IDENTIFICATION OF PESTS AND DISEASES USING ALEX-NET

DEVENDRA MORANKAR,
Department of E&TC, PICT, Pune, India
devendramorankar@gmail.com

DEEPAK M.SHINDE
Department of E&TC, PICT, Pune, India
dmshinde@pict.edu

SUVIDYA R PAWAR
Department of E&TC, PICT, Pune, India
srpawar@pict.edu

ABSTRACT
One of the essential tasks of agriculture is to identify epidemic because these diseases not only harm the production but can cause major environmental catastrophe. At least insecticides need to develop some effective techniques and solutions. It can be adapted to farming too for productivity, using agricultural science besides various image analysis techniques. We can use manpower to control the effect of pests. Some system reduces human effort and mistakes through automatic surveillance and this technique is a work in progress. In this project, the category of infection is caused by insect and leaf image. Then we have methods of an image processing which is used in agricultural management. Mobile is used for image editing and the same camera is used for a computer program designed to allow a computer user to interact easily with the help of Internet Protocol. These characteristics of the foliage structure are calculated by considering the gray-level co-event matrix. In the pattern recognition technique it is processed for training, validation and testing and its accuracy is 71.6%. Alex-Net is have been utilized for practice and classifying images. Alex-Net uses the Interactive Transfer Learning Network to arrange a new collection of images. This paper provides a fully automated advanced towards to the testimonial and assortment of pest diseases and their pests. This is especially useful for farmers likewise citizens who are doing gardening in the area of their homes.

KEYWORDS: Image Processing, Alex-Net, Machine Learning and Artificial Neural network.

INTRODUCTION
Most significant causes of the massive loss of agricultural crops in commercially important agricultural fields of the world are the rapid growth of insect and spread of diseases like pests. Therefore, insect-borne diseases are an important part of today's agricultural products. Integrated pest management (IPM) has become a dominant component of pest control since the late 1990s. This is globally endorsed by the Agency for scientific research and international development for agricultural policies. IPMs need to examine different pest species and their extent, so it is significant to develop recommendations for good pesticides that respond to economic, environmental, and sociological consequences. Therefore, accurate identification and quantity of insects is crucial for effective use of IPM. Due to the current cost-effective and time-consuming maintenance practices, IPM professionals are needed. Many of the world's food security processes have similarities, such as manually collecting data on field crops and classifying samples in the field, which are the hope of obstructing the extension of this technology area and require less technical support. Therefore, more affordable methods are needed like automation based on computer based system with machine learning technique. It has emerged as an exciting technology and using it we can solve this problem.

RELATED WORK
Hafiz Gulfam Ahmad Umar, Qaisar Abbas and Fatima Gulzar [1] presented that, classification is a challenging work in pest types. The challenge of classifying different species and the resemblance between

them is very complicated. In the present study, pests are classified using the Bayesian network, they have given different techniques and proposing pest identification schemes which detect color images of insects. Four diverse modules of pests were selected. Insects were categorized by size, characterization, and variation in their histograms and colors. The color of every image is different and also has its unique shape. Using Bayesian classification approach it can be useful medical and agricultural pathology and also allows the valuable applications in vector control effectively. Accurate organization of pests using the proposed framework and characteristic implications is very important. The classification model is very simple and very robust and fit for the general classification framework. This allows to easily accumulating a several of characteristics.

Gebert G., Murali Krishnan [2] submitted some points like the earliest patterns of growing coffee in India have increased the prevalence of insects and infections in tree cultivation. Plants that grow mono crops are prone to insects and infections, besides the risk of constant climate change, and these factors favour the development of pest populations. Considering these issues, algorithms have been suggested in MATLB for recognition of pests using image processing techniques. Planting images are edited at times that are equally separated using image editing tools. Such images are subject to transformation and clustering, before processing later.

Johnny L. Miranda, Bobby D. Gerardo, Bartolome T. Tanguilig [3] presented that finding pests in rice fields is a challenging task in agriculture; Therefore, effective measures must be advanced to resistance newly formed pest infiltration with less utilization of pesticides.

The methods of image scrutiny rely heavily on agricultural science and are applied to it, which in turn gives extreme safety to the crops, which ultimately helps in crop controlling and invention better yields. Manpower has to rely on manpower to monitor the growth of pests. Many mistakes happen while human endeavors are underway, and automatic monitoring is progressing to reduce them. According to this study, computerized recognition and image capture mechanism is established to estimate the pest density in the rice fields. They exceed implementing various image processing methods to detect insects. The results of the experiment show that the projected mechanism delivers a modest, effective and firm solution for pest detection in rice fields.

NEURAL NETWORK PATTERN RECOGNITION (NNPR)

An important application of neural networks is pattern recognition. Although the network is used, it recognizes the input marking and tries to output the corresponding output marking.

The capacity of the neural network exists when a sample is non-output, provided as an input. Pattern Recognition is essential due to it performs in many practical problems. That is also pattern recognition. Other useful scenarios where you want a computer to recognize something: an object in an image, an alert sound in an audio recording and so on.

Consider two classes; each scalar target value to either 0 or 1, showing which class the matching input belongs to. So, you can describe the two-class exclusive-or classification problem as follows:

inputs = [0 1 0 1; 0 0 1 1]; and targets = [1 0 0 1; 0 1 1 0];

Classification complications are concerning only two classes. It exist characterized using either format. The targets can comprise of either scalar 1/0 elements or two-element vectors, with one element being 1 and the other element being 0.

ALEX-NET

Alex-Net Pretrained network is convolutional neural network. This is trained for million images from the Image Net database. Alex-Net Pretrained network takes 8 layers. They can organize images into 1000 object categories. Consequently, the network has well-read extensive variety of images and their size of 227-by-227.

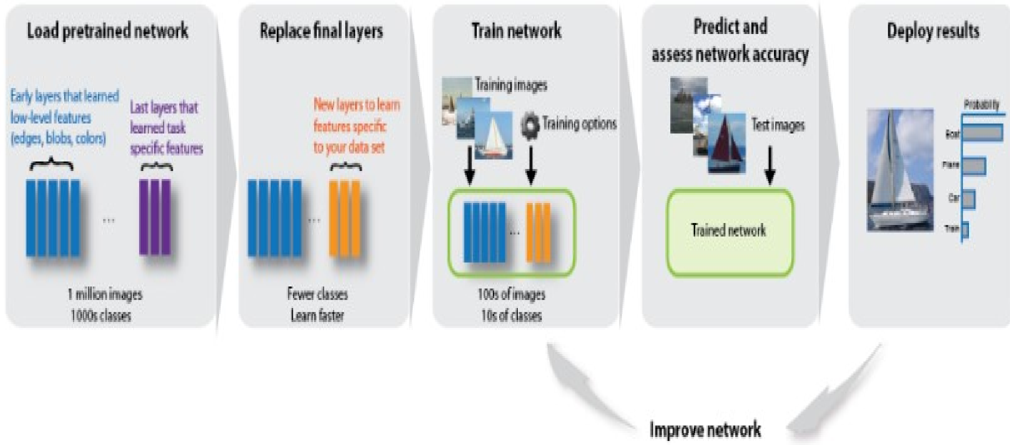

Figure 1: Alex-Net Pretrained network

1.1 Interactive Transfer Learning Using Alex-Net

It gives new collection of images is graded and It is essential to aware this is to get pretrained Alex-Net Networks open to transfer learning. This Alex-Net pretrained network is presented in Figure 1. This is more rapidly and informal than preparation a new network, because we use less exercise images and they utilize the features learned to complete new tasks. Alex-Net has been instructed for several images and can categorise images into 1000 object variety. The network has acquired knowledge of prosperous feature representations for an extensive range of images. The network conveys an image as input and outputs a label for the object in the image together with the extensive for each of the object variety.
Alex-Net can be categorized into 1000 object varieties. The network has acquired knowledge to represent an aspect of a broad range of images and carry out as input. It express the output has a label in the network image. It can also relate to the possibility of having a range of objects in it. We choose pretrained network and utilize a starting point for learning new tasks. Fine-tuning a network with transfer learning is very quick and easier than orientation a network with scratch-on-the-fly weight. Using a depressed number of orientation images we can fast carry acquire a knowledge of features to the new task.

1.2 Load Data

We can fill the new images as an image data store. Image data collection inevitably labels the images created on folder names then they saves data as an Image Data cache object. You can cache large image data in an image data store and it does not suitable in memory, and expeditiously read group of images during initiate of a convolutional neural network.

```
imds = imageDatastore('MerchData', ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');
```

We can classify the data into training and validation data group. Here 70% of the images utilized for training and around 30% for validation. Disconnect each label breaks the images data store into two new data stores.

```
[imdsTrain,imdsValidation]=
splitEachLabel(imds,0.7,'randomized');
```

1.3 Load Pretrained Network

Assign the pretrained Alex-Net neural network.
net = alex-net;
Use observes network to display a responsive visual image of the network architecture and take complete details about the network layers.
Analyse Network (net)

First layer shows the image input layer, also they involves input images of size around 227-by-227-by-3, and here 3 is always the number of color channels.

inputSize = net.Layers(1).Input Size
inputSize = 1×3
227 227 3
228

1.4 Substitute Final Layers

In the pretrained network remain three networks are configured for 1000 classes and which must be fine-tuned for the new sorting difficult situation. Release all layers; exclude the last three, from the pretrained network.

layersTransfer = net.Layers(1:end-3);

Here we can convey the layers to the new assortment task by restore the last three layers with a completely connected layer. This comprises a softmax layer, and an assortment output layer. The new completely attached layer correspond to the new data can be prescribe the options. They get the completely attached layer to have the same size as the number of classes in the new data. To acquire skill in quicker in the new layers than in the transferred layers, increase the Weight Learn Rate Factor and Bias Learn Rate Factor values of the completely attached layer.

numClasses = numel(categories(imdsTrain.Labels))
numClasses = 5
layers =
[layers Transfer fully Connected Layer (num Classes, 'Weight Learn Rate Factor', 20, 'Bias Learn Rate Factor',20)
softmaxLayer
classificationLayer];

1.5 Train Network

The network is in need of input images of size around 227-by-227-by-3, but the images in the image data cache have varying sizes. Use a grow image data cache to automatically and again resize the initiation images. Identify supplementary becoming greater in size functioning to execute on the training images. Every which way overturn the training images along the vertical axis, and indiscriminately translate them next value to 30 pixels horizontally and vertically. Data becoming greater in size helps prohibit the network from over fitting and remember the demand details of the training images.

```
pixelRange = [-30 30];
imageAugmenter = imageDataAugmenter( ...
    'RandXReflection',true, ...
    'RandXTranslation',pixelRange, ...
    'RandYTranslation',pixelRange);
augimdsTrain = augmentedImageDatastore(inputSize(1:2),imdsTrain, ...
    'DataAugmentation',imageAugmenter);
```

To automatically resize the validation images without acting forward data becoming greater in size, use an increase image data store without detail any additional pre-processing action.

Augimds Validation = augmented Image Data store (input Size(1:2),imds Validation);

We can identify the more training options. For transfer learning, continue to be the features from the early layers of the pretrained network means the transferred layer weights. To slow down learning in the shift layers, set the verify learning measure to a small value. In the earlier move, you increased the learning rate factors for the fully fix layer to speed up learning in the new final layers. This merging of learning rate situation results is not only in fast learning only in the new layers but also slower learning in the other layers. When playing transfer learning, you do not need to train for as many epochs. A time is a full training cycle on the complete training data set. Detail the mini-batch size and validation data. The software validates the network and gives validation frequency iterations during training.

```
options = training Options('sgdm', ...
    'MiniBatchSize',10, ...
    'MaxEpochs',6, ...
    'InitialLearnRate',1e-4, ...
    'Shuffle','every-epoch', ...
    'ValidationData',augimdsValidation, ...
    'ValidationFrequency',3, ...
    'Verbose',false, ...
    'Plots','training-progress');
```

Train the network consists of the transferred and new layers so train Network uses a GPU if one is available (requires Parallel Computing Toolbox™ and a CUDA® enabled GPU with compute capability 3.0 or higher). Then, it uses a CPU. You can also specify the execution environment by using the 'Execution Environment 'name-value pair argument of training Options.
Net Transfer = train Network (augimds Train, layers, options);

1.6 Classify Validation Images

Here we can classify the validation images using the fine-tuned network.
[YPred, scores] = classify (net Transfer, augimds Validation);

Also we calculate the classification accuracy on the validation set. Accuracy is the fraction of labels that the network predicts correctly.
Y Validation = imds Validation. Labels;
accuracy = mean(Y Pred == Y Validation)
accuracy = 1

RESULT AND DISCUSSION

1.7 Training using NNPR

Here we loaded the mat file for training and classification purpose which includes labelled data. Total 985 images were there out of that 689 practice for instruction, 148 for validation and 148 for testing.
Establishment and test data sets are individually set to 15% of the earliest data. With this background, the input vectors and target vectors will be every which way classify into three sets as follows: 1.70% are used for training.

2.15% are used to validate that the network is generalizing and to stop training before over fitting.
3. The last 15% are used as a completely independent test of
network generalization by-227.

Results

	Samples	CE	%E
Training:	689	1.05446e-0	67.99709e-0
Validation:	148	2.64644e-0	70.27027e-0
Testing:	148	2.65745e-0	71.62162e-0

Figure 2: Training and Validation Result of NNPR

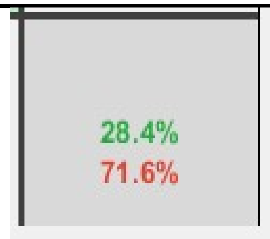

Figure 3: Accuracy of NNPR

Here we extracted total 12 features from each image such as Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness. There are total 11 classes with total 985 images. Figure 3 shows required accuracy of NNPR. In this case we got 71.6% accuracy which is quite low compared to some advanced machine learning algorithms.

1.8 Training using Alex-Net

Figure 4 and 5 is showing training progress of Alex-Net and accuracy of Alex- Net. We have dataset of disease affected leaves. Entire data is divided in 11 classes out of which 10 classes are of disease affected leaves and 1 class is of healthy leaves. Total 985 images were there out of that 689 used for training, 148 for validation and 148 for testing. Validation and test data sets are each set to 15% of the original data. With these settings, the input vectors and target vectors will be randomly divided into three sets as follows:

1.70% is used for training.
2.15% are used to validate that the network is generalizing and to stop training before over fitting.
3. The last 15% are used as a completely independent test of network generalization.

We don’t need to extract the features separately for classification purpose. In this case we got 96.0% accuracy.
Command used for classification is:

[YPred, scores] = classify (net Transfer, X);

Where, X is an input image and YPred gives name of class after classification.

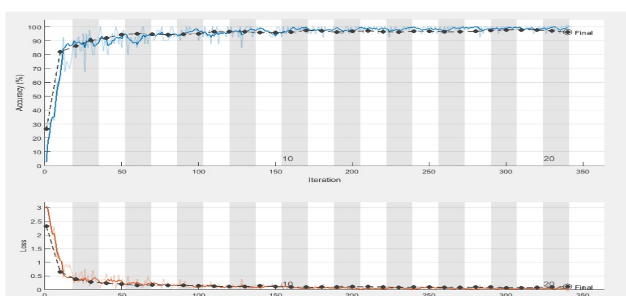

Figure 4: Training Progress of Alex-Net

Figure 5: Accuracy of Alex-Net

1.9 Final output of Recognized Pest's and Disease's

From Figures 6, 7, 8 and 9, we find that this type of image has been shown to be an approved pest for related diseases through image acquisition and pest identification.From these figures it is exactly clear that Alex-Net is used for training and classification of images and shows good accuracy in final output of recognized pests and diseases in Figure 6, 7, 8 and 9.

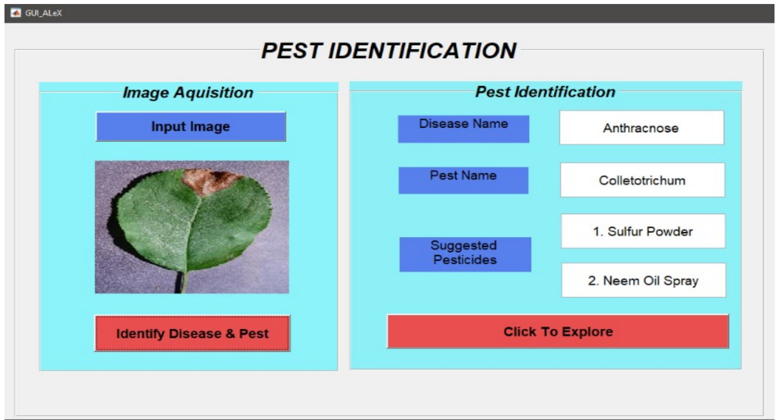

Figure 6: Recognized Pest for Anthracnose disease

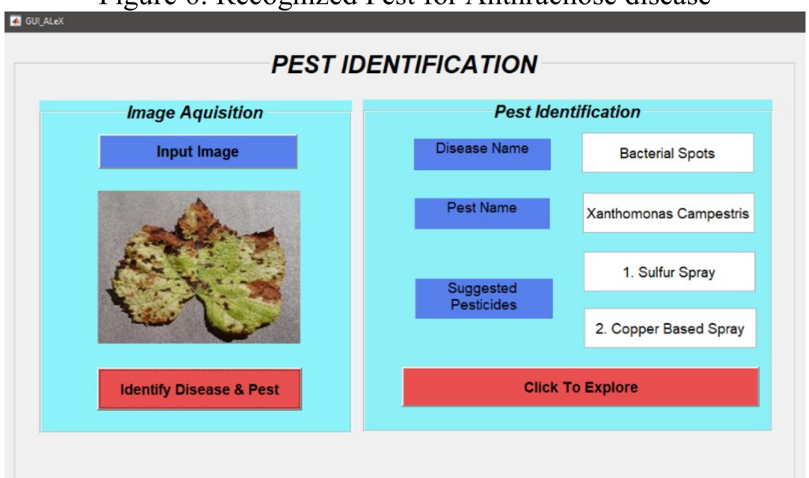

Figure 7: Recognized Pest for Bacterial Spot disease

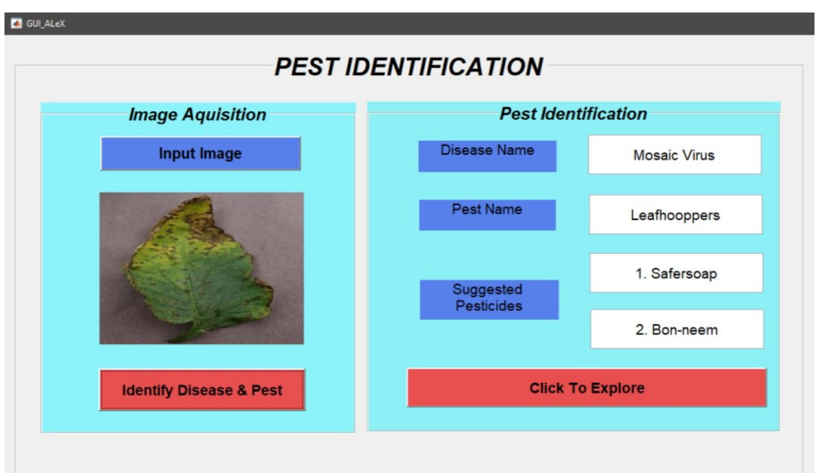

Figure 8: Recognized Pest for Mosaic Virus disease

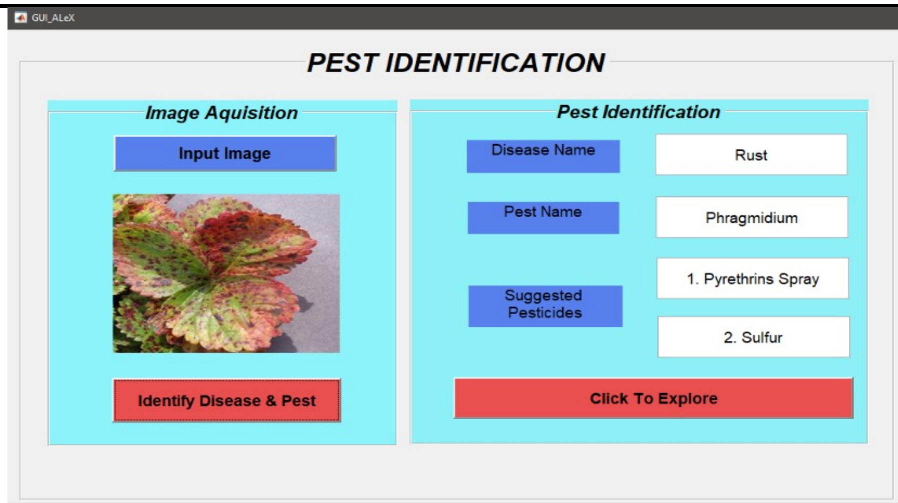

Figure 9: Recognized Pest for Rust disease

CONCLUSION

The world is digital and complex tasks can be simplified with the routine of advanced computers, even though it is somewhat lacking in methodology. The insects and viruses affected by the identification of insects make it easier to prevent the disease. In this project we have developed a system of verification of insects and infections. This system is capable of detecting pests and infectious diseases.This system proposed Image processing technique for human computer interaction. It is using executed effectively with accuracy similar with those of current submission. It has been experimented with leaves images captured by a mobile camera and achieved satisfactory result with accuracy of 96.00%. A NNPR method recycled for identification of pests and diseases using feature extraction but in that case accuracy was 71.6% which is lower. Hence, Alex-Net is recycled for orientation and assortment of images. Alex-Net uses Interactive Transfer Learning network to organize and categorise a new collection of images. Transfer learning is frequently employed in deep learning implementation. So we carry the pretrained network and exercise it as a starting point for learning new tasks. Here we can resolve that calibrate a network with transfer learning is normally considerably quicker. It does grow easy than training a network with every which way initialized weights from mark. This project provides full automated approach for verification and categorization of insect and infection caused by pests. Its main focus on useful for farmers but also for citizens who have gardens at home.

REFERENCES

1) Hafiz Gulfam Ahmad Umar, Qaisar Abbas and Fatima Gulzar “Insect classification using image processing and bayesian network”. Journal of Entomology and Zoology Studies 2017; 5(6): 1079-1082
2) Russakovsky, O., Deng, J., Su, H., et al. "ImageNet Large Scale Visual Recognition Challenge." International Journal of Computer Vision (IJCV). Vol 115, Issue 3, 2015, pp. 211–252
3) Johnny L. Miranda, Bobby D. Gerardo, and Bartolome T. Tanguilig III “Pest Detection and Extraction Using Image Processing Techniques” International Journal of Computer and Communication Engineering, Vol. 3, No. 3, May 2014
4) Jabert G., Murali Krishnan “Pest Control in Agricultural Plantations Using Image Processing.” IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) e-ISSN: 2278-2834,p- ISSN: 2278-8735. Volume 6, Issue 4(May. - Jun. 2013), PP 68-74
5) Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks." Advances in neural information processing systems. 2012.
6) Lowe, D. G.,"Distinctive image features from scale-invariant keypoints," International journal of computer vision, vol. 60, no.2,pp. 91-110,2004.
7) Prasad, S., Kudiri, K. M., & Tripathi, R. C, "Relative sub-image based features for leaf recognition using support vector machine," Proceedings of the ACM international Conference on Communication,

Computing & Security, pp. 343-346,2011.

8) T.S.huang ; W.F. schreiber ; O.J. Tretiak "Image Processing" Proceedings of the IEEE (Volume: 59, Issue: 11, Nov. 1971)
9) Subhra Pramanik1 , Samir Kumar Bandyopadhyay3 , Debnath Bhattacharyya2 , and Tai-hoon Kim2,* "Identification of Plant Using Leaf Image Analysis" Part of the Communications in Computer and Information Science book series (CCIS, volume123)
10) Dr.K.Thangadurai, K.Padmavathi, "Computer Visionimage Enhancement For Plant Leaves Disease Detection", 2014 World Congress on Computing and Communication Technologies.
11) Monica Jhuria, Ashwani Kumar, and Rushikesh Borse, "Image Processing For Smart Farming: Detection Of Disease And Fruit Grading", Proceedings of the 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013).
12) Chunxia Zhang, Xiuqing Wang, Xudong Li, "Design of Monitoring and Control Plant Disease System Based on DSP&FPGA", 2010 Second International Conference on Networks Security, Wireless Communications and Trusted Computing.
13) A. Meunkaewjinda, P. Kumsawat, K. Attakitmongcol and A. Srikaew, "Grape leaf disease detection from color imagery using hybrid intelligent system", Proceedings of ECTI-CON 2008.
14) Santanu Phadikar and Jaya Sil, "Rice Disease Identification using Pattern Recognition", Proceedings of 11th International Conference on Computer and Information Technology (ICCIT 2008) 25-27 December, 2008, Khulna, Bangladesh
15) Z. Wang, Z. Chi, D. Feng and Q. Wang, "Leaf Image Retrieval with Shape Features", R. Laurini (Ed.): VISUAL 2000, LNCS 192