

A Review on Fruit and Leaf Disease Detection Using Various Image Processing Approaches

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Abstract- This article reviews several image processing methods for detecting leaf disease. Digital image processing can quickly identify and categorize plant leaf diseases. The study uses artificial neural networks (ANNs) and clustering to classify diseases (used by several authors). Currently, we're investigating new ways to identify leaf disease and image processing techniques. This article also discusses how fruit disease causes economic and agricultural losses. Detecting sick fruit was formerly done manually, but advances in technology have enabled picture processing. There are two stages: training and testing. To identify whether the fruit is sick, and if so, which illness, all data related to infected and non-infected fruit is stored throughout the training phase. This article describes the current techniques for identifying tainted fruit. These techniques help growers identify fruit diseases early on.

Key Words: SVM, segmentation, leaf diseases, fuzzy logic, feature extraction, morphological processing CCV, K-means Clustering, LBP, SVM, and Back Propagation Neural Networks.

1. INTRODUCTION

India is an agricultural nation, and agriculture employs the majority of the people. Farmers have a

broad variety of Fruit and Vegetable crops to choose from. Technological assistance may help to enhance farming. Pathogens induce disease in plants under any environmental situation. In most instances, illnesses are visible on the plant's leaves, fruits, and stems; therefore, disease identification is critical to crop cultivation success. Pathogens, microorganisms, fungus, bacteria, viruses, and other microorganisms cause the majority of plant illnesses. Plant diseases are sometimes caused by an unfavorable environment, which includes soil and water.

There are many techniques for early detection of plant diseases. Traditionally, plant disease identification is done by hand, which is inefficient for large harvests. Using digital image processing to diagnose plant diseases saves time and money. Insecticides and time are saved. Various papers propose digital image processing for reliable plant disease diagnosis. Several scholars have developed image processing techniques. This article describes many types of Image processing is used to detect and categorize leaf and fruit diseases. Experts used to detect and identify illnesses. Professionals advise farmers on how to control the disease. To save time and money in developing countries, automated disease screening techniques were developed. Agriculture uses technology to boost production. Fruit yield and quality Using this technique may help

farmers avoid financial losses. Automatic fruit disease detection is critical since it detects symptoms early on, resulting in less economic loss per fruit. By monitoring current fruit conditions, producers may take preventive measures for next year. Some diseases may damage the tree's shoots and branches. Agrobacterium, rhinocladium, anthracnose powdery mildew, and red rust are all prevalent mango diseases. Diseases caused by pectobacterium and agrobacterium. Rhinocladium produces mango nausea. Anthracnose is caused by humidity, temperature fluctuations, and heavy rain. Powdery mildew blooms when rain or mist coupled with a chilly night. Alga causes red rust. Because mangoes are irregular in shape, eye inspection is inadequate.

2. LITERATURE REVIEW

Leaf Blast (*Magnaporthe Grisea*) and Brown Spot (*Magnaporthe Grisea*) are the subject of the article [1]. (*Cochiobolus Miyabeanus*). To extract traits from diseased leaf regions, the author first takes a photograph. It uses a SOM (Self Organising Map) neural network to zoom in on pictures of sick rice. Create a SOM input vector in two ways. It employs no padding and interpolates missing points. Fifty-fifths zooming uses interpolation to normalize spot size. It doesn't help to alter the frequency of the zooming algorithm. The zooming algorithm correctly classifies test images. With image processing, they can detect leaf and stem illness [2]. The author used five plants from the Jordanian al-Ghor leaf collection. Using image processing, you can see early burns and mold, as well as late burns and mold, as well as very little white spots. This technique captures images and then uses K-Means clustering to segment them. Then CCM is utilized to obtain textural characteristics from diseased leaf and stem. Then comes the back.

Plant diseases are classified via neural network propagation. Image processing shows that plant diseases may be properly detected and classified (about 93 percent). [3] utilized LABVIEW and MATLAB to identify chili plant disease. This method detects sick leaves. Stage 1 IMAQ LABVIEW recorded the image. MATLAB and Vision perform more image processing. For example, edge detection and Fourier filtering are both examples of picture preprocessing. Color clustering is used in feature

extraction to tell chili leaves apart from non-chili leaves. Then the health of each chili plant is determined using image recognition and categorization. Less hazardous chemicals in the chili manufacturing means cheaper costs and better quality chili. 4. Image processing for detecting *Malus Domestica* leaf disease. Histograms calculate rayscale picture intensity. In image segmentation, Co-occurrence matrix technique examines texture, whereas Kmeans clustering analyzes color. Texture analysis examines a picture's texture. The color gap between objects and the centroid of their class or matched cluster is reduced via color analysis. A pixel's value is compared to a threshold to identify an item. Photo comparisons of texture and color detect plant diseases. Bayes and K-means clustering are planned. [5] proposes image processing for plant bacterial infection detection. Bacterial leaf scorch is an early-stage plant infection. Image capture and conversion to a computer-readable format are examples of picture acquisition. Then K-means clustering separates the foreground and background images. The leaf area is emphasized by eliminating the base pictures' leaf clusters. K-means clustering, in contrast to fuzzy logic, is straightforward, quick, and low-maintenance. FPGA tools can use ADSP target boards. With image processing, they can detect damaged citrus leaf regions [6]. Four. These illnesses include canker and wilt. Anthracnose symptoms include citrus greening and overwatering. To start a database, the author suggested taking high-quality photos using a digital camera. Pre-processing does color space conversion and image enhancement. Color pictures are enhanced using discrete cosine transforms. These convert color spaces. But in feature extraction, The GLCM and graycoprops functions are used by the author to compute statistics like contrast, energy, homogeneity, and entropy. Citrus leaf diseases are classified using SVMRBF and SVMPOLY. Processing images to identify [7] proposes an article on orchid leaf disease. Leaf diseases in orchids include solar sunburn and black leaf mark. First, collect pictures and save them on a computer. An picture is pre-processed by adjusting histograms, intensities, and filtering. Boundary segmentation removes tiny things while retaining big ones. Segmentation uses a line's start and end points to trace edges. The ROI was added to the GUI. The image is then categorized using white pixels. This

method produces accurate results with little error. [8] suggests image processing to detect illnesses in tomato leaves. Image capture Photograph ill tomato leaves, with early blight and powdery mildew. These include reducing noise, resizing, isolating and eliminating background. The author used Gabor wavelet and SVM to identify and classify tomato diseases. The Gabor wavelet transform creates feature vectors for categorization. To detect tomato illnesses during classification, an SVM is trained. SVM creates decision trees using feature vectors and classes. Then came tomato leaf blight. These kernels are used in SVM. On-the-fly grid search with N-fold cross-validation Pre-processing removes noise and other elements from pictures. This is done by converting RGB images to greyscale using the equation $f(x) = 0.2989*R + 0.5870*G + 0.114*B$. Images are segmented for sick leaf identification utilizing boundary and spot detection. K-means clustering classifies items. From greyscale pictures, Otsu threshold generates binary images. We can tell a lot about plant diseases just by looking at them. Extract of HB leaf Color co-occurrence and components are used in image processing. An ANN or back propagation network classifies illnesses.

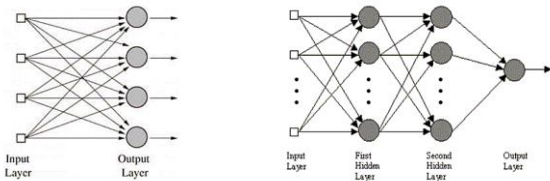


Figure 1: Basic Artificial Neural Network architectures (Single layer on the left and multi-layer on the right) [11]

Image processing is proposed in Article [10] for the detection of Scorch and Spot plant diseases. First, an RGB image of the plant is taken. To convert RGB color data to space, preprocessing is required. Then green-pixel masking. Inside infected cluster borders, unmask cells. Segmenting an image to remove useful parts By extracting color, texture, and edge characteristics. Neuronal networks classify illnesses. Research in the field will evaluate disease status of citrus plants. [11] suggests the use of image processing to detect illness in groundnut plants. Cercospora leaf spots appear in the early and late

stages of the season (*Cercosporidium personatum*). HSV colorization is used to leaf RGB images. Finding green pixels in a picture saves time. Cooccurrence matrices for color and texture extraction Texture feature extraction analyzes texture pictures in two ways. The first is structured, the second is statistical. This work used statistics. Back propagation classifies infectious groundnut illnesses. Back propagation has two steps: 1) a wide range of weights They were 97% accurate in their diagnosis of four different diseases. Then, for the RGB leaf image, create a color transformation structure and map RGB color values to the structure's spatial coordinates. The picture is then split using K-means. The green pixel masking step eliminates the unneeded space. To remove the leaf's green section, At this point, the infected cluster's borders are masked cells that have been calculated. With each cluster, an HSI matrix is generated. The GLCM function determines feature and texture statistics in step 4. The characteristics are then fed into a pre-trained neural network. They propose using image processing to identify sugarcane leaf disease [13]. We chose six. They are looking at Red Rot, Downy Mildew and Sugarcane Mosaic. Image acquisition captures pictures in TIF, PNG, JPEG, and BMP formats. RGB pre-processing The pictures are grayscaled and unnecessary data is eliminated. Image segmentation identifies healthy (green pixels) and contaminated (red pixels) regions. The feature extraction methods include linear SVM, nonlinear SVM, and multiclass SVM.

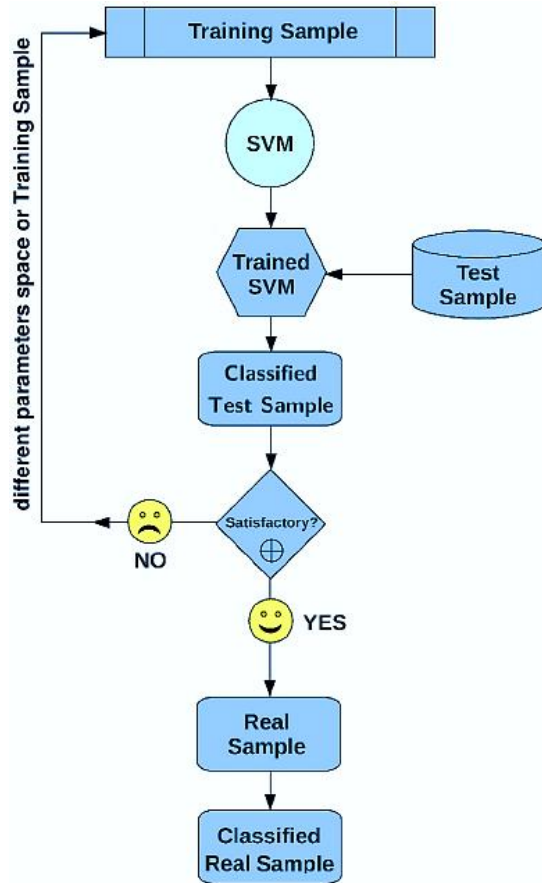


Figure 2. Schematic representation of the SVM algorithm classification process.

3. System Design

The picture should go through the following processes in order to identify disease:

- 1) Pre-Processing.
- 2) Segmentation-Process.
- 3) Feature Extraction-Process.
- 4) Classification-Process.

Image Pre-processing:

This phase removes noise and improves image quality. The super resolution technique may make a low-resolution image high-resolution. Morphological methods may eliminate noise. Prior to removing shadows and adjusting images, shadow reduction is essential for segmentation and feature extraction.

Image Segmentation:

Identifying the area of interest using specific algorithms, or generating clusters of areas by comparing adjacent pixels.

Thresholding:

When the backdrop and foreground contrast strongly, this approach is employed. Within a global threshold, all pixels are marked '0' and regarded in the background, while pixels marked '1' are considered in the foreground. The Otsu thresholding technique uses the infraclass variance pixels to calculate the threshold value.

Region Growing:

Using the area growth technique, a seed is chosen based on the surrounding pixels' properties. This method's seed selection is critical. R.O.I. expands based on pixel similarity.

k-mean Clustering:

k is the number of clusters in this technique. It's based on real-world data. Each observation is an object to K-mean. K-mean clustering identifies a partition in which elements in one cluster are closer to one another than in other groups. the gap between each item and its clustered centroid is reduced iteratively.

Fuzzy C-mean Clustering:

Iterative algorithms are employed in c-mean clustering. Initially, fuzzy cluster centers are calculated, and a fuzzy partition matrix is created. The goal function is decreased in the following iteration to determine the best location for the cluster.

When the maximum number of iterations is reached, the iteration process is automatically terminated.

Feature extraction

It reduces the number of sources needed to create a dataset by extracting useful information from the input picture.

Color: Color is a stable visual characteristic. The color systems utilized are RGB and HIS. A fruit's infection may be recognized by its color. Color image processing has three basic principles.

areas: the alteration of color Individual color plane spatial processing, Color vector processing

Texture:

Texture in a photograph describes how colors are distributed in an image. Fruits with diseases have a different feel. So we can use texture to assess illness kind.

Shape:

Morphology extracts picture components. Using morphological procedures, diseased fruit and leaf parts may be removed. The image's borders may be obtained via erosion.

Four major characteristics:

- 1) Geometric characteristics – Perimeter, area, the axis, the orientation angle, and many more terms are included.
- 2) Area description features – Region description features are provided based on a collection of characteristics specific to the target area.
- 3) Moment invariants: Using this feature, geometric properties like Hu invariant moments, orthogonal moments, and so on may be defined.
- 4) Fourier shape descriptor.

Classification

Data is properly partitioned using a Support Vector Machine (SVM) to create an N-dimensional hyper plane. Neural networks and support vector machines are closely linked. SVM assesses a wider range of data in an easy-to-understand manner.

4. CONCLUSIONS

This article describes how to use image processing to identify and categorize leaf diseases. To accurately diagnose illnesses, writers used

numerous techniques. Using image processing techniques may help identify leaf diseases early on. An artificial neural network (ANN) is a kind of machine learning algorithm. This article's methods save time and provide results.

Fruit Detection System's proposed technique based on fuzzification was tested, and it rapidly identified the feature for pattern recognition system using fuzzy curves and fuzzy surfaces Characteristics that are reliant on other important features are eliminated on fuzzy surfaces. It had proven efficient in the extraction of features. With the K-mean clustering technique, segmentation may be done quickly and accurately. Because it accurately maps input data, SVM has proved to be the best classification method. Dimensions feature space-linear or nonlinear mapping techniques. For low-quality images, the Intent Search Technique has been shown to be the most effective way to improve the image.

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