections.

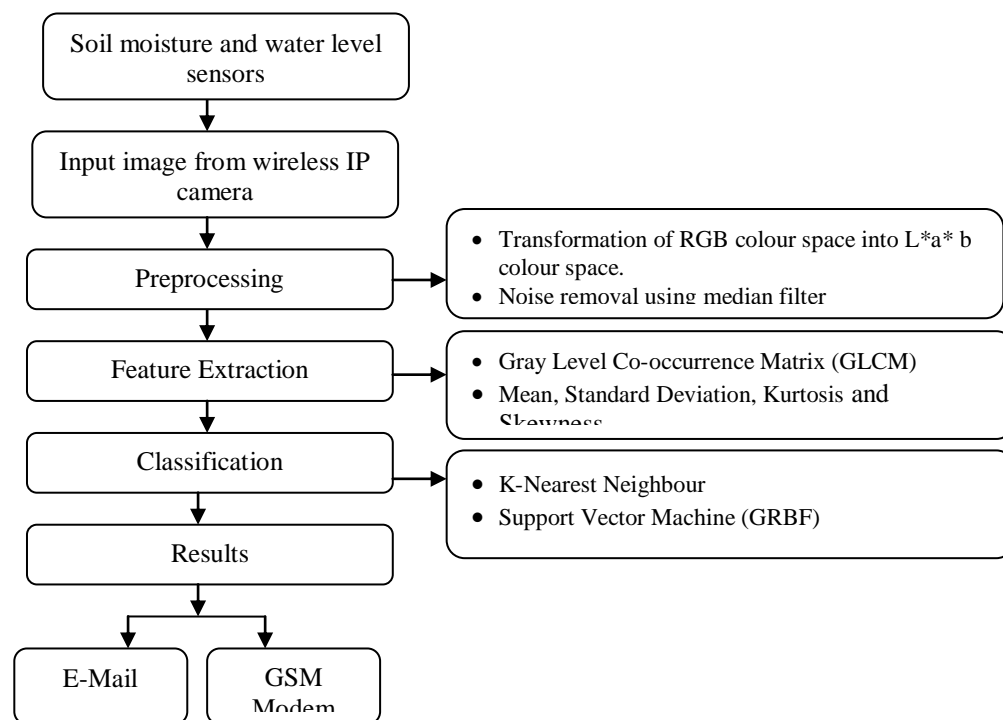


Figure 1. Block diagram of proposed approach

#### B. Image acquisition

A LabVIEW IMAQ Vision system was applied to acquire the paddy and wheat images through wireless IP camera. This camera capture a video using IMAQ AVI using file path tool box, IMAQ vision acquisition tool box. And it was converted into a number of frames using IMAQ AVI read tool box.

##### Median filter

The image acquired by camera having many kinds of noise. These noises are removed using median filter. Median filter is a nonlinear filter which replaces the center pixel value by the median of the gray levels in the image area enclosed by the filter. LabVIEW median

filter tool box using removal of noise. The image obtained by the IP wireless camera is an RGB color component; it is a device-dependent color space. To find the disease in the images, they had to be transferred to the device-independent color space. In the device-dependent color space, the resultant color depends on the equipment employed to produce it, whereas in a device-independent color space, the coordinates specify the color and produce the same color regardless of the device used to draw it. Therefore, L\*a\*b\* was developed as the device-independent color space transformation.

**C Feature Extraction**

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Texture contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. Textural features contain information about the spatial distribution of tonal variations within a band. In this paper, texture features are extracted using Grey Level Co-occurrence Matrices (GLCM).

TABLE I  
EXTRACTED FEATURES

| GLCM features | Formula  | Statistical features | Formula   |
|---------------|--|----------------------|---|
| Contrast      | $\sum_{i,j}  i - j ^2 p(i, j)$                                       | Mean                 | $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$                |
| Energy        | $\sum_{i,j} p(i, j)^2$   | Standard Deviation   | $s = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$ |
| Entropy       | $\sum_{i,j} p(i, j) \log_2 p(i, j)$                                  | Kurtosis             | $k = \frac{E(x - \mu)^4}{\sigma^4}$                     |
| Homogeneity   | $\sum_{i,j} \frac{p(i, j)}{1 +  i - j }$                             | Skewness             | $s = \frac{E(x - \mu)^3}{\sigma^3}$                     |
| Correlation   | $\sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i, j)}{\sigma_i \sigma_j}$ |                      |   |

**D Classification**

Classification is the final step of disease identification. In this paper Support Vector Machine and Nearest Neighbour classifier is used.

**E Support Vector Machine (GRBF)**

The Support Vector Machine (SVM) is a widely used for classification and regression analysis. It is a supervised learning models associated with learning algorithms that analyze data and recognize the patterns. It was first introduced in the 1992 by Boser, Guyon, and Vapnik (1992). The initial form of SVMs is a binary classifier where the output of learned function is either positive or negative. An input space represented by  $X = x_1, x_2, \dots, x_d$  is classified to output space, which is represented by  $C_1, C_2, \dots, C_j$ . To classify the data in input space, SVM tries to find the optimal separating hyperplane among all possible separating hyper planes. So, it maximizes the margin and obtains good generalization ability. A separating hyperplane is a linear function that can separate the training data into two classes (Class1=+1 and Class2=-1) in the separable feature space, as shown in Figure 2

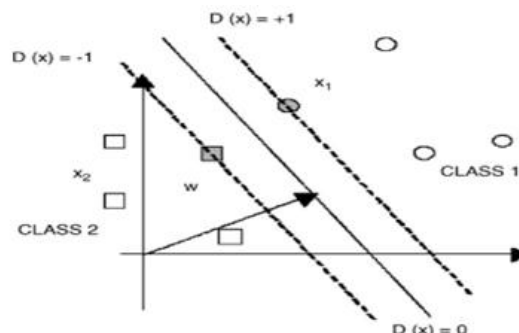


Figure 2. SVM classification

The following function describes a separating hyperplane function

$$D(x) = (\omega * x) + \omega_0 \text{ ----- (1)}$$

All separating hyperplanes must satisfy the following equation:

$$Y_i[(\omega * x_i) + \omega_0] \geq 1 \quad i = 1, \dots, n \text{ ----- (2)}$$

In this paper we used the kernel function while developing SVM model. Gaussian kernels are used to modify the input space into high dimensional feature space. The kernels having the following equation.

$$K(x_i, x_j) = e^{-\|x_i - x_j\|^2 / 2\sigma^2} \text{ (Gaussian radial basis function kernel) ----- (3)}$$

In this paper, Gaussian radial basis function kernel function is used.

**F K-Nearest Neighbors classification method (KNN)**

The KNN classification algorithm is a supervised method with a desirable computational speed along with the acceptable classification accuracy. The KNN-based classifier does not require the train stage and is based on a simple theory and mathematics. The structure of the KNN classifier imposes lower computational burden.

In order to formulate the KNN classification algorithm, suppose that the pair  $(x_i, \delta(x_i))$  contains the feature vector  $x_i$  and its corresponding label  $\delta(x_i)$  where  $\delta \in \{1, 2, \dots, n\}$  and  $i = 1, 2, \dots, N$  ( $n$  and  $N$  are the number of classes and the number of train feature vectors, respectively). For an arbitrary feature vector  $x_i$ , calculation of a defined distance between this feature and the feature vector  $x_j$  is possible as follows,

$$d(i, j) = f(x_i, x_j) \text{ ----- (4)}$$

Where  $f(x_i, x_j)$  is a scalar distance function. For instance,  $f(x_i, x_j)$  can be defined as

$$\begin{cases} \text{(a) } f(x_i, x_j) = (x_i - x_j)^T \Sigma (x_i - x_j) \\ \text{(b) } f(x_i, x_j) = (\sum_{k=1}^p (x_i(k) - x_j(k))^r)^{1/r} \text{ ----- (5)} \\ \text{(c) } f(x_i, x_j) = \frac{1}{p} \sum_{k=1}^p \text{abs}(x_i(k) - x_j(k)) \end{cases}$$

Where the first term of the Eq. (5) called generalized distance and for the weight matrix  $\Sigma = 1$  the famous Euclidean norm will be achieved. While the second term of the Eq. (5) is called Minkovski distance of degree  $r$  and for  $r = 2$ , again the Euclidean distance appears. The third term of Eq. (5) is called the City Block distance and is used in many pattern recognition cases. If the distance vector  $D(i)$  is defined by following equation

$$D(i) = \{d(i, j) | i = 1, 2, \dots, N_{train}\} \text{ ----- (6)}$$

By sorting the  $D(i)$  vector in an ascending fashion, and choosing the first  $K$  elements (which is called  $K$  nearest neighbors) as follows

$$D_N(i) = \underset{\text{Ascending}}{\text{sort}}(D(i)) \text{ ----- (7)}$$

$$V = \{\delta(D_N(i)(1)), \dots, \delta(D_N(i)(K))\} \text{ ----- (8)}$$

According to the KNN algorithm, the test feature  $x_i$  belongs to the class with the major votes in the  $K$ -nearest vote vector  $V$ . In order to determine the optimum  $K$  corresponding to the best accuracy, a simple way is to alter the  $K$  from 1 to a large enough value (in this paper  $k=10$ ) and choosing the  $K$  for which the best accuracy is obtained for all test features.

**IV RESULTS AND DISCUSSION**

In this paper, water level sensor and soil moisture sensor values are sending to WSN gateway through WSN node. The acquired result is higher or lower than the set point value, this information immediately send to the concerned person through message and Gmail. Water level sensor and soil sensor values are acquired in the WSN node and this information send to concerned person via message are shown in the figure 3.

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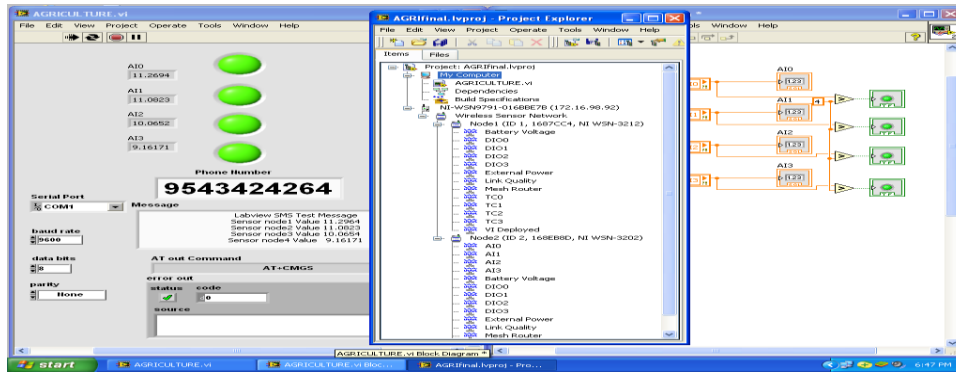


Figure 3. Water level sensor and soil sensor values are acquired in the WSN node

The paddy and wheat images are acquired using wireless IP camera. Moreover 200 samples of each diseases are collected. In this paper, Zinc deficiency and its gray image and Mycorellosiellaoryzae of paddy image and its gray image are shown in figure 4 and 5. Stripe rust and its gray image and Barley yellow dwarf virus attacked wheat image and its gray image is shown in figure 6 and 7.

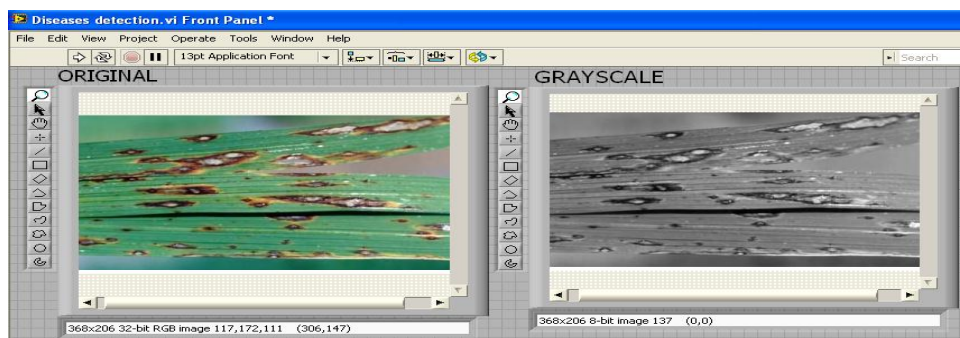


Figure 4. Zinc deficiency paddy and its gray image

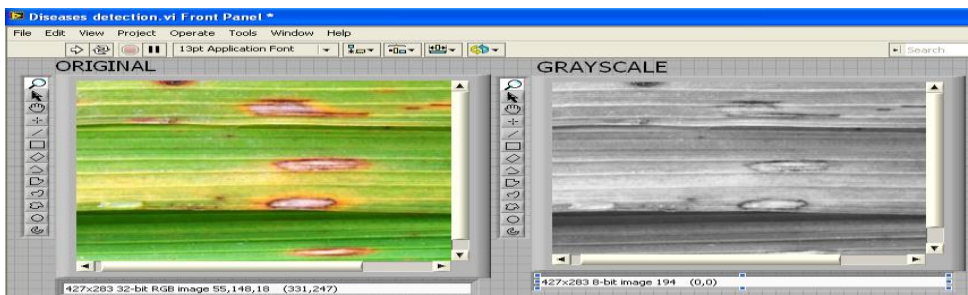


Figure 5. Mycorellosiellaoryzae of paddy and its gray image

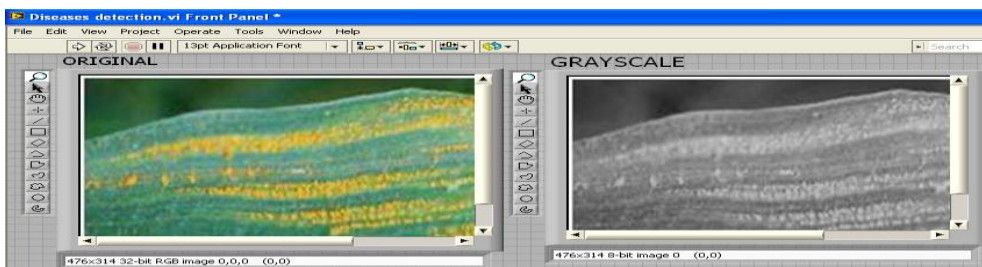


Figure 6. Mycorellosiellaoryzae of paddy and its gray image

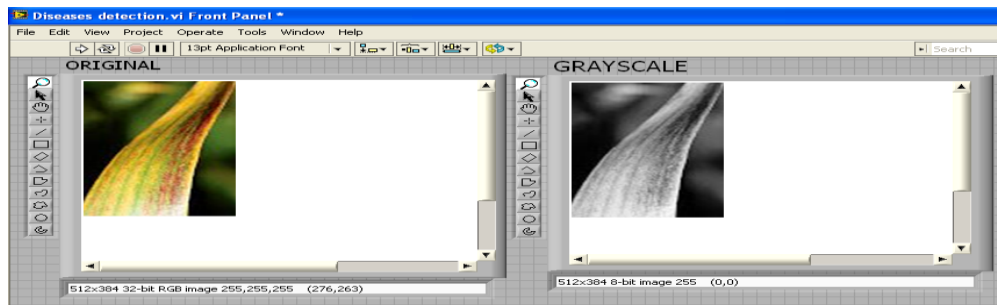


Figure 7. Barley yellow dwarf virus attacked wheat and its gray image

The acquired image is having some kind of noise due to transmission. This noise is removed using median filter. The texture features are extracted for the preprocessed image using GLCM and mean, standard deviation, kurtosis and skewness. The feature extraction results are shown in table 2 to table 11.

TABLE II  
GLCM FEATURES FOR NORMAL PADDY

| S. No   | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 1 | 6.8403  | 0.0673   | 0.9875      | 0.5702 | 0.9732      |
| IMAGE 2 | 6.3220  | 0.0783   | 0.9862      | 0.4031 | 0.9762      |
| IMAGE 3 | 6.8293  | 0.582    | 0.9858      | 0.4830 | 0.9763      |
| IMAGE 4 | 6.2015  | 0.0341   | 0.9881      | 0.5165 | 0.9832      |

TABLE III  
MEAN, STANDARD DEVIATION, KURTOSIS AND SKEWNESS FEATURES FOR NORMAL PADDY

| S. No   | Mean     | Standard Deviation | Kurtosis | Skewness |
|---------|----------|--------------------|----------|----------|
| IMAGE 1 | 149.3516 | 3.0039             | 684.2631 | -11.0540 |
| IMAGE 2 | 148.5908 | 3.7355             | 690.5899 | -12.7127 |
| IMAGE 3 | 148.7042 | 3.5482             | 687.6249 | -12.0819 |
| IMAGE 4 | 148.9201 | 3.8028             | 694.8445 | -12.5141 |

TABLE IV  
GLCM FEATURES FOR ZINC DEFICIENCY

| S.No    | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 1 | 7.8149  | 0.6178   | 0.9085      | 0.0731 | 0.8224      |
| IMAGE 2 | 7.8146  | 0.6171   | 0.9078      | 0.0726 | 0.8219      |
| IMAGE 3 | 7.8039  | 0.6133   | 0.9054      | 0.0619 | 0.8102      |
| IMAGE 4 | 7.8152  | 0.6182   | 0.9088      | 0.0736 | 0.8235      |

TABLE V  
MEAN, STANDARD DEVIATION, KURTOSIS AND SKEWNESS FEATURES FOR ZINC DEFICIENCY

| S.No    | Mean     | Standard Deviation | Kurtosis | Skewness |
|---------|----------|--------------------|----------|----------|
| IMAGE 1 | 160.3277 | 2.8723             | 72.3196  | -2.6600  |
| IMAGE 2 | 160.3270 | 2.8853             | 71.3006  | -2.7650  |
| IMAGE 3 | 160.3370 | 2.8053             | 74.3126  | -2.5550  |
| IMAGE 4 | 160.3290 | 2.8967             | 72.9854  | -2.6168  |

TABLE VI  
GLCM FEATURES FOR MYCORELLOSIELLAORYZAE

| S.No    | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 1 | 7.8037  | 0.6130   | 0.9052      | 0.0619 | 0.8101      |
| IMAGE 2 | 7.8147  | 0.6174   | 0.9080      | 0.0729 | 0.8228      |

| S.No    | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 3 | 7.8141  | 0.6165   | 0.9072      | 0.0721 | 0.8214      |
| IMAGE 4 | 7.8138  | 0.6161   | 0.9069      | 0.7118 | 0.8210      |

TABLE VII

MEAN, STANDARD DEVIATION, KURTOSIS AND SKEWNESS FEATURES FOR MYCORELLOSIELLAORYZAE

| S.No    | Mean     | Standard Deviation | Kurtosis | Skewness |
|---------|----------|--------------------|----------|----------|
| IMAGE 1 | 160.3316 | 2.8677             | 75.6889  | -2.5019  |
| IMAGE 2 | 160.3308 | 2.8904             | 75.6991  | -2.5010  |
| IMAGE 3 | 160.3435 | 2.7841             | 76.3897  | -2.4978  |
| IMAGE 4 | 160.3455 | 2.7741             | 76.4298  | -2.3697  |

TABLE VIII

GLCM FEATURES FOR STRIP RUST DISEASES

| S.No    | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 1 | 7.8136  | 0.6158   | 0.9065      | 0.7115 | 0.8208      |
| IMAGE 2 | 7.8042  | 0.6138   | 0.9059      | 0.0629 | 0.8109      |
| IMAGE 3 | 7.8151  | 0.6180   | 0.9085      | 0.0734 | 0.8233      |
| IMAGE 4 | 7.8143  | 0.6169   | 0.9077      | 0.0725 | 0.8218      |

TABLE IX

MEAN, STANDARD DEVIATION, KURTOSIS AND SKEWNESS FEATURES FOR STRIP RUST DISEASES

| S.No    | Mean     | Standard Deviation | Kurtosis | Skewness |
|---------|----------|--------------------|----------|----------|
| IMAGE 1 | 160.3352 | 2.8574             | 74.3024  | -2.5010  |
| IMAGE 2 | 160.3371 | 2.8064             | 74.3148  | -2.5561  |
| IMAGE 3 | 160.3378 | 2.7895             | 74.3356  | -2.5493  |
| IMAGE 4 | 160.3475 | 2.7234             | 76.1155  | -2.3986  |

TABLE X

GLCM FEATURES FOR BARLEY YELLOW DWARF VIRUS ATTACKED WHEAT

| S.No    | Entropy | Contrast | Correlation | Energy | Homogeneity |
|---------|---------|----------|-------------|--------|-------------|
| IMAGE 1 | 7.8137  | 0.6160   | 0.9067      | 0.0717 | 0.8209      |
| IMAGE 2 | 7.8153  | 0.6184   | 0.9091      | 0.0739 | 0.8237      |
| IMAGE 3 | 7.8029  | 0.6119   | 0.9041      | 0.0607 | 0.8089      |
| IMAGE 4 | 7.8135  | 0.6155   | 0.9063      | 0.7111 | 0.8202      |

TABLE XI

MEAN, STANDARD DEVIATION, KURTOSIS AND SKEWNESS FEATURES FOR BARLEY YELLOW DWARF VIRUS ATTACKED WHEAT

| S.No    | Mean     | Standard Deviation | Kurtosis | Skewness |
|---------|----------|--------------------|----------|----------|
| IMAGE 1 | 160.3339 | 2.8854             | 75.4926  | -2.4953  |
| IMAGE 2 | 160.3482 | 2.7124             | 76.1004  | -2.2986  |
| IMAGE 3 | 160.3291 | 2.8996             | 72.9794  | -2.6102  |
| IMAGE 4 | 160.3288 | 2.8922             | 72.9752  | -2.6098  |

The above feature extraction results are given as an input to the classifiers. In this paper KNN and SVM (GRBF) classifiers are used. The performance metrics are used for evaluating the classifiers. Cross Validation and confusion matrices are used to evaluate the performance of the classifiers. In this paper a 10 fold cross validation is used.



TABLE XII  
A CONFUSION MATRIX

| Actual Value | Predicted Value |          |
|--------------|-----------------|----------|
|              | Negative        | Positive |
| Negative     | TN              | FN       |
| Positive     | FP              | TP       |

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

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

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

$$PositivePredictiveValue (PPV) = \frac{TP}{TP + FP}$$

$$NegativePredictiveValue (NPV) = \frac{TN}{TN + FN}$$

TN (True Negative) – Correct Prediction as normal

FN (False Negative) – Incorrect prediction of normal

FP (False Positive) – Incorrect prediction of abnormal

TP (True Positive) – Correct prediction of abnormal

The overall effectiveness of the system can be measured by using accuracy. The accuracy which computes the proportion between correctly classified samples and total samples. Sensitivity and specificity are the most widely used statistics to describe a diagnosis test. Sensitivity measures the proportion of actual positives which are correctly identified as positives. Specificity measures the proportion of actual negatives which are correctly identified. (i,e) The sensitivity and specificity are used to approximate the probability of the positive and negative label being true. Positive predictive value indicates the positive results which were correctly predicted.

TABLE XIII  
PERFORMANCE METRICS FOR SVM (GRBF) AND KNN FOR ZINC DEFICIENCY

| Name of the classifier | Errors | FN | FP | TP  | TN  | PPV   | NPV   | ACCURACY (%) | SPECIFICITY (%) | SENSITIVITY (%) |
|------------------------|--------|----|----|-----|-----|-------|-------|--------------|-----------------|-----------------|
| KNN                    | 31     | 13 | 18 | 187 | 182 | 91.21 | 93.3  | 92.25        | 91              | 93.5            |
| SVM (GRBF)             | 27     | 11 | 16 | 189 | 184 | 92.19 | 94.93 | 93.25        | 92              | 94.5            |

TABLE XIV  
PERFORMANCE METRICS FOR SVM (GRBF) AND KNN FOR MYCORELLOSIELLAORYZAE

| Name of the classifier | Errors | FN | FP | TP  | TN  | PPV   | NPV   | ACCURACY (%) | SPECIFICITY (%) | SENSITIVITY (%) |
|------------------------|--------|----|----|-----|-----|-------|-------|--------------|-----------------|-----------------|
| KNN                    | 27     | 11 | 16 | 189 | 184 | 92.19 | 94.35 | 93.25        | 92              | 94.5            |
| SVM (GRBF)             | 25     | 10 | 15 | 190 | 184 | 92.6  | 94.87 | 93.75        | 92.5            | 95              |

TABLE XV  
PERFORMANCE METRICS FOR SVM (GRBF) AND KNN FOR STRIPE RUST DISEASE

| Name of the classifier | Errors | FN | FP | TP  | TN  | PPV   | NPV   | ACCURACY (%) | SPECIFICITY (%) | SENSITIVITY (%) |
|------------------------|--------|----|----|-----|-----|-------|-------|--------------|-----------------|-----------------|
| KNN                    | 33     | 14 | 19 | 186 | 181 | 90.73 | 92.8  | 91.75        | 90.5            | 93              |
| SVM (GRBF)             | 30     | 13 | 17 | 187 | 183 | 91.66 | 93.36 | 92.5         | 91.5            | 93.5            |

TABLE XVI  
PERFORMANCE METRICS FOR SVM (GRBF) AND KNN FOR STRIPE RUST DISEASE

| Name of the classifier | Errors | FN | FP | TP  | TN  | PPV   | NPV   | ACCURACY (%) | SPECIFICITY (%) | SENSITIVITY (%) |
|------------------------|--------|----|----|-----|-----|-------|-------|--------------|-----------------|-----------------|
| KNN                    | 26     | 11 | 15 | 189 | 185 | 92.64 | 94.38 | 93.5         | 92.5            | 94.5            |
| SVM (GRBF)             | 23     | 10 | 13 | 190 | 187 | 93.5  | 94.92 | 94.25        | 93.5            | 95              |

The experimental results presented in table 13, 14, 15 and 16 KNN and the SVM (GRBF). As observed by the experimental results, the SVM (GRBF) outperforms the KNN techniques in terms of classification performance such as accuracy, specificity, sensitivity, positive predictive value and negative predictive value. The system accuracy measures the effectiveness of the classifier. In this present study, SVM (GRBF) has a higher accuracy than KNN classifier. This indicates that the SVM (GRBF) has a better generalization capability for the classification four types of paddy and wheat diseases. Water level sensor and soil sensor values are acquired in the WSN node and disease detection results using SVM (GRBF) and KNN results are sent to concern person via Gmail.

## V CONCLUSION

In this paper, paddy and wheat diseases are identified with the help of SVM (GRBF) and KNN classifiers. Texture features such as GLCM and mean, standard deviation, kurtosis and skewness features are extracted. Water level sensor and soil sensor are sends the information to WSN gateway through WSN node. The disease detection results and Water level sensor and soil moisture sensor results are sent to concerned person through GSM and the data from both the sensors and details of detected diseases are also converted to excel sheet by every one hour. This excel sheet is sent to concern people through E – mail.

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