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Plant Disease Detection: A Survey

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Abstract
Agriculture is an important part in the human lives and economy of the countries. Agriculture based countries like India are greatly dependent on their agricultural outcome for feeding the large population. Crop yields plays a major factor in the economy of every country. Agricultural production and economic development are closely connected. Moreover, agriculture provides the vital food to feed all living creatures on earth. Plant diseases are a significant threat to farmers, food production and economic well-being of the country. Significant research in this domain is required to protect the vital resource of food. This paper studies/reviews/surveys the different areas of this computer vision problem, the challenges that exists for developing a robust plant-disease detection system, which can be utilized to plant diseases.

Keywords: Plant Disease Detection, Machine Learning, Image Features Classification

1. Introduction
Human beings need food to survive. Agriculture is the source of food for both humans and cattle. Agriculture effects everybody's life directly or indirectly. Cultivation of crops by farmers are the source of food that is eaten for meeting dietary needs. The crop productions meets the dietary needs of both rural and urban metro cities (since there is no food production in the urban settings yet maximum population resides in the metropolitan areas). Even the animal protein consumed is affected by the crop production as the cattle feed also comes from the cultivated products/by-products. The advent of civilization was directly linked to the agricultural outcome and most ancient civilization were agricultural society who stopped nomadic life to start farming and produce food from the land and water resources to feed the population. This is/was considered as the only definite source of food for both human and animal consumption.

Today we are experiencing a population explosion with increased demand for food. There is a steady migration towards urban centers and less people wants to engage with agronomy. Food production from through agriculture is in increased demand and there is a definite supply gap in the required production output. However, increased knowledge gained through modern research in agricultural sciences are contributing to maintain the balance in requirement and supply to meet the increasing food demand. Technology plays a vital role in modernizing farming techniques to yield larger crop production per unit agricultural land. Genetically modified disease resistant plants and use of pesticides, fertilizers are contributing towards increased crop yield.

The crop production faces certain challenges. Crop production in generally affected by natural calamities that regularly occurs in the form of drought, earthquakes, floods that results in the loss of crop yields. However, there is little control over such natural disaster apart from effective management of resources to reduce loss. There is a significant loss to crop quality and yield resulting from crop/plant diseases. The disease-producing agent generally modifies the crop development process resulting in poor quality and quantity of the crop yield. Protecting crop from disease using pesticides and a through lookout for diseases so that the disease infection can be minimized and prevent overall effect on the crop's functional capacity. Very often it is observed that the disease cause reduced growth, leaf falls and reduced (low quality) fruit yields The disease often spread across the crop and to other surrounding fields and to larger geographical area causing huge economic crisis. More often, such diseases are caused by pathogens that are fungi or some bacteria. There are certain viruses that are transferred with seeds and carry the disease from one place to another.

Plant pathologists and experts using eyeballing method were performing the process of identifying the crop disease. They observed the affected plants with their naked eyes and based on their heuristic knowledge and experience. This is however, a laborious, tedious, time consuming and costly task [1, 2]. Contemporary techniques are also available, like image processing, pattern identification and deep learning-based classification techniques that can automate and time saving than the methods that was being used earlier [3, 4, 5, 6, 7]. This will help in early detection and timely curing them [8]. Use of modern imaging techniques like photo acoustic imaging that use light absorption of tissues and creating heat signature resulting in the generation of photo acoustic signals. Use of other imaging modalities like magnetic resonance imaging, photo spectroscopies and fluorescence spectroscopy for identification of various physiological states of different plants are common. These techniques help in early identification from impairment caused due to nutrients deficiencies [9]. Modern hyper-spectral imaging technique for the detection of disease is further extended when used in tandem with conventional microscopy for higher resolution clear images. This helps in microscopic studies at the genotypic level of varied plant parts [10].

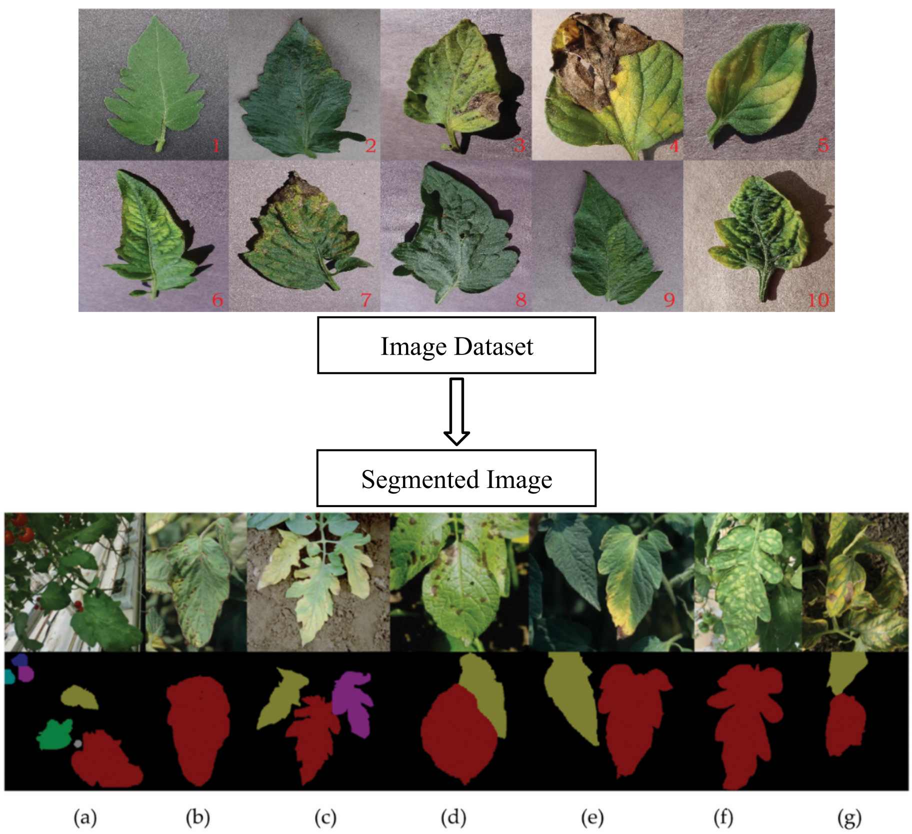
In India, agriculture plays an important role in the economic development of the country. Being an agriculture-based country with about 70% of Indian economy relies on agriculture, damage to the crops results in huge loss in the productivity and ultimately hurt the economy badly. The leaves are most sensitive part of plants and the disease symptoms can be viewed at its earliest manifestation [11]. The plants need to be closely monitored for diseases at the onset of the life-cycle till the crops are ready to be harvested. The manual methods, by using the bare eye, were used traditionally to monitor the plants and to detect any changes caused due to some diseases. While such manual observation technique was horribly time-consuming as the technique required plant-experts/farmers manually monitor the crop fields [12]. However, in the recent years, technological advancement has provided a number of modern techniques that have been adopted to develop automatic and semi-automatic plant disease detection systems. Implementation of such modern systems have made the detection process fast; inexpensive and better accuracy of detection can be achieved over traditional method of manual observation by farmers [13]. The scope for further research in this field of study and the application of more intelligent technological systems for plant disease detection (that do not require human intervention) is the need of the hour. The purpose of this paper is to review/survey (without critical assessment) various techniques/imaging modalities of plant disease detection and to briefly discuss about the methods of disease detection.

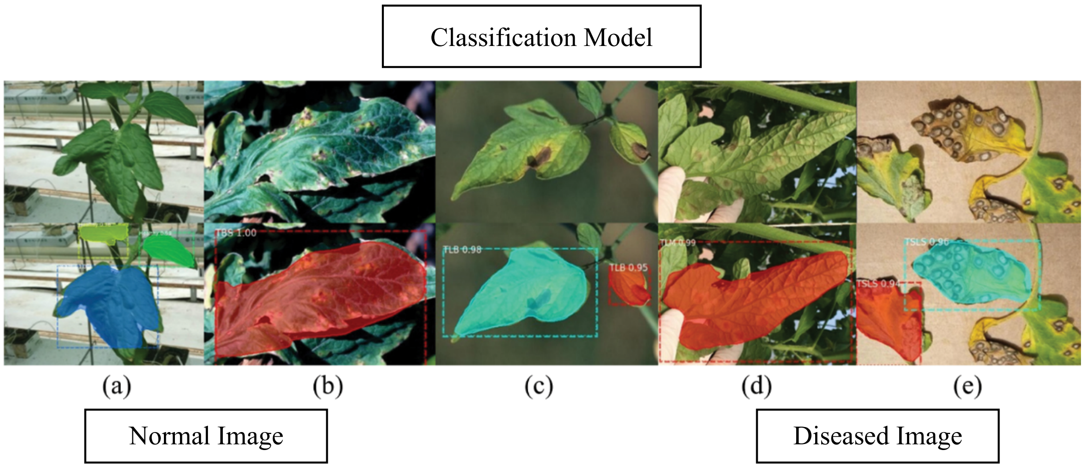
This paper is organized into the following sections. First section introduces the importance of plant disease detection. The following sections discusses standard workflow used in the Machine Learning based disease classification techniques. This is followed by a review/survey of previous work performed in this domain and reviews the modern techniques used for plant disease detection. The last section concludes the survey work done.

2. The Standard Workflow of a Classification Model

The process of disease detection in plants involves four phases. The first phase involves the acquisition of images. In order for the detection system to work, a well-defined dataset of images are required for the purpose of classification. The images can be obtained from different sources through different imaging modalities. In general, the images can be captured using a high resolution standard digital camera. Specification and parameters to be set so that similar dataset share the same parameters for image capture. A mobile phone or a digital webcam can be also a source for obtaining images. Plant images with annotation showing the disease conditions are also available in the web repositories. Images are available with ground truth so that supervised learning models can be applied on such images. Images are also obtained using different imaging modalities like microscopic images and images obtained using magnetic resonance imaging. A robust image database is responsible for the efficiency of any classifier that is implemented by the detection system [14].

Figure 1: Tomato Leave Disease Detection using Deep Learning Neural Network [16]





The images are pre-processed before it can be used for any meaningful purposes. Images may have noise that was possibly induced during the image capture process. Images need to be corrected for illumination and color correction (in case of color image modalities). The images are standardized in terms of size, resolution and other imaging parameters so that similar algorithms can be deployed on all the images. The vital process that is performed after pre-processing the images is Image Segmentation. The idea is to obtain the region of interest from the image thus simplifying and reducing the image so that it becomes easier and more meaningful to analyze [15]. Research works involving both rule-based system and machine learning models use several image segmentations approaches. The rule-based systems are usually thresholding methods like Otsu's algorithm for thresholding that is very popular in image segmentation. Unsupervised k-means clustering methods also can be used to segment objects or pixels based on a set of features into K number of regions. The grouping can be performed iteratively by minimizing the sum of squares of distances between the objects and their corresponding clusters. A well-segmented image is important so that the region of interest contains only regions that are useful for the further investigation while unnecessary regions are eliminated from the image. Feature extraction is the most important step for effective classification outcome. Features are present in the region of interest needs to be extracted for their use in the classification technique. These features are useful to determine the actual meaning of a sample image. Features can be in the form of morphological features like shape, size, eccentricity, color-based features, intensity of features, texture-based features like Gray Level Co-occurrence Matrices (GLCM) features. GLCM features carry statistical information regarding pixels and their relationship in the image. Texture features are important features in the disease detection as they carry a lot of information regarding diseased region. The features are collected and standardized so that they can be put on the same scale for classification.

The classification model determines the identification of an image that is diseased or is a normal plant. Image data in terms of feature set is the input to the classification system. The output of the system is the decision whether the classifier classifies the image as diseased or normal. There are supervised classification models that uses annotated/labelled feature set to train the model so that the machine learns from the labelled data. The test cases are predicted based on the rules generated by the systems through learning from the training set. Some of the most popular classifiers used by most research work are K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Naïve Bayes and Decision tree classification models. There are other unsupervised methods like Clustering methods K-Means

Clustering for classification. Neural Networks are increasingly been used for classification. Artificial Neural Network (ANN), Back Propagation Neural Network (BPNN) and Deep Learning models are also widely being used for plant disease detection and identification. All classification models have their advantages and disadvantages. However, SVM is simple to use and robust technique [17]. Figure 1 shows a research work of disease detection presented by Wu et al. [16] on the tomato leaves.

3. Literature survey

Using Normal Imaging

D.A. Bashish et al. [18] used k-means segmentation for leaf image into four clusters using the squared Euclidean distances and used color co-occurrence features along with textural features as an input to the Back Propagation of Neural Network (BPNN). The authors effectively segmented and classified diseased leaves from the normal leaves by this model.

M. Bhange et al. [19] devised a web-based tool for identifying fruit diseases using morphology and color coherence vector features. The tool could detect whether a fruit is diseased from the images uploaded over internet using k-means clustering for segmentation and SVM classifier to segregate infected and non-infected pomegranate fruits.

J.D. Pujari et al. [20] studied fungal infections on a number of crop types namely, fruit crops, vegetable crops, cereal crops and commercial crops. The authors used different methods for each of the crops and used leaf features for disease detection. The authors used k-means clustering for segmentation and Artificial Neural Networks (ANN) and k-nearest neighbor algorithm for classification results. In the case of vegetables, the authors have used Chan-vase method to achieve segmentation. The authors obtained the local binary patterns as texture feature and implemented SVM and k-nearest neighbor algorithm for classification of vegetables. Similarly, in the case of commercial cash crops grab-cut algorithm is implemented to achieve segmentation while wavelet features were used for PNN using Mahalnobis distance as the distance metric for classification. Finally, the authors have used Canny Edge Detection and k-means clustering for segmentation of the leaf images. To classify the images using SVM and k-nearest neighbor classifiers, the authors used morphological, color and texture-based features.

V. Singh et al. [21] implemented genetic algorithm for image segmentation. The authors used a small set of images for training and testing the k-mean clustering and the SVM classifier. The authors used four different leaf images namely, banana, beans, lemon and rose while the k-mean clustering used the Minimum Distance Criterion. Color based textural features like those that of color co-occurrence matrices were used as features for the detection system. The use of Minimum Distance Criterion along with genetic algorithm enhanced the accuracy of the detection process.

E. Kiani et al. [22], worked upon disease strawberry leaves on the fields under outdoor conditions. The authors implemented a fuzzy decision maker with a good overall segmentation and classification accuracy.

Ali et al. [23] utilized color difference algorithm to segregate disease and non-disease regions of the plants and used color based (RGB, HSV and LBP features) and texture-based features to classify using fine K-Nearest Neighbor (KNN) and Cubic SVM, Boosted Tree and Bagged Tree classifiers.

G. Saradhambal et al. [24] proposed an automated plant-disease detection system implementing k-means clustering algorithm and with Otsu's thresholding for leaf image segmentation. Different morphological and shape features were extracted including area, color axis, length, eccentricity, solidity and perimeter. Similarly, contrast, correlation, energy, homogeneity and mean were used as texture features. The authors implemented ANN to classify the disease plants.

4. Other Imaging Modalities

Anne–Katrin Mahlein et al. [25] used non-invasive, thermography sensors for detection of plant diseases. These are hyper-spectral sensors for recording chlorophyll fluorescence. Fang and Ramasamy [26] also used fluorescence imaging for disease identification and classifications in plants.

Lowe et al. [27] used hyperspectral imaging method to detect the early beginning of disease. The authors developed important indices to detect specific criteria for vegetation. Mahlein et al. [28] discussed the development of different disease index for crop plants such as sugar beet and the leaf diseases as leaf spot, sugar beet and others. The hyper-spectral signatures were used to identify both healthy and diseased leaves.

Yang et al. [29] used infra-red thermal imaging technique to identify disease in tea leaves. Xu et al. [30] used comparison of different temperature distribution with virus strain-TMV on three species of tomato plant leaves.

Different imaging techniques yielded images which were ultimately used as a set of image data to the computer vision, classification was performed to segregate normal and diseased plant parts.

5. Conclusion

This paper outlines the importance of plant disease detection. The paper reviews/surveys different research work and summarizes various techniques of plant disease detection using image processing, machine learning and neural networks. The use of different classifiers and feature set that was used by different authors over the past few years was discussed. The advancement in imaging have opened up new imaging modalities and has given the research workers in this domain many opportunities for better detection solutions. Computer vision problems have their own challenges; hence, automation of disease detection system increases the challenge even further. The scope of work is not limited to the development of automated disease detection systems for wide variety of crops, but also to, implement modern technologies for better and faster predictions. This can prevent loss of crop yields due to plant disease.

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