A Study Of Crop Leaf Disease Detection Using Image Processing Techniques.

Poonam R. Gohad, Dr. Sajidullah Khan

Abstract: The image processing techniques have become very significant due to the wide spread of computer technology. Crop disease detection has been a popular topic of research recently. While designing of systems, more often for the interpreting or manipulating picture information, various operations needs to be performed which are segmentation, feature extraction and classification. The input images can be Digital camera images or Thermal or Hyperspectral image. This image is partitioned on the basis of various parameters. Segmentation finds the boundaries, objects as well as other relevant data from an image. From the segmented image features can be extracted which are color, texture, intensity. These features then help to classify the segmented object into categories which involves use of support vector machines, fuzzy c-means, back propagation etc. This paper consists of the study of various methods of crop leaf disease detection.

Index Terms: Thermal, Hyperspectral, Segmentation, Feature Extraction, Classification.

1. INTRODUCTION

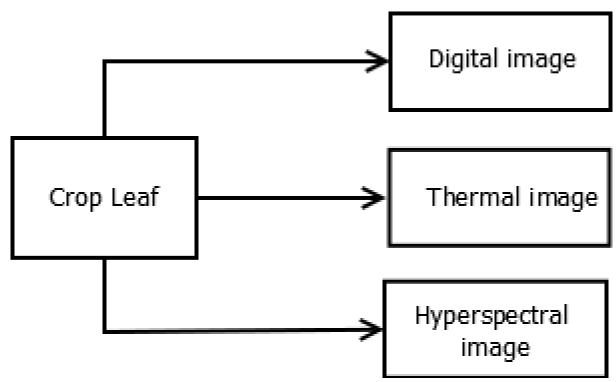
IN most image studies where operations need to be carried out, the objects need to be divided from the image individually, so the further the details of those objects will be transformed in a proper structure for processing by computer. Image segmentation and classification are important steps for many image processing and computer vision algorithms. The interest is motivated by applications over a wide spectrum of topics. For example, analyzing different regions of an aerial photo is useful for understanding plant/land distributions [1]. In case of agriculture, image processing helps for forecasting occurrences of a disease by identifying the early symptoms. This requires the designing of crop disease detection systems. They could be using remotely sensed images, UAV images or manually taken images. These images from the fields are of different types, Firstly, visible images where it is possible to look at the image and give conclusion, Secondly Thermal images, The Military developed thermal imaging technology has recently become the topic the research interest. For instance, hand held and airborne thermal imaging systems are now accessible with more sensitivities than an order-of-magnitude better than the units used in early studies. Thermal imaging can simply be described as the process in which infrared (IR) radiation (heat) are converted into images (visible) showing spatial distribution of the temperatures variation in a thermal camera scene. The detection as well as display of the thermal radiation electronically with electromagnetic waves (long) is called as thermal imaging. The metabolic heat is generated due to biological activity which leads to increase in product temperature. In case of plant leaves, they consist mainly of water. The water content of leaves ranges from 70%-98%, which depends on the plant species.

- *Poonam Gohad is currently pursuing Ph.D. in Computer Science and Engineering in Sandip University, India. E-mail: prgohad@mail.com*
- *Dr. Sajidullah Khan is Associate Professor in Computer Science and Engineering Department in Sandip University, India. E-mail: sajidullah.khan@sandipuniversity.edu.in*

2 DIGITAL IMAGE CLASSIFICATION

2.1 Segmentation

Mostly used traditional clustering and thresholding segmentation techniques are Fuzzy C-means (FCM) and



Otsu, respectively. Segmented results were not good in case of both methods, because of the complexity of background and the non-uniform illumination images captured in the natural environment. Hence, an improved method based on thresholding segmentation which is integrated with an inverse technique that was able to partition natural images correctly. Implementation was carried out on fruit images using three segmentation techniques. In order to properly separate the area of interest and its background using only the Otsu and FCM method was not sufficient. Even though it is suitable to implement thresholding-based segmentation for segmenting image from its background, a complementary technique is required to segment images captured under natural environment. Objects that have a bright surface area like yellow and green mostly appear clearer under natural light illumination. However, object with dark surface color blend with its shadow in the background. Therefore, techniques like modified thresholding -based and inverse techniques must be applied [2].In Orchid Leaf Disease Detection with Border Segmentation Techniques [3], filtering technique as well as morphological processing technique was used for the images. The technique can distinguish for two types of leaf diseases in orchid plant. For classification of the different orchid leaf diseases, other segmentation technique have to be used.For classification of orchid leaf disease of other types, new or other segmentation technique have to be used. This is because they need many combination of the processing technique to find robust for border segmentation technique. From the results obtained, the accuracy of border segmentation technique used is 86.36%. Therefore it has moderate accuracy to classify the types of orchid leaf disease.

2.2 Feature Extraction and Classification

A grey level method includes grey level co-occurrence matrix and Gabor filters with color spaces RGB and HSV used. CLCM methods were applied to separate color channels of the color images. The CLCM acquired high precision for the retrieval of color texture, reaching 90% and described the research on extraction and classification of color texture information [4].In other approach, RGB images are converted into HSI color space. At the first step extraction of the connected components from original diseased image was done. Next with graph theory the unwanted regions were removed from the connected components which produced a binary image. For feature extraction performed considering specific features and segmentation done on diseased area basis. Hence the HSI had given clear discrimination of diseased spot. Initially the RGB color leaves were converted into HSI. Next, identification of the mostly green pixels and threshold value is computed based on Otsu method. The infected region is segmented into number of patches. Here the color co-occurrence method is followed for extracting the features. The development of color co-occurrence was done with the help of spatial gray level dependency matrices. Two texture features were computed following shade and cluster prominence. Hence co-occurrence features obtained and shown significant differences can easily categorized. The proposed approach in [5], extracts 15 features from leaf using Canny Edge Detector and is used to classify 22 different types of plants using SVM classifier. The 22 classes' leaves were used and a classifier was implemented and tested using 220 leaves of different classes from the dataset. The overall accuracy of the system is 85% to 87% when the worst case is considered. In [6] the leaf images of cotton are classified by using the Back propagation neural network. Here the system is trained by extraction of seven invariant moments of three types of images of diseased leaves. The average classification accuracy shows 85.52% result. The algorithm for snake segmentation appears to be an effective method to isolate the diseased spot but the process is slow.

3 THERMAL IMAGE CLASSIFICATION

3.1 Detection of Diseased Tomato Plants

Tomato plants infected with O. neolycopersici can be detected by combining the information from thermal images as well as images of stereo visible light with machine learning methods which provide high accuracy to improve remote images use. Similar work can be implemented to plants with other diseases as well. The algorithm proposed consists of image registration, depth estimation, feature extraction and classification. Classification was performed using support vector machine [7].Considering a local setting, Firstly potential disease area is detected in a plant which then classifies the plant either healthy or diseased on the basis of information which is collected from the areas prone to disease. Considering the global approach, aim is to detecting disease from the entire plant. The average percentage of agreement among the outcomes of the classification generated through local as well as global set of features was approximately 90% on 13th day. However, the results of disease detection were less stable as well as more sensitive to environment conditions in local setting. Secondly, set of global features with days, depicts slower increase in accuracy of detection as compared with set of local features.

3.2 Bacterial Blight in Rice Plant evaluation

Data Preprocessing is required as the images with different temperature and humidity are obtained in diverse environmental conditions. Flir Tools software was used to ensure uniformity to the environment. Two types of feature need to be extracted the rice leaves thermal images mainly, texture and temperature. Temperature feature extracted using the software tools by flir and using GLCM (gray level co-occurrence matrix) texture features were extracted. The probability density functions and summary statistics help to analyze variation in these features. The analyzed results indicate that the temperature variation statistics is noticeable for three stages of disease only which are normal stage, primary stage and highly infected [8]. Therefore, in lead blight forecast, it illustrates the thermal features' statistical significance with a p-value less than 0.05.

4 HYPERSPECTRAL IMAGE CLASSIFICATION

For identifying the Peronospora infection in the vineyards, the proximity based approach is used [9]. It compares the results of two hyperspectral cameras in identifying different levels of infection as detectable from the assessment of the leaf surface characterized by acquisition of different spectral ranges. For classifying healthy, infected and necrotic leaves, a Partial Least Squares Discriminant Analysis (PLS-DA) model was developed. On the basis of following two rules, classifications were carried out: Strict class prediction and most probable prediction, respectively. In Class Prediction Strict, A sample is said to belong to a class if its probability is higher than the threshold probability value which is specified for one and only one class. If there is no class having probability greater than the threshold, or if there is more than one class having a probability exceeding it, then in this case the sample will be assigned to class zero which shows no class has been assigned. Sensitivity as well as Specificity is the statistical measures of binary classification test performance. The actual positive values being identified are measured by Sensitivity while the the negative values which are correctly identified are measured by Specificity. The results show that VIS-NIR interval between 400 and 1000 nm, is the most appropriate spectral range in order to classify healthy, Peronospora infected and necrotic leaves. Built in this interval, the PLS-DA classification model can be a powerful method for diagnosing the early stages of the vineyard disease.The hyperspectral disease detection for sugar beet leaves [10], was aimed at discriminating diseased leaves from non-diseased, the considered categories were Cercospora leaf spot, leaf rust and powdery mildew, for identifying diseases even before its symptoms became visible. Data of hyperspectral images of leaves inoculated with the pathogens Uromyces beta, Erysiphe betae and Cercospora beticola, which cause the sugar beet rust, powdery mildew and Cercospora leaf spot. To evaluate the suitability of Vegetation Indices to identify and discriminate between foliar diseases, Vegetation Indices related to different physiological parameters have been calculated mainly focused on supervised learning techniques, i.e. Trees, ANNs and SVMs decision. Supervised learning demands labeled samples of training to learn a model that allows the classifier to predict the class of unseen pattern SVMs have proved to be effective tools for classifying automatically. When compared with various classifiers it is seen that SVMs optimally use the inherent vegetation indices information.

5 CONCLUSION

The purpose of this paper was to overview leaf disease detection studies for thermal, digital and hyperspectral images using various classification techniques. The segmentation methods are applied in order to identify the required area. The methods help to separate required region from its background. Based on threshold value, gray scale image, Color image the segmentation methods vary. For feature extraction as well various methods like Grey level co-occurrence matrix, Histogram intensity etc. is used. For classification of leave disease back propagation, artificial neural networks and support vector machine are used, where support vector machine provides most satisfactory results for each type of image.

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