IMAGE PROCESSING BASED DETECTION OF DISEASES IN CEREAL PLANTS

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Abstract: ***The productivity of crops is being decreased due to the plant leaf diseases. Since early features of the cereal plant leaf diseases are invisible to the naked eye (microscopic), the cereal plant disease detection is restricted by human visual perception. Because of this reason farmers need constant observation of the field by specialists to diagnose the diseases at an early stage which are more exorbitant, it consumes more time and the results are not accurate. So an automatic recognition and classification of the cereal plant leaf diseases are particularly desired in the field of agricultural information to improve the recognition rate and speed of diagnosis. The goal is to develop a methodology for identification and classification of the cereal plant leaf diseases based on the texture, shape and color features. The cereal plants such as wheat, maize, and rice are considered for study and common diseases for each plant are classified. A diseased RGB leaf image is initially pre-processed using wiener filter to remove the noise. After removing the noise in order to enhance the quality of the leaf image histogram equalization is applied. The Region Of Interest (ROI) is segmented by fuzzy C-means clustering method and Haralick texture features, shape features, color features are extracted. The FRVM is used for the classification of disease type. The proposed methodology shows better results when compared with existing method.***

Key words: Fuzzy C-means clustering, region of interest, Haralick texture features, Fuzzy Relevance Vector machine.

1. Introduction: In the world, the edible plant species are more than 50,000, in this a few 100 come up with human food repository. In the cereal family even though there are over 10,000 species, over the past 2,000 years a few had been mostly cultivated. Three-fourths of the worldwide populace lived on a dietary regime in view of staples such as rice wheat and maize which are taken for study in this paper. Totally 15 cereal crop plants provide 90% of the world's nourishment vitality admission complex with rice, maize furthermore wheat comprised two third of human nourishment utilization. About 80% of the global populace depends on these three crops as there staple food and half of the mankind sustains on rice. The most important crops in the world are these three crops and these are commercial crops in most of the countries [4].

Like any other crops cereal plants also susceptible to diseases due to bacteria, fungi and viral [4]. Some of the common diseases in these three plants are leaf blight, leaf rust, leaf spot and leaf streak which are taken for study in this paper. The major sources of financial growth of the country are due to the cultivation of these crops and most of the agricultural land is used to cultivate these cereal crops. The loss of the crop yield and economic losses are faced by farmers in every year due to the pests and plant diseases.

At an early stage, the plant disease diagnosis is very expensive and time-consuming, farmers require continuous monitoring by experts. Automatic detection of disease is required in the field of agriculture by using image processing techniques. The best method to identify and to classify the diseases accurately is using image processing techniques. By this, it is also possible the identification of the diseases early and accurately so that the quality and quantity of the yield is increased. By using Image processing techniques the efforts of the humans are reduced in significant scope. Image processing techniques are extensively used for distinct farming implementations such as image analysis, remote sensing and pattern recognition. The operation of grouping all the intensity values of an image into a limited number of individuals is known as image processing [11].

The steps involved in image processing techniques for disease identification are 1)Image acquisition 2)Image preprocessing 3)Segmentation 4)Feature Extraction 5)Classification.

2. Related work: (C. C. TUCKER, 2008) [1] Described a programming software that detects and characterizes lesions of diseases on a leaf. The image acquisition is done by using the combination of color camera and grabber. They developed an exclusive, dense and transportable hardware for assessment of the diseases. (A. Camargoa, 2009) [2] Reported an engine perception technique for recognition symptoms of the plant leaf diseases. The SVM classifier is used to classify the diseases by training and testing the classifier. The survey is done to identify the best classifier. (Di Cui, 2010) [3] Reported the outcomes of the research and developed image processing techniques for qualitatively recognizing the severity of the rust disease of images. From plant leaves to segment the infected areas they initially developed a fast physical threshold-setting technique based on HSI color model. (D S Guru, 2011) [4] They mainly concentrated on seedling diseases namely frog-eye spots and anthracnose of tobacco leaves. A PNN classifier is considered to classify the diseases. The techniques developed effectively recognized and classified the seedlings lesions of the tobacco leaves with an accuracy of 88.5933 %. (T. Rumpf, 2010)[5] Based on SVM and SVI they introduced a procedure for detecting and differentiating the early symptoms of the sugar beet diseases. They discriminated the healthy sugar beet leaf with diseased sugar beet leaf and resulted in a classification accuracy of 97%. (Samy S. Abu Naser, 2010)[6] For detection of the plant diseases in the initial stage they initially developed an expert system. The methods used are graphical representational methods and step by step descriptive method. The graphical representational method was best suited than step by step descriptive for an expert system. (Sindhuja Sankaran, 2010) [7] Health monitoring sensor is developed which is a reliable, cost-effective and rapid and that would make easy the betterment in agriculture. They explained the most advanced technologies and the sensor system which is ground based is developed for observing the leaves conditions of plants. (Jayamala K. Patil, 2011) [8] Made much more improvements in technologies using image processing which is used to study the diseases of the plants. The improved techniques increase the throughput and while identifying the diseases the subjectiveness appeared from the experts are reduced. (Heba Al-Hiary, 2011) [9] They developed a software methodology that recognizes and classify the diseases automatically in plant leaves. This algorithm had more accurate and faster solutions. (Barbedo, 2013)[10] Is a survey paper that explains the technologies based on the digital image processing methods to recognize, enhance, quantify and classify the plant diseases. (M. Z. Rashad, 2011)[11] The texture properties based methodology was developed for plant classification and CCL quantization vector classification is used. The CCL and RBF method has better performance results (accuracy) when compared with other methodologies. (Abdul Kadir, 2011) [12] Shape, color, vein and texture features are integrated by introducing a novel method. This novel method as high system performance accuracy of 93.75% because they considered lacunary and color based texture features for classification. (C. S. Sumathi, 2012) [13] In the frequency domain the Gabour filter method is developed to extract the feature fusion. The obtained features were integrated with the edge based feature extraction for the classification of the image. The higher accuracy of 85.93% is obtained using Sobel edge detection classifier. (C. H. Arun, 2013) [14] Feature computation technique is used to develop an automated system that identifies the medical plant leaves automatically. The gray textures, the local binary pattern operators, and gray tone spatial dependency matrices are considered for classification. These features are extracted from the image without performing any steps of pre-processing. The classifier results in better classification performance of 94.7%. (Kue-Bum Lee, 2013) [15] Developed the plant leaf identification system using shape and the leaf vein features of the plant leaves for the classification. FFT is used in the methodology in order to obtain better results from the classification.(Zhong-Qiu Zhao, 2015) [16] The author concentrated on scanned legume species segmentation and classification. It is veins based classification. Properties of the leaf are not used for classification. The acquisition process of the method is expensive and time-consuming when compared with other systems. (Cem Kalyoncu, 2015)[17] The author developed a novel methodology for plant leaf classification. LDC is used as the classifier and trained with shape and texture features. Selecting the feature type depends on the type of the leaf. For identical shape leaves with distinct texture symptoms, texture features are prioritized and vice versa. The methodology has a better accuracy of 97.9%. (Mónica G. Larese, 2013)[18] The author developed an efficient scale-invariant feature transform based Retrieval System for plant leaf detection. In this method color and shape features are extracted and used for classification. It has better accuracy when compared with other methods. (Abdul Kadir, 2011)[19] The author concentrated on enhancing the precision and processing time by presenting a novel segmentation approach for image segmentation. The Sobel edge detector is used to extract the shape features of the leaf. The approach has higher accuracy and simplified process when compared with other methods. (Ji-xiangDu, 2013)[20] The author is concentrated on identifying and differentiating the crop and weed. The shape features are extracted and used for classification. The neural networks are used as the classifier. The automatic classification is done with the highest accuracy compared with other methods.

3. Methodology: This paper implements a methodology for the detection and recognition of the human and microscopic visual symptoms of the cereal plant diseases, by analyzing the colored images. In the cereal plant leaves the diseased regions such as stains and spots are identified, filtered, enhanced, pre-processed, segmented, and a set of image features are extracted from each area. Feature selection is done to recognize the prominent features having the most information about the image domain among the extracted features. An FRVM is used as a learning machine (classifier) to recognize the diseases of the cereal plants. The figure1 shows the methodology for the classification.

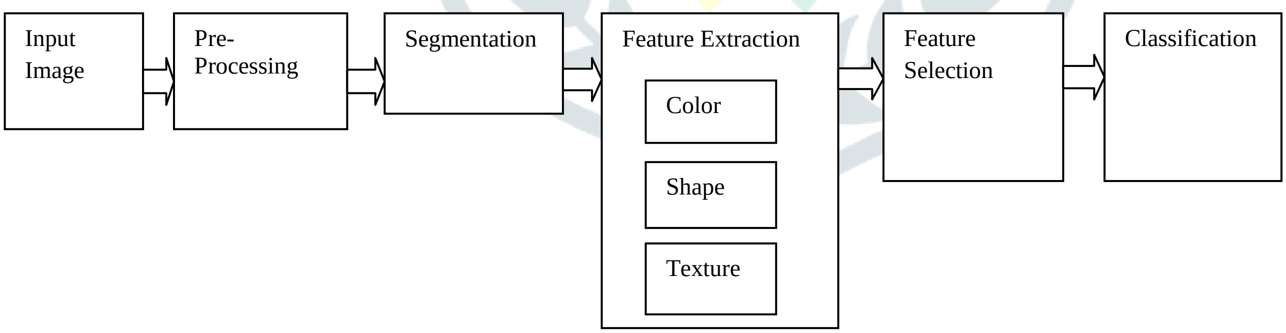

figure1: Methodology for the classification

3.1 Image acquisition: The set of images of rice, maize and wheat crops used in this paper was obtained from the ImageNet, Plant Village and Google. The diseases selected for the study are leaf blight, leaf spot, leaf rust and leaf streak. The diseases of leafs are shown in the figure 2. (figure2 a) shows the leaf blight disease of maize plant, (figure2 b) shows the leaf spot of rice plant, (figure2 c) shows the leaf rust of the maize plant, and (figure2 d) shows the leaf streak of the maize plant. In all cases, the image format used is JPEG and 256x256.

figure2: (a) Leaf Blight (b) Leaf Spot (c) Leaf Rust (d) Leaf Streak

3.2 Image Pre-processing:

Image Resize: The RGB input image is resized to 256*256 pixels in order to decrease the storage memory and time for processing.

Noise Removal: The random variation of brightness in images is known as noise, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. The process of removing adaptive noise is known as filtering. A 4*4 matrix masking is done on the complete image in order to remove the noise.

Histogram Equalization: To enhance the contrast of the image by adjusting the image intensity values Histogram equalization technique is used. Histogram equalization adjusts the image intensity values of the input image so that the intensity values of each pixel distributes uniformly in the output image. The technique can be applied to a complete image or just on a part of an image. Let x be a given image represented by m_r by m_c matrix of integer pixel intensities ranging from 0 to N-1. N is the number of possible intensity values, often 256. Let q denote the normalized histogram of x with a bin for each possible intensity value. So

$$q_n = \frac{\text{no of pixels with intensity } n}{\text{total no of pixels}} \quad n = 0,1,\dots.N-1$$

The histogram equalized image h is defined as

$$h_{i,j} = floor((N-1)\sum_{n=0}^{f i,j} p_n)$$

Where floor () rounds down to the nearest integer. This is equivalent to transforming the pixel intensities, p of x by the function

$$T(p) = floor((N-1)\sum_{n=0}^{k} p_n)$$

The below figure3 shows the results of pre-processing

figure3: Results of pre-processing

3.3 Segmentation:

RGB to YC_BC_R image: YC_BC_R is a family of colour spaces used as a part of the colour image in video and digital photography systems. Y is a luminance component, C_B and C_R are the blue-difference and red-difference chroma components. In a digital camera, the cathode ray tube is controlled by three colours such as red, blue and green, but these colour signals take more memory for storage and consume more time for transmission since these colour signals have high redundancy. The infected part can be easily identified in the YC_bC_r image. The intensity and chromatic components can be used separately. While converting to a YC_bC_r image separate the Y, C_B, and C_R components as shown in the figure. The values of Y, C_B, and C_R are computed by the equations

$$Y=65.481R -37.797G+ 112B+16$$

$$C_B = 128.553R-74.203G-93.786B+128$$

$$C_R = 24.966R+112G-18.214B+128$$

The diseased area of the leaf is more visible in C_R component as shown in figure, so that C_R component image is selected for segmentation. The below figure4 shows the YC_BC_R image.

figure4: YC_BC_R image

Fuzzy C-means Clustering: The partitioning of one piece of data to two or more clusters is known as clustering and Fuzzy C-means clustering is one of the best methods for clustering. This process is employed to separate the diseased part of the leaf. Here the image is divided into four clusters(c=4) so that we need to select four cluster heads (maximum repeated pixel values). Each pixel value is compared with the cluster head and the pixel value is added to the cluster which has the minimum difference. This process is repeated for whole image (0-255). The segmented clusters are multiplied with an enhanced image. The cluster formation is shown in the figure5. The fourth cluster has the diseased part of the leaf image. This image is considered for extracting the features.

figure5: Fuzzy C-means clustering

3.4 Feature Extraction: The segmented image is analyzed using several colours, shape and texture feature. The extracted shape features in this paper are area, major axis length, centroid, eccentricity, minor axis length, equivalent diameter, extent, orientation and perimeter, Region Props algorithm is used to extract shape feature.

The colour features are extracted by converting the RGB image to HSV image because the main drawback of RGB model is, it does not describe all the colours visible to the human eye instead it describes the computer-supported colours. HSV model is designed in such a way that it is approximate to human vision. The main reason behind to work on the HSV images is, the Hue component makes the algorithms reliable and robust because it is invariant for lighting variations. The six-colour features are extracted such as

- Mean and Standard deviation of Hue.
- Mean and Standard deviation of Saturation.
- Mean and Standard deviation of Value.

Haralick Features describe the correlation in an intensity of pixels that are next to each other in space. Haralick proposed fourteen measures of textural features which are derived from the co-occurrence matrix a well known statistical technique for texture feature extraction. It contains information about how image intensities in pixels with a certain position in relation to each other occur together. The texture is one of the most important defining characteristics of an image. The texture features extracted are Angular Second Moment (Energy), Variance, Sum Average, Contrast, Sum Variance, Entropy, Difference Entropy, Difference Variance, Correlation, Sum Entropy, Information Measure of Correlation I, Inverse Difference Moment (Homogeneity), Information Measure of Correlation II, Maximal Correlation Coefficient.

The performance (accuracy) of the classifier is increased by using haralick texture features, shape and colour features instead of GLCM texture features.

3.5 Feature Selection: From each image, all the available features are extracted. But in the available features, there may be features which are not prominent for classifying the diseases of the cereal plants. The time complexity may increase to train the classifier with all the features of an image. So feature selection is done to select or to identify the best or prominent features among the extracted features using feature selection technique called kernel based PSO method. Particle Swarm Optimization (PSO) is a computational method where the random 50 features are grouped into one population. The number of populations is taken as 20. Now the fitness value is calculated for each population (pbest) and the population with low fitness value will have the best 50 features. This is one complete iteration and the procedure is continued for 2000 iterations. For every iteration, the best fitness value is calculated. The fitness function is estimated by

$$f = F1 * S1 * R1 + F2 * S2 * R2 / S1 * R1 + S2 * R2$$

$$S1 = D1/D1+D2 \text{ and } S2 = D2/D1+D2$$

Where D1 and D2 are the distances from the first and second reference points with fitness F1, F2 and reliability R1, R2.

3.6 Classification: The Fuzzy-Relevance Vector Machine (FRVM) classification method is used for classifying the type of diseases in the cereal crops. The FRVM classifier is based on the machine learning techniques and the classifier has the unique function form which is better when compared with the SVM classifier. The SVM classifier has few disadvantages such as time complexity, insufficient transparency and while choosing the kernel type in SVM for processing it has a lack of information. The FRVM is used to overcome these disadvantages. In this paper, we are considering three types of cereal plants as mentioned above and for each plant, we are considering four diseases, so twelve different diseases are considered for classification which has similar symptoms. Firstly the classifier is trained with 70% of the dataset for each disease. The classifier creates a mat file for storing the training data. Now the remaining 30% of the data is tested based on the training data. The performance of the classifier is calculated using the measures explained below in results.

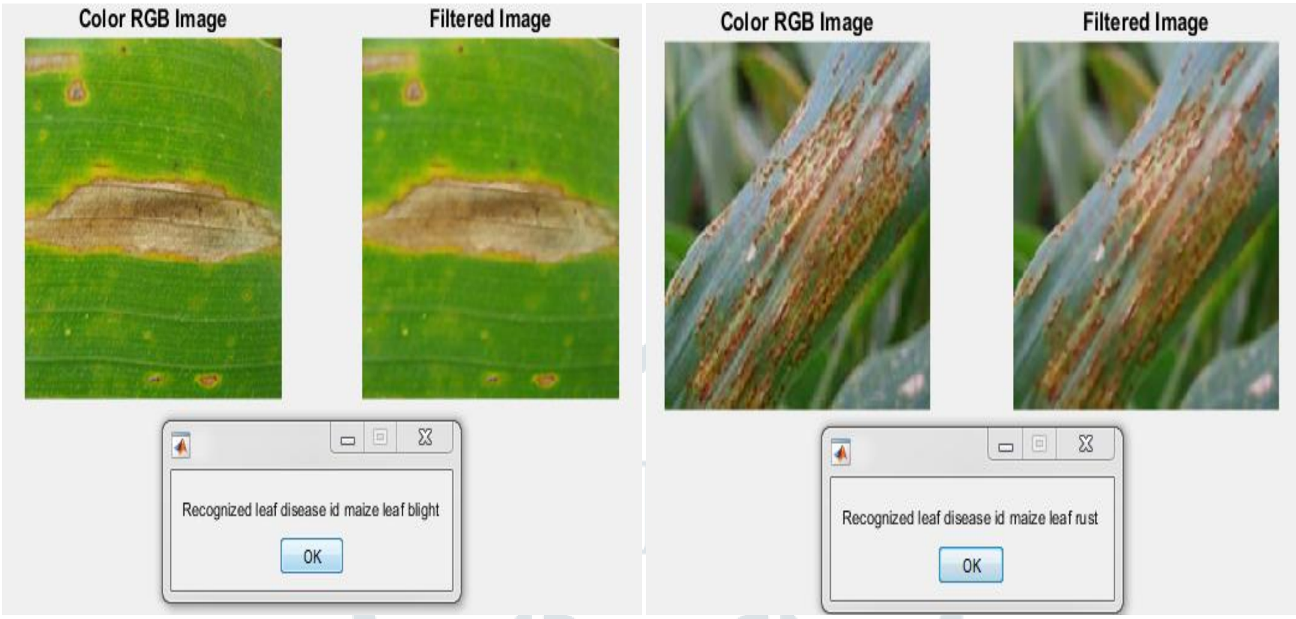

figure6: FRVM Classification

4. Results and Discussion: The obtained results of the methodology used in this paper for the identification of various diseases in a few cereal plants are analyzed. The cereal plants like rice, wheat, and maize are considered for the study. The dataset contains 10 diseases and for each disease, the number of the training set and testing set images are listed in table 3. Firstly the sample images are collected from the Google in JPEG format which is more suitable for processing. The leaf image is pre-processed by filtering and histogram equalization. The filtering is done to remove the noise using the Wiener filter. The histogram equalization is done to enhance the contrast of the image. The result of pre-processing is shown in the figure3. Then the RGB image is converted into a YCbCr image as shown in figure4. The CR component image is selected for segmentation because the diseased part of the image is more enhanced in this component. The segmentation is done to segment the lesion part of the image using Fuzzy-C means clustering. Figure5 shows the clustered image.
After Segmentation colour, shape and Haralick texture features are extracted. In the existing method, the author calculated the accuracy of the classifier by considering the shape, colour and texture features separately. In the proposed method the overall accuracy is calculated by combining all the features and selecting prominent features using feature selection method called kernel based PSO. The prominent feature vector is given as input to train the FRVM classifier. After training the classifier, the classifier is tested with the remaining dataset to calculate the Precision, Accuracy, Specificity, and sensitivity are the measures that evaluate the performance of the classifier. The same procedure is repeated for the SVM classifier. The accuracy for each disease for both classifiers is shown in table 3. The performance of both classifiers is compared as shown in table 4. The accuracy of the proposed method is better when compared with the existing method where the accuracy of FRVM is 90.990 and SVM is 78.494. The bar graph of the performance is shown in the figure7. The figure 8 and 9 shows the False Rejection Ratio and False Acceptance Ratio where the similarity score is the number of iterations. If the number of iterations is increased, accepting the false classification is decreased and rejecting the false classification by the classifier is increased as shown in the graph. The ROC(Receiver Operating Characteristic) curve is plotted which is the ratio of FRR and FAR as shown in figure10.
Accuracy, Specificity, and Sensitivity **Accuracy, Specificity and Sensitivity**

Accuracy: The percentage of the correctly classified diseases is known as accuracy**.**

$$\textbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TotalValue}}$$

Sensitivity: The measure of correct classification of the actual positives is known as sensitivity.

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

Specificity: The measure of correct classification of the actual negatives is known as Sensitivity.

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

Confusion Matrix: The performance of the classification model can be described by the table of confusion matrix for the user dataset. The confusion matrix explains the number of True Positives, True Negatives, False Positives and False Negatives. From this information, the performance of the classifiers can be calculated easily. The table 1 and table 2 show the confusion matrix of the FRVM and SVM classifiers.

Confusion Matrix	**Prediction Table**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**38**	**15**	**15**	**1**	**2**	**2**	**3**	**3**	**1**	**1**
2	**0**	**19**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
3	**0**	**0**	**20**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
4	**0**	**0**	**0**	**9**	**0**	**0**	**0**	**0**	**0**	**0**
5	**0**	**0**	**0**	**0**	**15**	**0**	**0**	**0**	**0**	**0**
6	**0**	**0**	**0**	**0**	**0**	**11**	**0**	**0**	**0**	**0**
7	**0**	**0**	**0**	**0**	**0**	**0**	**14**	**0**	**0**	**0**
8	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**7**	**0**	**0**
9	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**6**	**0**
10	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**5**

Table1: Confusion Matrix for SVM Classifier

Confusion Matrix	**Prediction Table**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**22**	**3**	**2**	**3**	**2**	**2**	**3**	**0**	**1**	**0**
2	**5**	**21**	**4**	**0**	**1**	**1**	**0**	**0**	**2**	**0**
3	**3**	**0**	**25**	**0**	**2**	**0**	**1**	**2**	**1**	**1**
4	**0**	**0**	**1**	**9**	**0**	**0**	**0**	**0**	**0**	**0**
5	**0**	**1**	**0**	**0**	**15**	**0**	**0**	**0**	**1**	**0**
6	**0**	**0**	**0**	**0**	**1**	**11**	**1**	**0**	**0**	**0**
7	**0**	**0**	**0**	**0**	**1**	**0**	**14**	**1**	**0**	**0**
8	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**8**	**0**	**1**
9	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**6**	**0**
10	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**5**

Table2: Confusion Matrix for FRVM Classifier

Cereal crop	Disease type	No of images used for training	No of images used for testing	Accuracy (%)	
				FRVM	SVM
Maize	Leaf Blight	40	20	92.312	80.256
	Leaf Rust	40	20	91.152	76.125
	Leaf Spot	35	21	90.123	79.543
	Leaf Streak	20	09	91.546	78.145
Rice	Leaf Blight	20	10	90.523	79.147
	Leaf Brown Spot	20	13	90.125	78.146
	Leaf Blast	20	10	90.025	79.145
	Leaf Scald	30	15	91.585	75.149
Wheat	Septoria	30	10	91.258	80.145
	Leaf Rust	20	09	91.256	79.145
Overall Accuracy (%)				90.990	78.494

Table 3: Classification Results of each disease

Parameter	FRVM	SVM
Accuracy (%)	90.990	78.494
Sensitivity (%)	85.317	88.330
Precision (%)	84.375	78.125
Specificity (%)	94.826	93.376
Time	0.087804 s	54.486 s

Table 4: Evaluation measure of FRVM and SVM

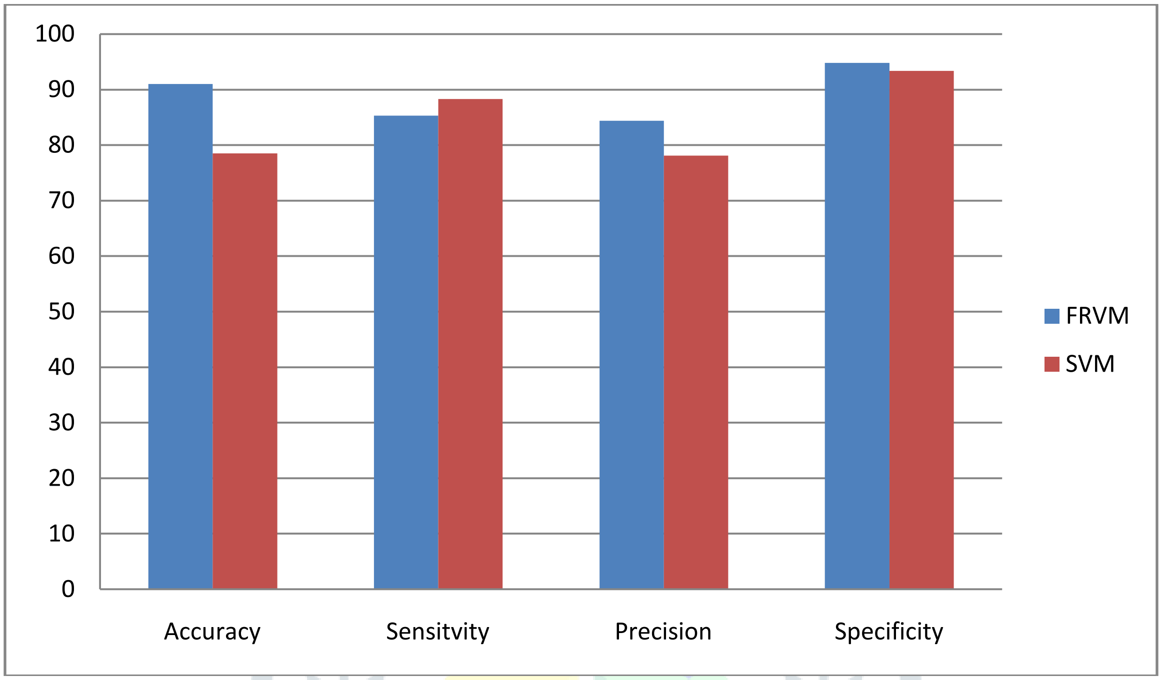

figure7: Bar Graph of the performance measures of FRVM and SVM classifiers

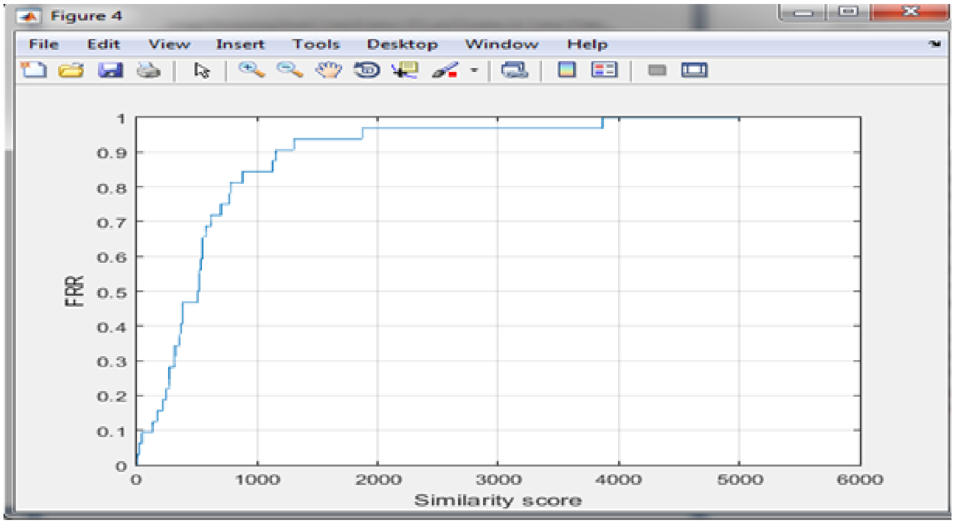

figure8: False Rejection ratio curve

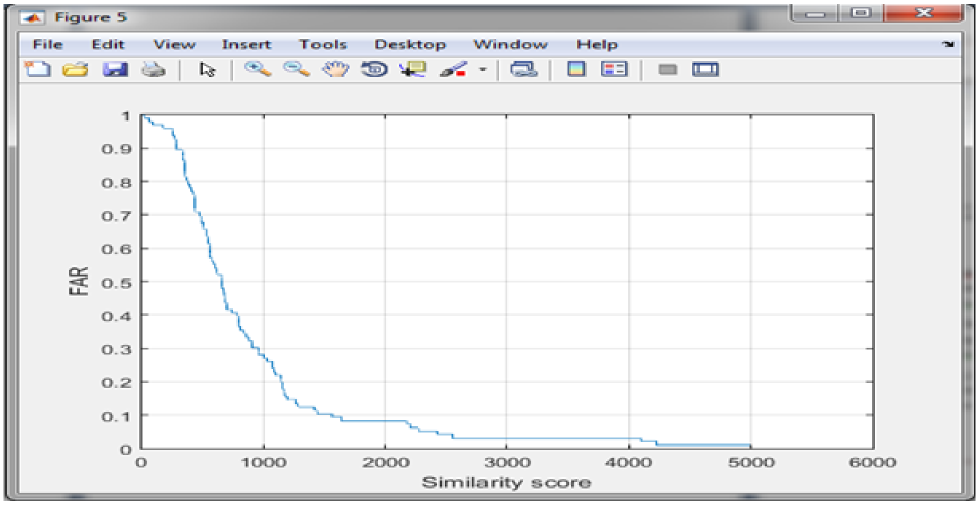

figure9: False Acceptance Ratio Curve

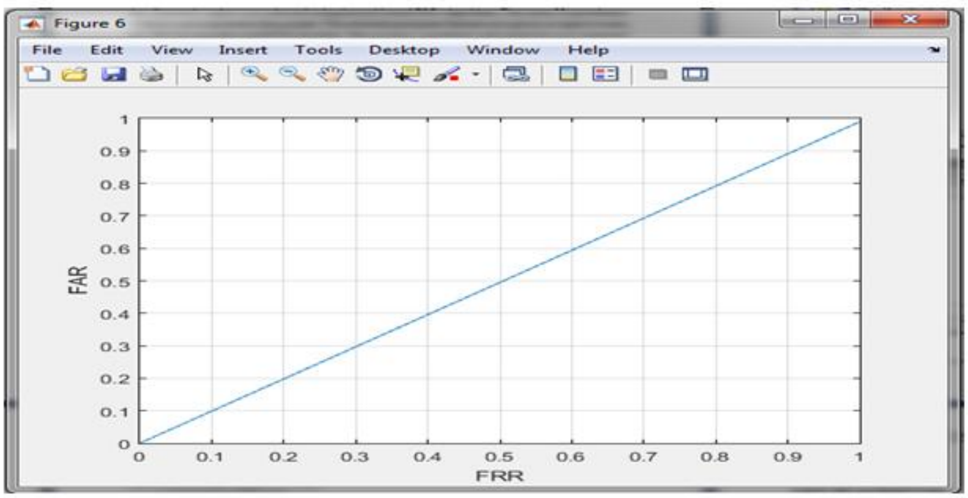

figure10: ROC curve

5. Conclusion and Future Work

In this paper, a methodology is developed for identifying and classifying the cereal plant leaf diseases. The techniques in Image processing like filtering, histogram equalization, segmentation, extraction of features, feature selection and the classifier is used for classification. In feature extraction, colour, shape and haralick texture features are extracted and these features are given to FRVM and SVM classifiers as input. For testing and training of every single disease, a distinct database is used. The techniques proposed in this paper have been tested for three cereal plants and four diseases for each plant mentioned above using two classifiers, FRVM and SVM. The recognition rate (accuracy) obtained from two classifiers are 90.990% and 78.494% respectively. The recognition rate of the classifier used in this paper and the recognition rate of the SVM classifier are compared and from the results we can see that the proposed FRVM classifier is better in aspects such as i) reduced the time complexity, ii) increased the rate of accuracy, iii) number of diseases are covered.

In this paper, the dataset is collected from the websites like ImageNet, village plant etc, instead of this real-time dataset can be collected from the agricultural land and can be checked for the impact on the performance of an algorithm. There are other cereal crops except for three and four diseases for each crop covered in this work. Further Research can make a try on other different cereal crops and all the diseases occur in these plants for real-time application by using the same techniques of image processing in Matlab with some improvements.

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