



Plant Disease Detection Using Deep Learning

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ABSTRACT

Food is a key aspect of our lives because it is the most fundamental necessity of all living things on our planet. Because agriculture provides the majority of our food, it is extremely significant. Agriculture works to produce food goods for the expanding population, but plant diseases also impede the growth and nutritional value of food crops. Here, we'll focus on five different plants: the tomato, the hibiscus, the spinach, the mango tree, and the bitter melon. This paper suggests a CNN-based method for earlier disease detection in plants. The method involved the following steps: image segmentation, feature extraction, and picture pre-processing. A Convolutional Neural Network (CNN) classifier is created using the outcomes of these three phases. To conduct research and analysis, an image of the plant's diseased portions is obtained, compared to the desired dataset, and used to predict the disease and provide subsequent treatment options. Following the diagnosis of the disease, the pesticides, their quantity, and the area where they should be applied are displayed. Additionally, it will display the vicinity where pesticides can be found.

Keywords: Agriculture, Machine Learning, CNN, Image Segmentation, Feature Extraction, Automatic disease Recognition, Classification, etc.

I. INTRODUCTION

With the advancement of recent innovations, agriculture will become more well-known because it is now used to feed the basic populace and is widely used in various applications. In India, farming is most likely to capture people's interest. This corporation plays an essential part in the Indian economy. Farming employs 70% of the rural population. More than 17% of GDP is dedicated to providing jobs for 60% of the total population. This work discusses five different types of leaves. During the expansion phase, Brown Spot and Late Blight emerge. During the expansion phase, Bacterial Spot appears. Septoria a Leaf Spot, a yellow-curl disease, is most likely to appear during seeding. Many farmers may incur financial losses as a result of substantial output losses and disease eradication costs. This means that the traditional strategy for identifying agricultural ailments necessitates the expertise of field professionals in order to be successful. The traditional method employs image processing techniques and a convolutional algorithm. Using an iterative strategy, the K-Means clustering methodology is an unsupervised learning method that partitions a dataset into k non-overlapping clusters or subgroups. The dataset is separated into K non-overlapping independent clusters or subgroups based on their

attributes in this method, and the process is repeated numerous times. The goal is to keep the clusters as close together as feasible while keeping the data points between them as comparable as possible. Clustering is performed when the squared distance between the centroid of a cluster and the data points is smaller than a preset value. The HSI (hue, saturation, intensity) color system also HSI (hue, saturation, intensity) color system describes the intensity component from the color-carrying knowledge in a graphic image (hue and saturation). The HSI replica is a powerful method for advancing image processing techniques that use sapient color parameters. The RGB color tag is used to specify the value of a color's pace. The color intensity is entered as a number between 0 and 255 with each of the three criteria (red, green, and blue). As a result, CNN has emerged as the most popular deep learning technique for heterogeneity reduction, extraction, and classification. Filter-based convolutional techniques gather the essential properties of the data, and frameworks are used in conjunction with multi-scale perception to create estimators. CNN can distinguish pixels in a way that ANN cannot distinguish pixels in a way that ANN is unable to do by taking the features of a picture. Deep learning models are more reliable and well-founded when it comes to their computation during the creation process than statistics models. Pooling Layer for InCNN: Another name for its downsample. As the name implies, it reduces the amount of data in each aspect obtained from the convolutional layer.

II. LITERATURE SURVEY

Shruthi et al. described the stages of a general plant disease detection system as well as their research on machine learning algorithms for plant disease detection. They demonstrated that a convolutional neural network (CNN) can detect a wide range of diseases with great accuracy [1]. P. Srinivasan et al. created software to identify and classify groundnut leaf diseases. Using image acquisition, image preprocessing, segmentation, feature extraction, and the K nearest neighbor algorithm (KNN), they classified groundnut crop diseases such as Early leaf spot, Late leaf spot, Rust, early and late spot Bud Necrosis [2]. L. Sherly discussed many types of plant illnesses and distinct classification algorithms in machine learning that are used for recognizing diseases in different plant leaves and their advantages and disadvantages. This study summarised various algorithms for identifying and detecting bacterial, fungal, and viral plant leaf diseases [3]. Gurleen Kaur et al. examined plant leaf disease detection methods. The following approaches were used for picture segmentation, feature extraction, and classification: BPNN, SVM, K-means clustering, Otsu's algorithm, CCM, and SGDM [4]. Md. Selim et al. identified the disorders using eleven statistical variables and the Support Vector Machine classifier (SVM). This boosts the detection, identification, and classification process's efficiency. It provides 93% accurate illness classification results [5]. Monzurul Islam et al. combined image processing and machine learning to diagnose illnesses from potato plant leaf photos. It achieved 95% illness classification accuracy utilizing Colours threshold, GLCM, and multiclass SVM [6]. Jobin Francis et al. estimated the damaged leaf ratio for identifying leaf diseases in pepper plants. To isolate the leaf from the background, masking, and threshold-based segmentation were used. Backpropagation algorithms were used to identify two types of illnesses [7]. For leaf image segmentation, Vijai Singh et al. used a genetic algorithm. The advantages of this strategy are that plant diseases can be discovered at an early stage, with low computing effort and the best results [8]. Mrunmayee et al. offers disease identification and classification approaches based on image processing and neural networks. Color photos are preprocessed, and k-means clustering is employed for segmentation. The texture features are retrieved and fed into the artificial neural network using the grey-level co-occurrence matrix (GLCM) approach. This approach has an overall accuracy of 90% [9]. Sachin D. Khirade et al. explored plant disease detection segmentation and feature extraction algorithms. Neural network methods such as self-organizing feature maps, backpropagation algorithms, SVMs, and others have been proposed for disease classification in plants [10].

III METHODOLOGY

The proposed plant disease is a real-time prediction method that employs plant images as input. Figure 1 displays a block diagram of the proposed approach. The database images from the Kaggle collection were used to create this. The datasheets are preprocessed in the first phase by reducing the input photos. The photographs are standardized and segmented based on the features selected from the processed augmented image. The photos are classified using the CNN algorithm. It detects the disease that infected the plant and suggests solutions to avoid the problem in the future.

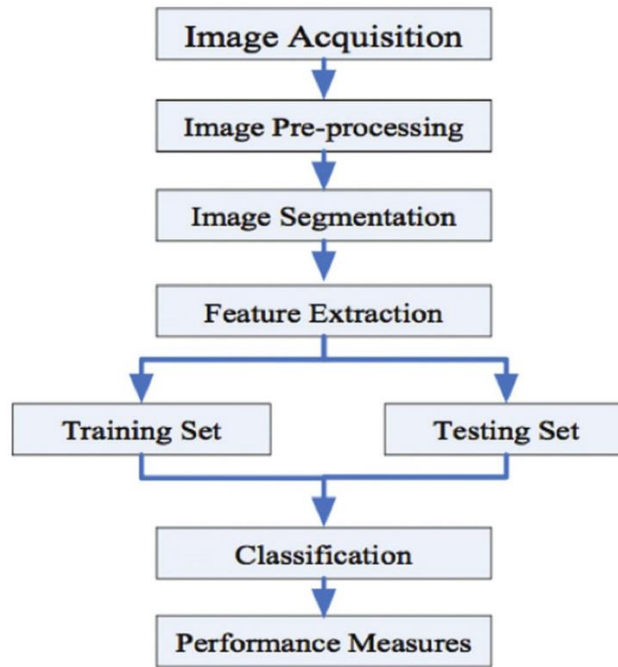


Figure:1

A: Leaf image dataset: The significance of measuring and producing high-quality datasets in safeguarding the integrity of research labor and study outcomes cannot be emphasized. Plant images for databases, On the other hand, a high-resolution digital camera or a smart camera can be used to acquire. However, for our research performance analysis, we used tomato leaf photographs from the Kaggle dataset, which includes images of healthy and damaged plants. Figure 2 depicts pictures of unhealthy (A) Tomato late blight and healthy (B) Raspberry leaves from the collected dataset.



Figure: 2

B: Image processing: Pre-processing allows you to improve the quality of your leaf images by deleting unwanted bits of the information you receive as input. These Processes include data cleansing, integration, reduction, and transformations.

C: Image Segmentation and Feature Extraction: This method divides method for dividing a digital image into several pieces that may be easily analyzed. In computer graphics, RGB is the most widely used color representation system. The input to image segmentation will be a data set supplied by us, and the output will be cluster data. The K-means clustering method is used to partition the image. The picture feature vectors

of the leaf disease can be retrieved using the CNN-based detection framework's feature extractor. The feature extraction technique analyses color, structure, and surface properties such as color, structure, and surface in a leaf image.

D: Classification based on CNN: A classification model is required to properly train our data set and test fresh photos of sick plants so that the appropriate insecticides and pesticides can be sprayed on the farm to treat the illness and prevent the spread of any pathogen, fungus, bacterium, or other infections. In this article, we trained our dataset using a convolutional neural network. Once trained, a convolutional neural network can be used to determine model accuracy for training and validation. The trained model is used to project the disease in the test dataset.

IV EXISTING SYSTEM

Previously, the author of [1] employed techniques such as image processing, image segmentation, and feature extraction. Furthermore, the output of those three stages is categorized using the KNN algorithm. Affected Area, Disease Name, Total Accuracy, Sensitivity, and Elapsed Time are just a few of the other details that may be gathered from a leaf sickness diagnostic.

The author discusses a comparative examination of numerous plant leaf diseases and all machine learning models used to diagnose plant leaf disease in [2]. It was done this way to avoid the paper becoming too big or too small. Suggestions are grouped into three categories: recognition, severity evaluation, and characterization. As a result, the calculation's basic specialized structure is divided into each of these groups. The outcomes of this study could be useful to plant and vegetable pathologists.

V PROPOSED SYSTEM

A. Training data set:

It can be seen in the pre-processing stage, where the quality of the leaf image is improved and unaffected areas are removed, as illustrated. Finally, the GLCM computation is involved. After assessing the texture of the image, it is converted to a grayscale so that it may be seen in greater detail. The k-mean approach uses structural information to distinguish between different materials. The information is grouped using the k-mean clustering algorithm based on how similar they are at the focus point. This database contains a record for each and every time a cluster divides. Clustering, or K-, indicates that the leaf has been divided into four halves. The infection could be contained within one or more of the leaf's four sections/clusters, implying that the leaf is affected by many diseases. To utilize the CNN classifier, we must first enter the number of the group. We can learn the name of the disease as well as its location by utilizing the CNN classifier.

B: Testing data :

In this scenario, the data can be trained or untrained. After Extraction is complete, entering data into the category is permissible to enter data into the category. If the data has not yet been trained, the number of segments for segmentation must be specified. The textural-based k-mean clustering algorithm is then calculated. Once the focus point is determined and the Euclidian separation is computed, information is sorted based on its similarity in k mean clustering. The number of people in our ROI group (Region of Interest) will be entered. After entering the cluster number, we'll utilize the CNN classifier to generate a definitive defective sickness term utilize the CNN classifier to generate a definitive defective sickness term after entering the cluster number.

C. PSEUDOCODE:

Step 1: Select a Dataset or snap a photograph.

Step 2: Collect data for testing.

Step 3: Gather information for training purposes.

Rearrange the Dataset in Step 4

Step 5: Using the k means clustering technique, assign identifiers and attributes to the segmentation process.

Step 6: Converting labels to categorical data and normalizing X.

Step 7: Separate X and Y for CNN.

Step 8: Use CNN to locate the disease.

V RESULTS AND DISCUSSION

This implementation's results can be utilized to make a variety of observations and inferences. The overall performance score of the various techniques has improved. The convolutional neural network is being tested for the detection of leaf diseases, with the hope of improving accuracy. This approach will be valuable in the automatic identification of plant leaf disease and will boost agricultural production through disease detection. The diseased leaf's results will take you to its treatment or insecticide, which several purchasing websites offer.

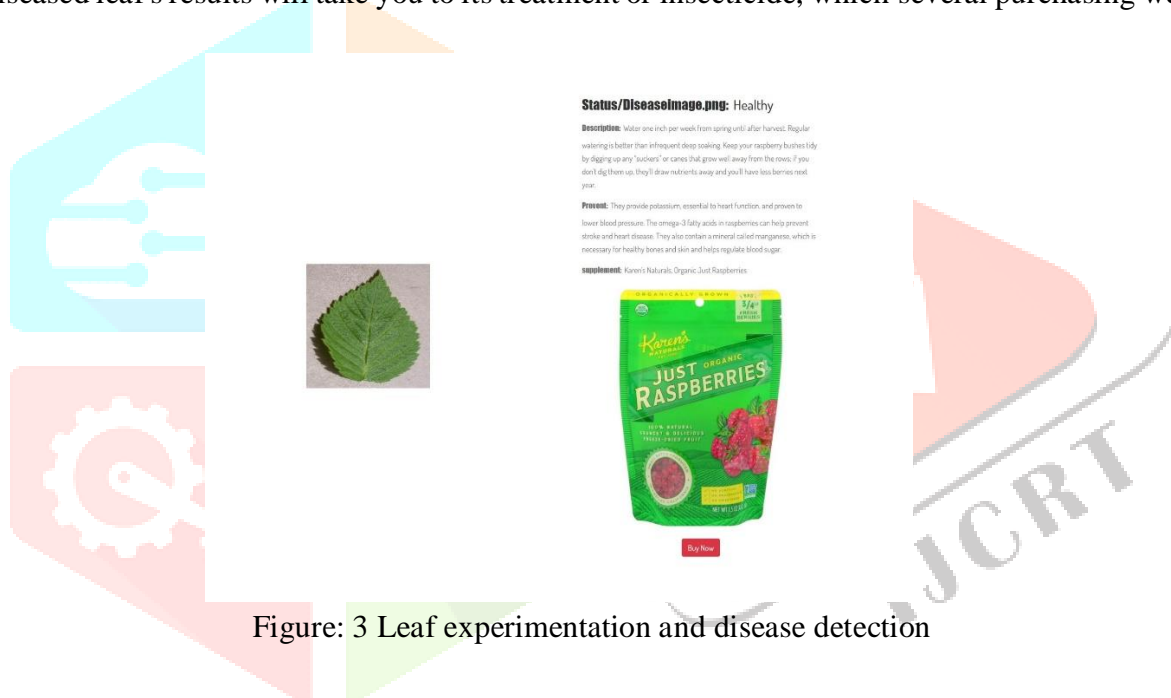


Figure: 3 Leaf experimentation and disease detection

Status/Diseaseimage.png: Late Blight

Description: Late blight is caused by the oomycete *Phytophthora infestans*. Oomycetes are fungus-like organisms also called water molds, but they are not true fungi. There are many different strains of *P. infestans*. These are called clonal lineages and designated by a number code (i.e. US-23). Many clonal lineages affect both tomato and potato, but some lineages are specific to one host or the other. Late blight is a potentially devastating disease of tomato and potato, infecting leaves, stems and fruits of tomato plants. The disease spreads quickly in fields and can result in total crop failure if untreated. Late blight of potato was responsible for the Irish potato famine of the late 1840s.

Prevent: Sanitation is the first step in controlling tomato late blight. Clean up all debris and fallen fruit from the garden area. This is particularly essential in warmer areas where extended freezing is unlikely and the late blight tomato disease may overwinter in the fallen fruit. Currently, there are no strains of tomato available that are resistant to late tomato blight, so plants should be inspected at least twice a week. Since late blight symptoms are more likely to occur during wet conditions, more care should be taken during those times. For the home gardener, fungicides that contain maneb, mancozeb, chlorothalonil or fixed copper can help protect plants from late tomato blight. Repeated applications are necessary throughout the growing season as the disease can strike at any time. For organic gardeners, there are some fixed copper products approved for use; otherwise, all infected plants must be immediately removed and destroyed.

supplement: ACROBAT FUNGICIDE



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Figure: 4

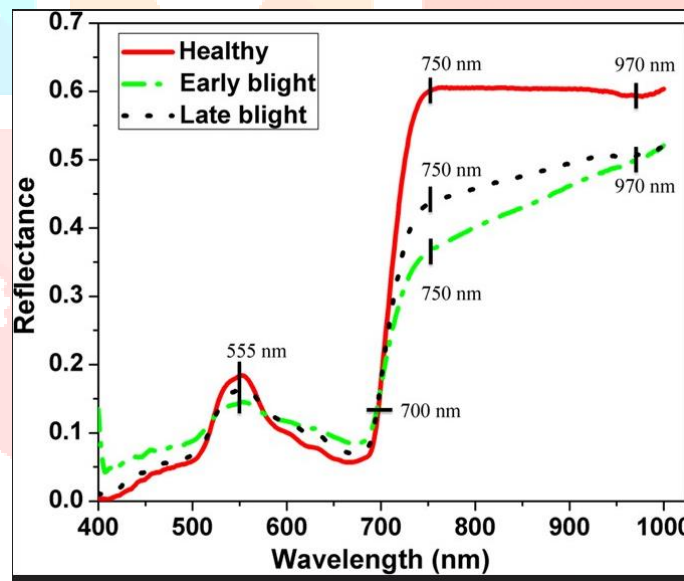


Figure 5: Early and late blight disease detection on tomato leaves using hyperspectral imaging.

VII. CONCLUSION

In our proposed work, we used several leaf pictures to detect leaf diseases. We used a segmentation method known as K-means clustering. CNN is used to detect frameworks. Color, shape, and texture are all considered by the feature extraction algorithms. We may use this technology to precisely locate various illnesses in leaves. The collection comprises leaf pictures from several diseased regions, including bacterial spots, bacterial blight, brown spots, late blight, Septoria Leaf spots, and Yellow Curved disease. The findings reveal the affected location, the fraction of the disease impacted, and the pesticide used to treat the condition. With its depth and pesticides, the accuracy level for illness diagnosis is 99.8%. A larger dataset and a higher level of accuracy could be included in future research.

VIII. REFERENCES

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