Vietnam Journal of Science and Technology ***62*** *(5) (2024)*

doi:10.15625/2525-2518/18914

Towards robust crop disease detection for complex real field background images

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Received: 14 September 2023; Accepted for publication: 13 May 2024

Abstract. Most of the work done in image processing-based crop disease detection focuses on images with plain background. This paper presents a technique for crop disease detection for complex real field background images. A segmentation technique is presented to extract leaf patches from the entire image. Transform domain cepstral analysis is proposed for obtaining cepstral coefficients, to attain two level classifications. The first level classifies the crop species while the second level classifies the species into healthy leaf or leaf with specific type of disease. The work is tested on three crops Banana, Soybean and Grape and is checked on plain background laboratory images and on complex real field images. Suggested technique give species level accuracy of 94.33 %, 94.11 % and 98.44 % and disease level average accuracy of 97.75 %, 96.66 % and 97.95 % for Banana, Soybean and Grape, respectively. Comparison with standard features like texture and shape indicate that the presented technique gives the best results for both plain and complex background images suggesting its utilization in crop disease detection to reduce the agricultural and economic losses.

Keywords: Crop disease detection, machine learning, image segmentation, feature extraction, cepstral coefficients.

Classification numbers: 4.7.3, 4.7.4, 4.8.2

1. INTRODUCTION

Agriculture is one of the important sectors and has an immense influence on the economic growth of the country. It is the principal source of food, income and living, for most of the people in rural areas. However, the decline in the agricultural share is alarming due to the food losses and wastes [1]. The required acceleration in the productivity is hindered by the ever changing climatic conditions, increasing soil and air pollutions and the accelerated spread of pests and diseases. Controlling the spread of diseases with timely and effective efforts will help limit crop and economic losses [2]. The conventional method of consulting a phytopathologist is time intensive and expensive, while random use of pesticides on the crops can severely affect the soil quality.

Since many years researchers are working on effective, automated and time efficient techniques for prompt detection of crop diseases [3]. Automated techniques can help in overcoming the limitations of human expertise. However, automated plant disease detection using visual features is challenging and difficult, not only due to real field conditions but also due to the fact that many diseases have similar visual symptoms. Also, these symptoms can appear on any region of the plant like the stem [4], fruits [5], and the whole plant [6]. But maximum work has been done on the leaf images. Data analysis using artificial intelligence can help improve the recognition rate and diagnosis accuracy. The use of artificial intelligence with image processing approach is an effective research area working towards efficient crop disease detection. It includes techniques such as pre-processing, segmentation, feature extraction and classification. Image pre-processing techniques such as resizing, contrast enhancement, noise removal, etc. make the images suitable for further working and improves the quality of input images [7]. After pre-processing, the region of interest is detected using various segmentation techniques [8, 9]. For detection of plant diseases, the region of interest is the infected area. The most commonly used isolation techniques are colour based K-means clustering [10], region growing, etc.

Segmentation is succeeded by feature extraction and classification methods. Feature extraction is the key step in pattern recognition and machine learning applications. It helps in getting the most suitable details from the original data and helps in representing it in lower dimensionality. Features like shape, colour and texture [5, 11] are most commonly used for representing the information. The feature vector is supplied to the classifiers that are used for training so as to group the features related with each disease that are to be detected. Numerous feature extraction methods have been established for detecting crop diseases in past years. Ali *et al*. [12] suggested a technique for detection and classification of citrus diseases. They used colour histograms of red, green blue and hue, saturation, value channels and used local binary pattern (LBP) for textural descriptors. The presented work classified the diseases with 99.9 % accuracy and 0.99 area under the curve. Hassanien, A. E. in [13] extracted texture features using Gabor filters and proposed a moth flame optimization technique developed upon rough set theory for tomato disease detection. The suggested work was effective in terms of various performance metrics. The plant leaf disease detection technique proposed by Singh and Misra in [14] used colour co-occurence matrix to extract texture features for Banana, Bean, Lemon and Rose. The authors used gentic algorithm for segmenting the diseased portion and achieved an overall classification accuracy of 95.71 % using support vector machine (SVM) and 93.63 % using minimum distance criteria with the proposed algorithm. Bhagwat R. *et al*. [15] suggested a framework for soybean leaf disease detection using texture and region based features. They used two segmentation phases for segmenting the leaf from the background and used SVM that gave an average classification accuracy of 95.33 %.

Singh. V. [16] presented a sunflower leaf disease detection technique. The study used particle swarm optimization technique for segmentation and used colour co-occurence matrix with minimum distance classifier for classification. Their study attained an average classification accuracy of 98 % for six sunflower leaf diseases. Pantazi, X. E. *et al*. in [17] proposed automated crop disease detection for several leaf images. The presented method used vine leaves for training the model and used various crops for testing to achieve generalization behaviour. Local binary patterns were utilized for feature extraction and classification as achieved using one class classification to get a success rate of 95 %. Hlaing, C. S. *et al*. [18] proposed a classification technique for tomato plant diseases using texture and colour features. They used statistical information such as shape, scale and location for the texture features using scale invariant feature transform and colour statistic features such as mean, standard deviation and moments for training the multiclass SVM classifier. The work by Sharif, M. in [5] used optimized weighted segmentation technique and used colour, texture and geometric features for identification and classification of citrus diseases. Their proposed work achieved the best classification accuracy of 97 % using multiclass SVM.

Chouhan, S. S. *et al*. [19] introduced an identification and classification technique for plant diseases using radial basis function neural network trained with bacterial foraging optimization. Using region growing method for feature extraction, the work was done on fungal diseases and the suggested technique resulted in higher classification accuracy. In [20], Mathew, D. *et al*. illustrated a technique for classification of foliar diseases in Banana. The authors converted the segmented images to transform domain using DWT, DTCWT and Ranklet transform. The work used local binary pattern and its variants for extracting texture features. The elliptical local binary pattern variant gave the best classification accuracy of 95.4 %.

Although various techniques are applied for crop disease detection in the literature, most of the work done is on leaf images with plain background. The proposed work gives a comprehensive system that can analyze the visible symptoms on images with a plain background as well as images with complex real field conditions. The work proposes a segmentation technique that can be used for images having complex real field background conditions. Also, the work in the literature primarily focuses on the feature extraction done in the spatial domain. The presented work uses transform domain for extracting cepstral coefficients. Cepstral analysis involves Fourier transform that gives frequency domain advantages such as shift and scale invariance to the cepstral features. The analysis includes logarithmic operation that gives an added advantage of amplitude (illumination) invariance. Visual symptoms on the leaves are used for developing an automated crop disease detection system. The presented method classifies images at two levels, the first level classifies the crops and the second level further classifies them based on diseases. Experimentation is done using leaf images having plain background and with leaf images having real field conditions with complex background. The work aims to check the potential of cepstral coefficients to handle variations in scale, translation, illumination, etc. for detection of crop diseases. The experimental results show improved classification accuracy and prove cepstral coefficients as effective features that can be used for crop disease detection.

The main contributions of this paper are as follows:

- The paper presents a novel segmentation technique for leaf images having complex real field backgrounds.
- It utilizes the proposed cepstral coefficient extraction technique for crop disease detection. The work analyzes the potential of cepstral coefficients as a viable feature in handling the translation and illumination variations for complex background images.

The remainder of the paper is organized as follows: Materials and methods are explained in Section 2, results and discussion are presented in Section 3, and Section 4 contains the conclusion.

2. MATERIALS AND METHODS

The present section gives the particulars about the dataset employed, features extracted and the classifiers used in the work. The system diagram illustrating the proposed methodology for crop disease detection is given in Figure 1. The system is able to handle images with plain background as well as images with complex real field backgrounds. The methodology proposes a segmentation technique that can be used to extract a leaf patch from the images having real field background conditions. This leaf patch is further used for extracting the proposed cepstral coefficients. These coefficients are robust in handling the illumination variations that can occur in images with real field background conditions, thus giving a robust system that can handle images with plain background as well as images with busy real field background.

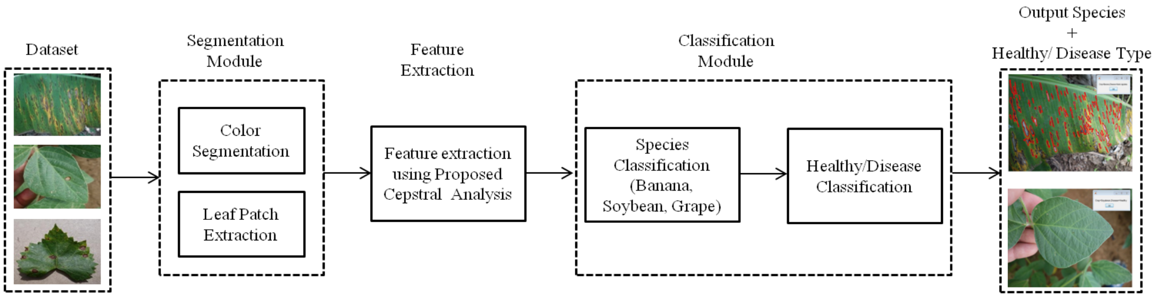


Figure 1. System diagram.

2.1. Dataset

Table1. Dataset details.

Sr. No.	Species	Class	Background
1	Banana	Banana Healthy	Complex
2		Banana Black Sigotaka	Complex
3		Banana Speckle	Complex
4	Soybean	Soybean Healthy	Complex
5		Soybean Frogeye Leaf Spot	Complex
6		Soybean Septorial Leaf Blight	Complex
7	Grape	Grape Healthy	Plain
8		Grape Black Rot	Plain
9		Grape Leaf Blight	Plain

Figure 2. Sample images.

Images of healthy and infected leaves from Plant Village repository [21] are used in the work. Three crops (Banana, Soybean and Grape) are selected from the plant village dataset with a total of 900 images. The dataset used has images with plain background as well as images having complex background with real field conditions. Each crop species has three classes as healthy, Disease type 1, Disease type 2. Images of Banana and Soybean have complex real field conditions while the grape leaf images have plain background. All the images are stored in .jpg format. Table 1 presents the details of the dataset used and Figure 2 shows the sample images.

2.2. Colour segmentation

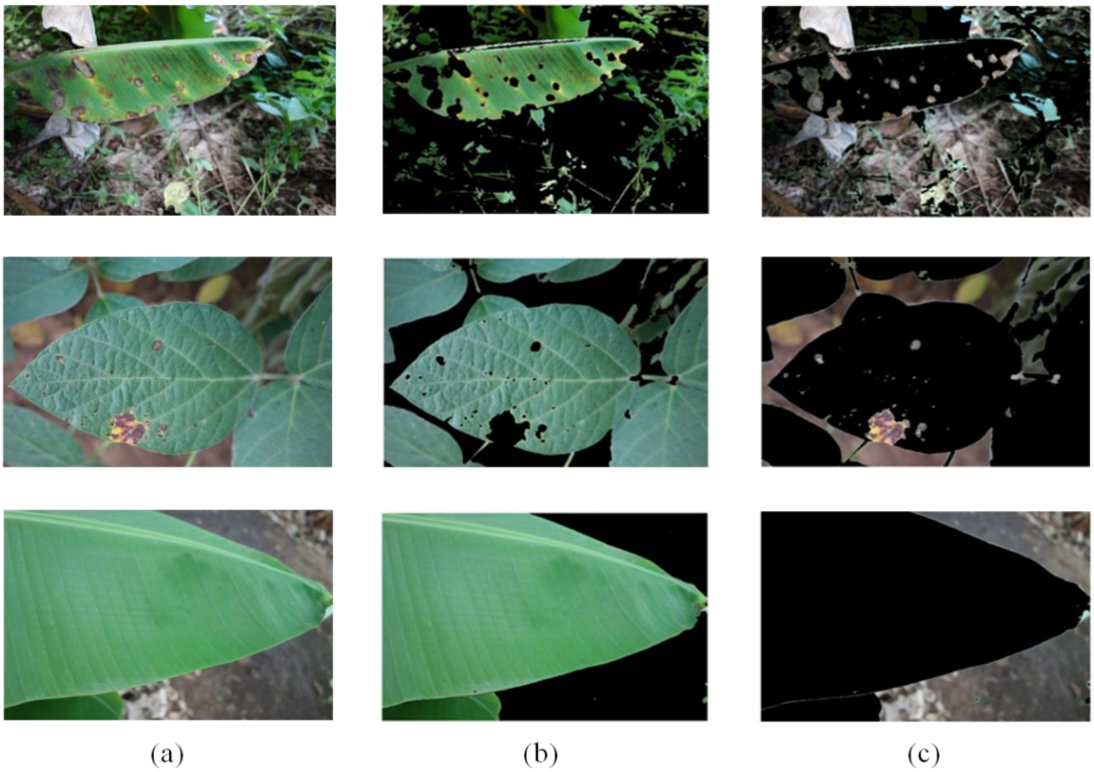


Figure 3. Segmentation output: (a) original image, (b) Cluster 1 (leaf cluster), and (c) Cluster 2 (non-leaf cluster).

Early symptoms of infection in plants are normally in the form of discoloration of the infected areas. Hence segmentation based on colour is the most widely used practice to distinguish the infected area in plant disease detection. Colour based K-means clustering is used for segmentation in this work. K- means clustering is an iterative algorithm that partitions the pixels in the image depending upon the Euclidean distance metric. Two clusters are generated at the output, one with green pixels representing the healthy region and green background (leaf cluster), while the other with non-green pixels representing the infected region and non-green background (non-leaf cluster). Figure 3 presents the original image and the segmented output given by K-means clustering algorithm.

2.3. Leaf patch extraction

The cluster with green pixels representing the healthy region and green background (leaf cluster) is further analysed to get a patch of the leaf. As can be seen from Figure 3, for images with real field conditions identifying the actual leaf is difficult due to other green background objects. Hence, considering that in the leaf cluster, the maximum portion of the cluster will be occupied by the leaf region, the largest connected component is identified and its centroid is used to extract a 128×128 patch. The steps involved for extracting the leaf patch are mentioned in Algorithm1 and Figure 4 shows the leaf cluster and its extracted patch. One extracted leaf patch is used for the first level species classification while nine such patches are extracted from the leaf to get the second level of disease classification.

Algorithm 1: Extract leaf patch from the leaf cluster

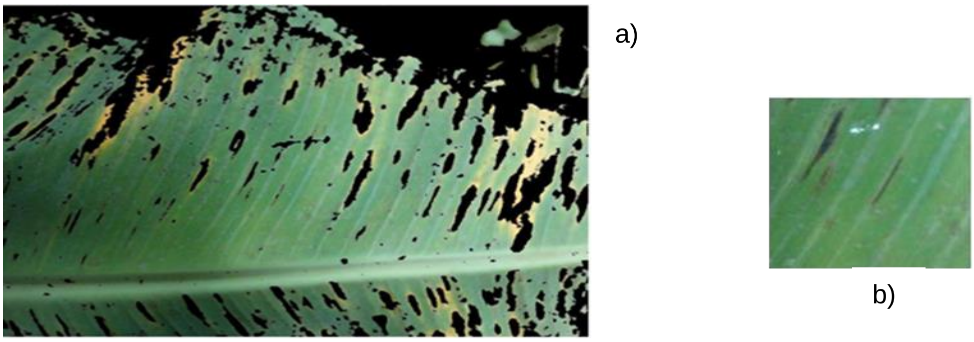
Input: Cluster with leaf and green background (leaf cluster)

1. Convert the RGB leaf cluster into binary.
2. Determine all the connected components in the image.
3. Determine the centroid of the largest connecting component.
4. Using the centroid calculated, extract a leaf patch of size 128×128 from the original image using the following equation:

$$I_{RGBpatch} = I_{binary} \otimes I_{original}$$

I_{binary}= BW image of the leaf cluster, $I_{original}$= original leaf image and
$I_{RGBpatch}$= extracted leaf patch

Output: RGB leaf patch of size 128×128



a)

b)

Figure 4. Leaf patch extraction: (a) Leaf cluster and (b) Extracted leaf patch.

2.4. Feature extraction using proposed cepstral analysis

The potential of the algorithm in pattern recognition largely depends upon the features that are extracted. Extracting relevant features that characterize the crop and the corresponding diseases is very important. Although most of the feature extraction techniques proposed in the literature make use of the traditional spatial domain features that directly use the pixel values of the image, recently, researchers are studying the use of features extracted in other domains for getting more performance from the networks.

Cepstral analysis is a principal technique used for feature extraction in speech processing. But researchers have also employed it for 2D image processing in areas such as hand gesture recognition [22], fingerprint recognition [23], image quality assessment [24], face recognition [25], iris feature extraction [26], etc.

Inspired by its performance in 2D image representation, its application as one of the viable features for detecting crop diseases is studied in this work. 2D Cepstrum is a quefrency domain approach that uses Fourier transform and logarithm operation. Usually, the energy of natural images decreases at high frequencies as these images are inherently low pass. Due to this, the influence of high frequency components is suppressed by high value low frequency components. However, the high frequency components are important as they represent discriminative features like abrupt changes due to the presence of infection on the leaves. In order to get the important information from low as well as high frequency components, two sets of cepstral coefficients are extracted in this work. The first set is obtained from the original image patch and to capture more details of high frequencies, the edge map of the original image patch is used to get its cepstral coefficients that act as the second set of cepstral features. In both the cases the frequency domain data after DFT is normalized to control the influence of high value lower frequency components over the higher frequency components. Both the sets are then combined to give the accurate representation of the image.

Cepstral coefficients are calculated from the extracted leaf patch. The main idea is to extract the global and local discriminative features. For this, the image is partitioned into non-overlapping blocks. Big blocks are able to capture the global features while small blocks represent the local features present. Cepstral coefficients give an advantage of translation invariance due to the Fourier transform and the logarithmic operation involved gives amplitude or gray scale invariance that gives robustness to illumination changes [25]. The procedure for extracting proposed cepstral coefficients is described in Algorithm 2.

Algorithm 2: Extraction of cepstral coefficients

Input: RGB image patch of size 128x128

1. Select number of cepstral coefficients(ncep) to be calculated.
2. Convert RGB image patch to Gray scale (img).
3. CC1 = **getcepstralcoef(img, ncep)**.
4. Sharpen the gray scale image and generate the edge map (img1).
5. CC2 = **getcepstralcoef(img1, ncep)**.
6. $$CC = CC1 \cup CC2$$

Output: Cepstral coefficients

Functiongetcepstralcoef(img, ncep)

1. Compute the discrete Fourier transform of the img.
2. Compute the power spectrum (P_S).
3. Partition the power spectrum (P_S) into 8x8 non-overlapping blocks for calculating the mean block power (BP_a), r = c = 128.

3.1 $k \leftarrow 1$
3.2 **for** p $\leftarrow$ 0 to r step i **do**
3.3 **for** q$\leftarrow$ 0 to c step j **do**
3.4 $blk\_ps = P_s(p:(p+i), q:(q+j)), \quad i \leftarrow 8, j \leftarrow 8$
3.5 $BP_a(k) = \left(sum\left(sum(blk\_ps)\right)\right)/(i*j)$
3.6 $k = k+1$
3.7 **endfor**
3.8 **endfor**
4. Generate a DCT II matrix (dctm)
5. CC $\leftarrow$ dctm* log(BPa)
6. **return** CC

2.5. Classification

The final step involves classification of images into the corresponding plant species and further classifying as either healthy or into one of the disease types. For the first level species classification, only one extracted leaf patch is used while for the second level classification, nine such patches are used to extract features and to categorize the images further. K-nearest neighbour (KNN), SVM and Artificial Neural Network (ANN) are the most commonly used traditional classifiers. Hence to study the potential of cepstral coefficients for crop disease detection, the performance of the suggested algorithm was checked using the most commonly used conventional classifiers. Out of these ANN's are the most famous classifiers for pattern recognition. They belong to the class of learning algorithms and since last few years, deep learning networks have formed a new category that has a large number of processing layers and is able to get high classification results in almost all domains including agriculture [27-33].

3. RESULTS AND DISCUSSIONS

In this work, standard features like texture and shape are assessed against the proposed cepstral coefficients. The work is tested for traditional features, fusion of traditional features and proposed cepstral coefficients. The dataset is split into training and testing sets with 80:20 ratio giving 720 training and 180 testing images. The experimentation is carried out in three phases. In the first phase the standard features are extracted from the images and their performance is measured using three different classifiers. In the second phase the standard features are fused and tested while in the third phase the proposed cepstral analysis is carried out to get the cepstral coefficients that are tested for leaf disease classification. The classification efficiency is evaluated using Accuracy, Precision, TPR (Recall or Sensitivity), TNR (Specifictiy) and Type 1 error.

3.1. Performance using traditional features

Conventional features like texture and shape are used in the study in the first step. Texture information is extracted using GLCM and Gabor filters to get 16 and 202 texture features, respectively. Geometric properties are used to extract 11 shape features.

The performance measures for individual features using three different classifiers are presented in Table 2, which shows that the texture features using GLCM gives the maximum accuracy for all three plant species and for all three classifiers. Grape images give the best results while Soybean images give the lowest performance for all the classifiers. This could be because the Grape images are captured with plain background while Soybean and Banana images have real field complex background conditions. Also, Soybean images have high occlusions compared to Banana images. Real field conditions affect the classification performance due to the uncontrolled conditions such as occlusions, shadow, variance in lighting conditions, etc. Table 2 also indicates that ANN shows the best performance compared to KNN and SVM, hence for all further processing ANN is used as the classifier. Table 3 gives the performance measures for the GLCM texture features using ANN as classifier.

Table 2. Classification accuracy for standard features using various classifiers.

Features	**KNN**			**SVM**			**ANN**		
	Banana (%)	**Soybean (%)**	**Grape (%)**	**Banana (%)**	**Soybean (%)**	**Grape (%)**	**Banana (%)**	**Soybean (%)**	**Grape (%)**
Texture Features using GLCM	87.54	86.21	89.36	90.89	89.67	91.33	92.88	90.00	93.66
Texture Features using Gabor filters	86.11	85.77	87.65	87.24	86.37	88.01	88.71	87.15	89.00
Region properties	84.52	83.80	86.06	85.37	84.56	86.89	86.96	85.60	87.37

Table 3. Performance measures for texture features using GLCM for ANN classifier.

	Banana	**Soybean**	**Grape**
Accuracy (%)	92.88	90.00	93.66
Precision (%)	90.36	82.81	93.90
Recall or Sensitivity (TPR)	0.87	0.88	0.90
F1 score	0.90	0.85	0.90
Specificity (TNR)	0.95	0.90	0.97
Type 1 error	0.04	0.09	0.02

3.2. Performance using fused traditional features

The next step of the experimentation is done by combining the region properties with the texture features, to exploit its effect on classification performance. Hence in this phase the region properties are fused with GLCM based texture features and with Gabor filter based texture features. Table 4 presents the classification performance for the fused features using artificial neural network as classifier. As indicated in Table 4, the classification accuracy does not show any notable improvement in the performance. This could be due to the fact that in plant disease detection the lesion shapes can vary and various diseases can have similar lesion shapes due to which shape features may not impact the classification performance.

Table 4. Classification accuracy for fused standard features with ANN classifier.

	Banana	Soybean	Grape
FGLCM, Region (%)	92.98	90.42	93.77
FGabor, Region (%)	89.14	88.56	90.57

3.3. Performance using proposed cepstral analysis

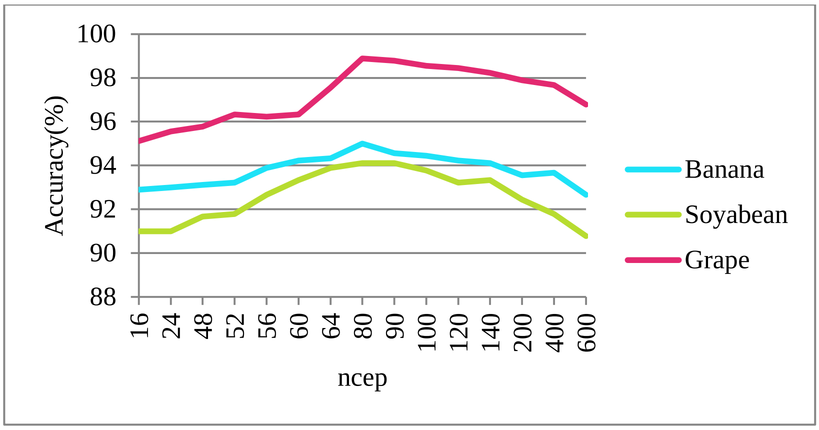


Figure 5. Accuracy using different cepstral coefficients for ANN.

To extract the cepstral features, the input image patch is sliced into non-overlapping blocks. The main idea is to extract the global and local level features. Big blocks will be able to capture the global features while the small blocks represent the local features. Experimentation is done for various block sizes. The results show that the block of size 8×8 gives the best results. The number of cepstral coefficients (ncep) used is also another variable parameter in the experiment. It is found that forty cepstral coefficients from the original image and forty coefficients from the edge map give maximum performance. Hence these parameters are used for further experimentation. Figure 5 shows the changes in the classification accuracy derived from the number of cepstral coefficients (ncep). Table 5 shows the performance measures for the first level species classification using the proposed cepstral coefficients with ANN classifier, while Table 6, Table 7 and Table 8 show the second, disease level performance measures for Banana, Soybean and Grape, respectively. For the second level classification, nine patches extracted from the leaf are used to extract the features and the classifier probability score is calculated for each patch. The maximum probability score is considered as the final class. Figure 6 shows the final classification result indicating the crop species and detected disease. As cepstral analysis is a Fourier transform based method, the cepstral coefficients obtained are invariant to translation and the use of logarithmic operation makes the coefficients invariant to amplitude changes, thus making the coefficients resilient to illumination changes. This is a powerful attribute for a system to be robust to images captured in complex real field conditions.

Table 5. Performance measure of species classification for proposed cepstral coefficients with ANN.

	Banana	**Soybean**	**Grape**
Accuracy (%)	94.33	94.11	98.44
Precision (%)	93.68	89.45	97.35
Recall or Sensitivity (TPR)	0.89	0.9333	0.98
F1 score	0.91	0.91	0.97
Specificity (TNR)	0.97	0.94	0.98
Type 1 error	0.03	0.05	0.01

Table 6. Disease level performance measures for Banana using proposed cepstral coefficients and ANN.

	Banana healthy	**Banana speckle**	**Banana black sigotaka**
Accuracy (%)	97.75	97.37	98.12
Precision (%)	96.77	98.35	98.36
Recall or Sensitivity (TPR)	0.96	0.96	0.96
F1 score	0.96	0.96	0.97
Specificity (TNR)	0.98	0.97	0.98
Type 1 error	0.01	0.02	0.01

Table 7. Disease level performance measures for Soybean using proposed cepstral coefficients and ANN.

	Soybean healthy	**Soybean downy mildew**	**Soybean frogeye leaf spot**
Accuracy (%)	96.42	96.07	97.5
Precision (%)	96.87	91.01	96.84
Recall or Sensitivity (TPR)	0.93	0.96	0.95
F1 score	0.94	0.93	0.96
Specificity (TNR)	0.98	0.95	0.98
Type 1 error	0.01	0.04	0.01

Table 8. Disease level performance measures for Grape using proposed cepstral coefficients and ANN.

	Grape healthy	**Grape leaf blight**	**Grape black rot**
Accuracy (%)	98.63	97.27	97.95
Precision (%)	95.91	95.91	98.97
Recall or Sensitivity (TPR)	1	0.95	0.95
F1 score	0.97	0.95	0.97
Specificity(TNR)	0.98	0.97	0.99
Type 1 error	0.02	0.02	0.005

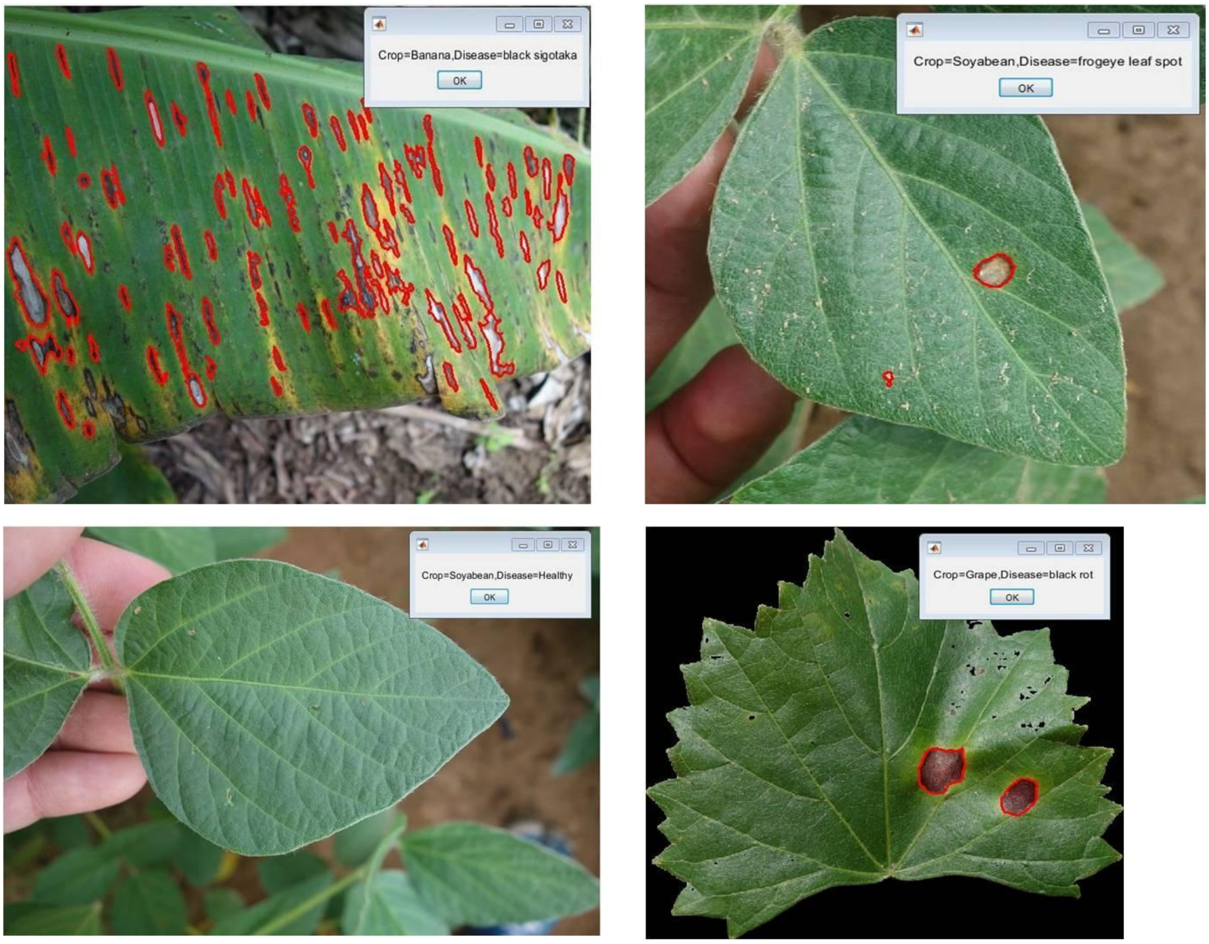


Figure 6. Classification output.

4. CONCLUSIONS

The paper presents a segmentation technique for leaf images having complex real field background and also utilizes the proposed cepstral coefficients for crop disease detection. The work involves three stages of testing on images having plain background and also on images having complex real field background. In the first stage of experimentation, the standard features like texture and shape are extracted from the images and are tested individually for classification. This stage shows that the texture features obtained using GLCM gives the maximum accuracy with ANN classifier. In the second stage, the standard features are fused to check for any improvement in the model performance. However, no significant improvement is achieved with the fused traditional features. In the third stage of experimentation, cepstral analysis is suggested to extract cepstral coefficients from the images. The suggested cepstral coefficients are validated to give the best results for the first species level as well as for the second disease level classification. The first level classification accuracy is 94.33 %, 94.11 % and 98.44 % for Banana, Soybean and Grape, respectively. The second level involves the disease classification that gives an average classification accuracy of 97.75 %, 96.66 % and 97.95 % for Banana, Soybean and Grape diseases, respectively. The experimental results prove the significance of cepstral coefficients for detection of crop diseases for images with plain as well as complex background conditions. The future work will focus on a superior segmentation technique for the real field complex background images that will aid in controlling the losses and improving crop yield.

CRediT authorship contribution statement. Radhika Bhagwat: Methodology, Experiment, Investigation, Formal Analysis. Yogesh Dandawate: Supervision, etc.

Declaration of competing interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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