

# Improved Detection of Plant Diseases in Jute using Multi-SVM Classifier based on Machine Learning

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## ABSTRACT

Detecting stem diseases of plants by image analysis are still in an inchoate state in the research field. This work has been conducted on detecting the stem diseases of jute plants which is one of the most important cash crops in some of the Asian countries. An automated system has been implemented to take pictures of the disease affected stems of jute plants and send them to the dedicated server for assaying. On the server side, the affected portion from the image will be segmented using customized thresholding formula based on hue-based segmentation. The consequential feature values will be extracted from the segmented portion for texture analysis using colour co-occurrence methodology. The extracted values will be compared with the sample values stored in the pre-defined database which will lead the disease to be identified and classified using multi-SVM classifier.

*Keywords: Plant disease, SVM, Machine Learning*

## I. INTRODUCTION

Half of the world population is dependent on agriculture which is quite evident by the amount of agricultural land in our earth. Agriculture is one of the main sources of revenue in the world. Apart from being a source of nutrition, the remains obtained after harvesting are also used for increasing the income of the country (For example: Jute, wax, oil etc.). Researches are being conducted to increase the productivity and improve the quality of crop at a reduced expense. Therefore detection of disease for the crops plays a vital role in production and to avoid loss. Traditional disease detection methods adopted by farmers and experts are naked, continuous

and obsolete as it is time consuming, costly and strenuous. Besides some countries do not have proper facilities for agriculture, therefore consulting an expert is beyond their reach. Therefore, to overcome these complications the researchers are automating the process of disease detection with the help of Image Processing Techniques. Machine Learning algorithms are designed and applied by researchers to identify the diseases affecting the plants in an efficient and precise manner. This in turn reduces the labour effort and improves the productivity.

Plant disease detection using image processing techniques has been playing a role of immense importance in agricultural industries for the recent years. Jute is considered as the Golden Fiber of Bangladesh for its huge contribution to our economy in past though the production of jute has been hurdled by various factors from the recent years. One of the factors is the inaccessibility of expert's opinion to the root level cultivators or farmers. This system will help the farmers to get accurate solution in order to cultivate healthy crops. Although visual supervision by experts has been considered as the primary way of detecting crop diseases, the use of technology can alleviate the level of reliability as well as save valuable crop of the diligent cultivators by providing correct information in the fastest way. This research will be beneficial to the farmers who struggle to get expert's guidance and suggestions to keep their crop safe from several fatal diseases. The mobile application interface of this system is very user friendly and people with no prior technological knowledge can use this system and get benefited by it. In this research, the five most common diseases have been detected followed by providing respective control measures. The diseases are named as Anthracnose (*Colletotrichum Corchori*), Black band (*Botryodiplodia Theobromae*), Die back (*Glomerella Cingulate*), Stem rot (*Macrophomina Phaseolina*) and Soft rot (*Sclerotium Rolfsii*). By using various image processing techniques, the system can recognize these diseases from the image of the affected stem and provide users with disease identification and proper control measures within three seconds. Therefore, the system has every scope to serve the emergent field of plant disease detection by providing the classification of stem diseases within a short period of time with higher level of accuracy and a very simple user interface. The rest of this paper is arranged as follows. Section II discusses related work. Section III explains the entire system overview. Section IV demonstrates experimental results and analysis for detecting jute diseases. Section V concludes this paper with a brief summary.

### *Type Of Diseases in Plant Leaf*

Fig. 1 shows the common diseases of the agricultural plants presented in the form of two categories namely,

1. Infectious Diseases
2. Non- infectious Diseases

### A. Fungal Diseases

Fungi are the primary causes for most of the diseases in vegetables. Fungus infects the plant by killing their cells and thereby stressing out them. There are a variety of sources for fungal infections that include infected seed, inappropriate soil, crop rubbish, nearby crops and weeds.

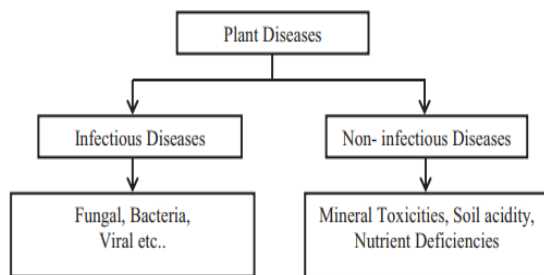


Fig. 1. Types of Agriculture Plant Diseases

Apart from air which is the primary source of spreading the fungus, they can also spread through water wading and even by the infected soil, animals, workers, machinery, tools, seedlings and other plant material. The natural openings such as the stomata in the plants act as their focal points through which they gain entry inside them. Sometimes artificially created wounds resulting from pruning, harvesting, flood, insects, other diseases, and mechanical damage also pave way for fungal entry inside plants.

### B. Bacteria Diseases

There are various parts of a plant like stems, leaves and roots that could get infected from bacteria. Bacteria could even affect a plant internally without showing any external symptoms till a certain stage. Plants infected by bacteria expose symptoms that include cankers, leaf spots, over growths, scabs, wilts, and others to name a few. Most of these infections take place internally which become quite difficult to recognize at a later stage and apply appropriate diagnosis. A plant infected by bacteria can act as source of infection to its nearby plants, thereby spreading the infection at a rapid rate. Hence it becomes necessary to spot and apply the required remedial measures so that the bacterial infection can be curbed at an early stage.

### C. Viral Diseases

Viral infections on plant leaves are the most difficult ones to diagnose. Most of the viruses are of hidden nature which cannot be easily observed till a certain stage. Viral infections are often confused with nutrient deficiencies and herbicide injury. Virus can be easily spread through numerous common carriers like aphids, leafhoppers, whiteflies, cucumber beetles and insects.

## II. LITERATURE REVIEW

Identifying and classifying plant disease by using appropriate image processing and machine learning approaches in the agriculture field is a critical job. Some of the good recently used techniques for diagnosing leaf diseases had been reviewed below. Vijai Singh et al [1] had presented a type of

soft computing practice for detecting the plant leaf diseases. The authors had used genetic algorithm for image segmentation to detect and classify the plant leaf diseases. The proposed technique was tested using various plant leaves and was capable in detecting the diseases at the early stages. In [2] authors had explored the plant diseases detection using pattern recognition technique to compute the crop images. Gabor Wavelet Transform (GWT) method had been integrated with pattern recognition to detect the plant diseases with 89% accuracy. Shitala Prasad et al [3] had described an innovative method called automated mobile vision for diseases detection. The authors had used a hybrid technique called GWT-GLCM to detect the diseases in plants. The authors had used an optimized IP algorithm for segmentation. Using this hybrid approach the plant diseases are identified with 93% accuracy. According to paper [4], the rice plant diseases were identified rapidly using FCM-KM and R-CNN. FCM-KM technique is to clustering the class, based on firefly, chaos theorem and Max-Min. The combined approach had produced an accuracy of 96.71% with respect to identifying the diseases in the rice plant.

Authors in paper [5] had proposed that citrus fruit diseases could be precisely identified using DeltaE method. In their research the researchers had classified the diseases based on image level and diseases level using KNN and cubic SVM. Ahmed et al. [6] had presented a methodology called wavelet and pyramid histogram to detect the plant diseases. The authors had applied haar wavelet transforms and pyramid histogram techniques in the original images for segmentation. The diseases identification was done by applying Random Forest supervised learning algorithm and this approach had identified the diseases with an accuracy of 95%. In [7], authors had presented a disease detection approach based on deep learning technique in image processing. Using deep convolutional neural network learning technique, the authors had trained the system with available dataset images. The CNN based trained system was used to classify the images on crop species and led to the identification of disease on images. The CNN technique had identified the diseases on the plants with 99.35% accuracy. Dhakal et al [8] had presented an image based diseases detection using artificial neural network concept. The authors had identified three types of diseases (late blight, bacteria and curl virus) on the plants. The authors had obtained an accuracy of 98.59% using artificial deep learning technique. Zhang et al [9] had explored the diseases identification on apple leaf based on GA. The segmentation process was done using RGM approach. Using correlation method, feature extraction was carried out and classification was done using SVM. The proposed approach had produced the diseases identification accuracy of 90%. According to the paper [10], the authors had presented a class classifier to target the diseases (Powdery Mildew, Healthy, Downy Mildew and Black Rot) of the plant (vine). The OCSVMs method was used to classify the diseases. Finally, the disease was labelled using the nearest support vector strategy. The proposed approach had produced 95% accuracy.

Chouhan et al [11] had presented automatic detection of plant diseases identification using Bacterial foraging method. The

authors had combined radial function neural network concept with bacterial foraging to speed up the network and get more accuracy for identifying and classifying various diseases of the plants.

### III. PROPOSED SYSTEM

The proposed system block diagram is described as below. The algorithms follow the phases like capturing the RGB image, Preprocessing, segmentation, feature extraction, feature selection, Classification and detection of plant disease.

For our work, we have examined with two different cases for extracting the features for texture analysis from the training images. In case 1, we have calculated the features from the training images without applying the hue-based segmentation method on them. In this case the diseased portion is not segmented from the image and the features are calculated along with the background, unwanted portions and noise of the images. As a result, when the segmented part of the test images is classified

based on those feature values, it provides a dissatisfactory classification outcome. On the other hand, in case 2 at first the diseased portion is segmented from the training images after being preprocessed and then the features are extracted. The latter case succeeds in providing a satisfactory outcome in classifying the diseases. From the observation of both cases, we found that case 1 provides us with 60 percent of accuracies in detecting the diseases whereas case 2 provides an accuracy of around 86 percent which is far better than case 1. Comparing both the accuracy results, we have decided to proceed with the method applied in case 2.

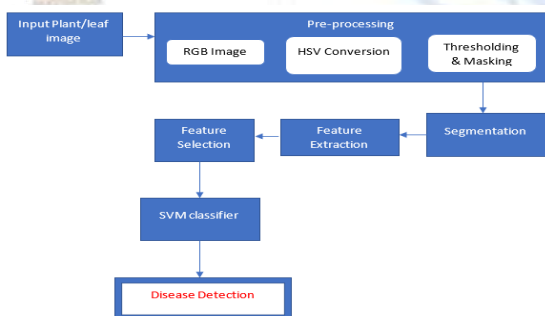


Fig. 2. Block diagram of proposed Plant Disease Detection Algorithm

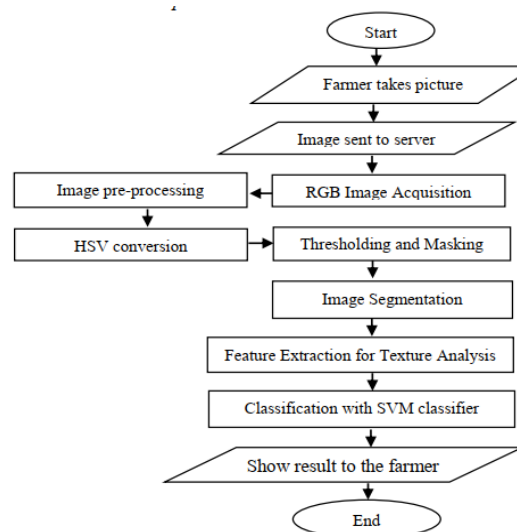


Fig. 3. Flow Chart

The following flowchart describes the way the algorithm is been carried out.

**1) Image Preprocessing:** Before proceeding towards image analysis the image should be processed in order to acquiring better result. Images taken from camera phones contains different factors which alters the result of the analysis. The image preprocessing procedure is performed by following certain steps consists of image resizing, image enhancement and noise removal.

a) **Resize Image:** To perform the classification, the size of the input image must match the size of the images stored in the database. Thus, the input image must be resized to a fixed dimension at the very first stage.

b) **Enhance Image:** In this step the image intensity values or colormap has been enhanced by adjusting the contrast of the image by defining the upper and lower limits of the pixel values that will be used for stretching the image. The limits are specified by considering the bottom 1% and the top 1% of all pixel values of the image [6].



Fig. 4. A Jute stem infected by anthracnose (a) Original Image (b) Enhance Image

c) **Noise Removal:** The uploaded images may contain noise. Noise can alter the features of an image and leads to obtain unexpected and deceptive result. Thus it is very important to remove the noises from the image. In this research, a bilateral

smoothing filter has been used for noise cancellation. The bilateral filter is the technique which smoothens the image by replacing the intensity value of each pixel with the weighted average of the intensity values of neighboring pixels [7].

2) Hue-based segmentation: In this paper, the hue-based segmentation method has been used to segment only the affected portion from the image. As the entire process has been conducted on stem diseases it is not possible to simply mask the green pixels from the image likewise the ones done in case of detecting leaf diseases. Therefore, the hue-based segmentation method has been applied along with a customized thresholding formula.

**a) HSV Conversion:** At first, the RGB spaced image has been converted to HSV color space. In HSV, hue image conveniently represents the original color whereas saturation works well to mask the image and extract the region of interest [8]. Then the individual channels have been extracted to separate the hue, saturation and intensity images

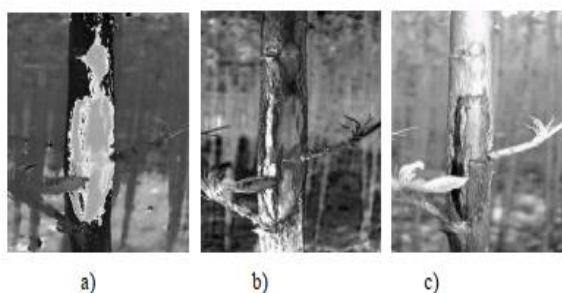


Fig. 5. (a) Hue (b) Saturation & (c) Intensity Image

**b) Thresholding:** Image thresholding is an effective way of dividing an image into a foreground and background. In this research, a threshold formula has been introduced to mask only the disease affected part of the stem from the image. At first, the saturation image has been manipulated with a theory described by R.C Gonzalez where a binary mask is generated by thresholding the saturation image with a threshold value which is equal to ten percent of the maximum value of the image [8]. Any pixel value greater than the threshold value is set to 1 (white) and all others are set to 0 (black) [8]. After that the masked saturation image has been multiplied with the hue image. Now at this point the region of the stem from the image should be separated. However, this approach solely does not accomplish the goal to extract only the disease affected portion of the stem and discard the rest. To achieve the goal, the product image has been masked again with a threshold value of 0.5 as the pixels with value greater than 0.5 prominently identify the disease affected region. Therefore, the comprehensive formula for thresholding appears as followed.

$$\text{MaskedImage} = M > 0.5$$

where  $M = \text{Hue} * (\text{Saturation} > (\text{Max}(\text{Saturation}) * 10\%))$



Fig. 6. Masked Image

**c) Blob Detection:** The masked image still contains some unwanted regions which are definitely needed to be get rid of. For that purpose, the morphological analysis has been performed which includes erosion and dilation and for the largest connected component has been extracted using eightway local neighborhood measurement.

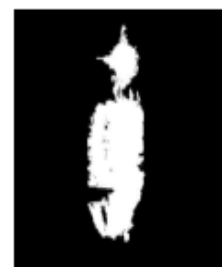


Fig. 7. Segmented Blob

**d) RGB Conversion:** For further analysis, the segmented portion needs to get back to its original color by being converted to RGB color space.

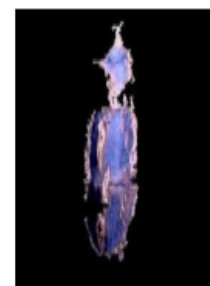


Fig. 8. Segmented RGB Image

**3) Feature Extraction:** The significant features from the image need to be extracted in order to perform the texture analysis. For that purpose, the color co-occurrence methodology has been used which is developed through the GLCM (Grey-level Co-occurrence Matrices). GLCM is used for sampling an image statistically in a way certain grey-levels occur in relation to other grey-levels [1]. It also provides feature information about the position of the pixels of the image in relation to their neighboring pixels. For this research, thirteen [9] feature values have been reckoned for each of the training images and the input image to perform texture analysis. The features are mentioned below:

1. Contrast
2. Correlation
3. Energy
4. Homogeneity
5. Mean
6. Standard Deviation
7. Entropy

8. RMS (root mean square) contrast
9. Variance
10. Smoothness
11. Kurtosis
12. Skewness
13. IDM (Image difference-measure)

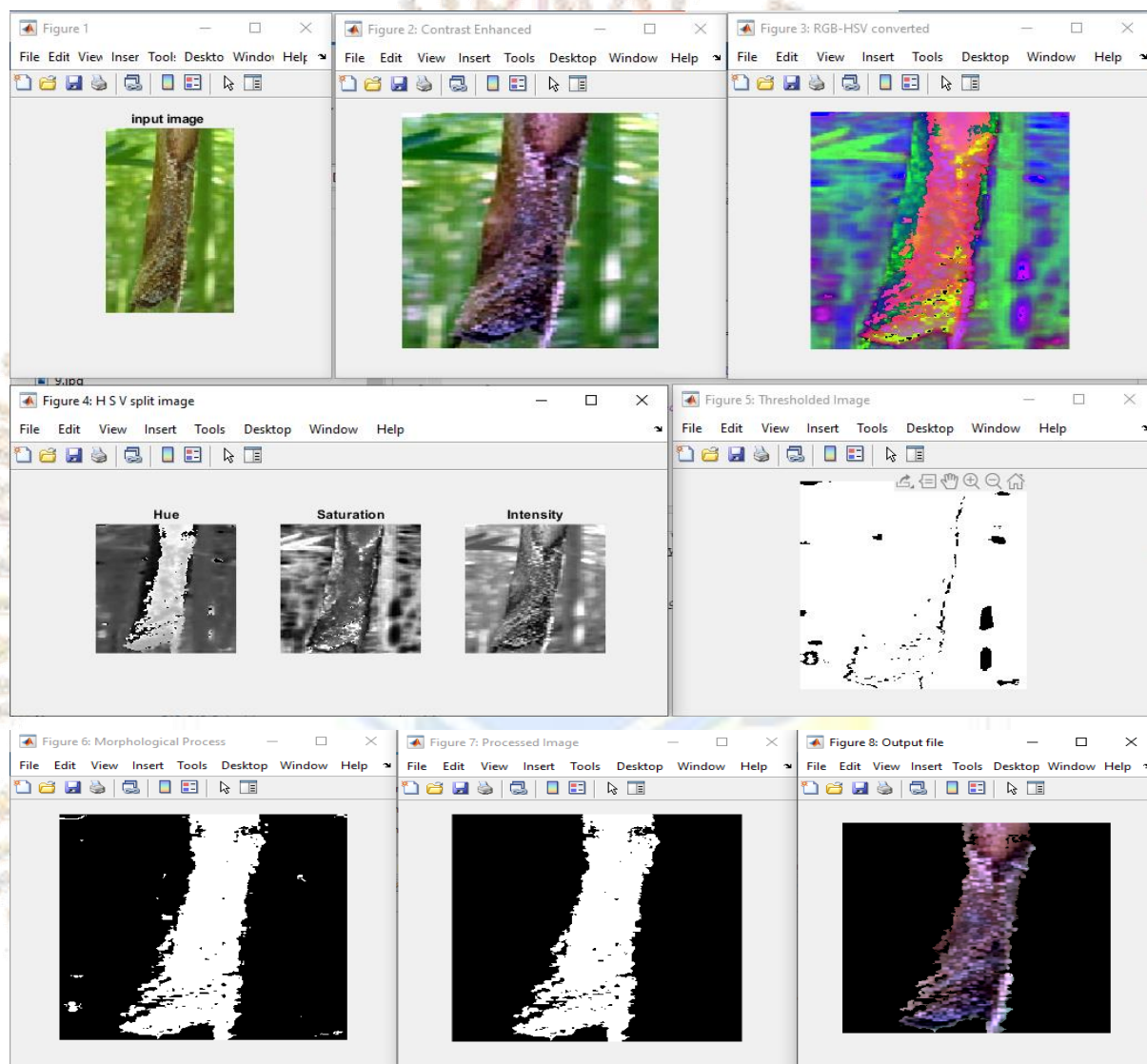
The above features are calculated from the GLCM using their corresponding formulas.

**4) Classification:** After the extraction, the necessary features are compared with the pre-calculated dataset stored in a .mat file. The SVM (Support Vector Machine) classifier is used for classifying the disease. Support vector machines (SVMs) are

a set of related supervised learning methods used for classification and regression [1]. Supervised learning refers to the process where a given set of labeled observations are stored in the database and an unknown sample has been analyzed and compared to assign it with a label in accordance.

As there are five diseases to be dealt with there must have to be five classes. Thus, a multi-class SVM classifier has been used. In this case, the classification of new instances or input images has been performed where the classifier with the highest output function assigns the class and detects the particular disease.

#### IV. EXPERIMENTAL RESULTS AND OBSERVATION



**Fig. 9. Simulated experimental output detection of plant disease run1**

Figure 1 is the input query image, that is been enhanced for contrast shown in figure 2. Figure 3 portrays the HSV conversion process. Figure 4 splits the Hue, Saturation and Intensity levels of the converted plant stem from RGB-HSV. After this splitting process, the image is thresholded and then subsequently morphological process is carried out to obtain/ detect the plant disease.

**Table. 4.1. Simulated Metrics**

| S.No. | Parameter          | Resulted Value |
|-------|--------------------|----------------|
| 1     | Contrast           | 0.0757         |
| 2     | Correlation        | 0.9739         |
| 3     | Energy             | 0.6091         |
| 4     | Homogeneity        | 0.9782         |
| 5     | Mean               | 0.0914         |
| 6     | Standard_Deviation | 0.1876         |
| 7     | Entropy            | 2.5899         |
| 8     | RMS                | 0.1334         |
| 9     | Variance           | 0.0172         |
| 10    | Smoothness         | 1.0000         |
| 11    | Kurtosis           | 6.7966         |
| 12    | Skewness           | 2.1042         |
| 13    | IDM                | 110.4732       |

The average outcome gained from the evaluation test provides an overall impression about the efficacy of the system where three out of five farmers preferred using this application to detect diseases along with manual inspection. Most importantly, the accuracy level obtained from the hands-on use (80%) almost matches the accuracy level measured from the test images (86%)

### CONCLUSION

In this paper, we have built an automated system to detect stem-oriented diseases for jute plants using image segmentation and feature extraction with along with potential machine learning. Application of machine learning specially image analysis and texture analysis in practical cases are now more common and encouraged than ever before. Although visual analysis done by human is simpler technique but it cannot be accessible always. On the other hand, providing the farmers with an automated and reliable system for crop disease detection to be used from their mobile phone can bring an insurgency for agricultural industry. The research work does not contain disease detection technique for the leaves. In future, it will be a great challenge for us to build a universal app that can be used to detect any sort of disease of the jute plants considering both stems and leaves.

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