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LEAF DISEASE DETECTION

USING DEEP LEARNING

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ABSTRACT:

Farming supplies food for all humans, especially in times of rapid growing populations. This is advised that illnesses of plants be predicted at the earliest stages in this field of farming in order to provide food to the whole population. However, it is difficult to forecast illnesses in the initial phases of plant growth. The purpose of this study is to educate farmers about cutting-edge technology for reducing illnesses in plant leaves. Tomato is a common vegetable, techniques based on image processing and machine learning along with a reliable algorithm have been found to identify leaf illnesses in tomato plants. Defective tomato leaf samples are considered in this study. These pathological samples taken from tomato leaves allow farmers to identify diseases based on early signs. First, the tomato leaf sample is scaled down to his 256x256 pixels. Histogram equalization is then performed to improve sample quality. Clustering with K-Means is used to divide the data space into voronoi cells. Edge tracking is used to determine the bounds of the sheet collection. Several classifiers such as discrete wavelet transform, principal component analysis, and grayscale co-occurrence matrix are used to determine important characteristics of leaf data. Finally, the derived features are classified using Convolutional Neural Networks (CNN) with tomato leaf disease detection dataset from kaggle with 92% accuracy.

Index Terms: Cutting–edge technology Convolutional Neural Network, clustering, K-Means, Voronoi cells, Gray scale co factor matrix. Discrete wavelets transform, Kaggle.

INTRODUCTION:

Over 70% of India's population is engaged in agriculture. Plant disease detection is very important to avoid yield loss. It is really difficult to observe plant diseases in individuals. It requires a lot of effort, plant disease expertise and a lot of time. This helps machine learning-based image processing and algorithms to detect plant diseases. In this task, we developed an approach to detect plant diseases from leaf images. Image analysis is a subset of signal processing that extracts image attributes and useful information. Machine learning is a branch of AI that acts autonomously or is given instructions to perform certain tasks. The main purpose of neural networks is to understand training data and integrate this training data into algorithms that are useful to humans.

It has a large amount of training data to help you make better decisions and predict the correct outcome. They are classified according to characteristics such as leaf color, degree of leaf damage, extent of leaf damage and texture. In this study, we examined different image metrics or features for detecting different plant leaf diseases to achieve the highest accuracy. In the past, plant disease detection was done by visual inspection of leaf surfaces or by chemical methods by specialists. This requires a large team of experts and constant monitoring of plants, which is costly on large farms. In such cases, the proposed approach is suitable for monitoring large crop fields. Comprehensive diagnosis of disease can be made simply by observing signs on plant leaves, making the process easier and less expensive. By using statistical machine learning and image processing algorithms, the proposed plant disease detection solution has lower computational complexity and shorter time required for prediction than existing deep learning-based systems. Deep learning for leaf disease detection is an approach to identify and diagnose plant leaf diseases using neural network technology. The technology has received a lot of attention in recent years as it has the potential to improve crop productivity and reduce pesticide use by helping farmers detect and treat crop diseases early. Plant diseases are usually detected by expert inspection, which can be expensive and error prone. Advances in machine learning and computer vision approaches have made it possible to develop machine learning algorithms that can identify and classify crop diseases from leaf photographs. Deep learning techniques such as convolutional neural networks (CNNs) are widely used for leaf disease detection because they can automatically learn important traits from photographs. The algorithm used is trained on a huge dataset of annotated photographs of healthy and diseased leaves of plants to learn how to recognize the features and traits that distinguish leaf health from diseased leaves. . Once trained, deep learning algorithms can reliably detect and diagnose diseases affecting plant leaves by analyzing photos of plants. When the technology detects signs of disease, it sends real-time alerts to farmers, helping them take immediate action to prevent the disease from spreading to other crops.

EXISTING SYSTEM:

This version relies on an existing method developed with the assistance of deep mastering algorithms. This method makes use of ResNetS1, a switch learning method, although it does not provide precision and disease in plant. Techniques for automatic detection of modern leaf diseases are lacking, and detection of early-stage diseases by the naked eye is a major challenge. As a result, farmers suffer huge economic losses. Identification of foliar disease using mechanical methods is advantageous as it can significantly reduce labor in large farms. Image segmentation method is an approach used to automatically identify and classify diseased leaves.

Disadvantages:

a. Less precision.
b. Less comfort characteristics.
c. We can't find disease

PROPOSED APPROACH:

To overcome the problems of an existing system, the proposed method has evolved. The proposed system is developed to identify disease in plant along with accuracy by using conventional neural network. Here we will load dataset from kaggle then preprocessing is applied then image segmentation feature extraction is done to the uploaded dataset using RGB into HIS model, Otsu method etc. along with GLCM, then CNN classification technique is applied to find plan disease through tomato plant leaf.

Advantages:

a. High precision.
b. Less complexity.
c. High overall performance.

METHODOLOGY:

Tools Used: The whole system is implemented using python programming language in CO LAB.

Workflow: I completed this entire project using Python and CO LAB. The necessary libraries are imported, the data is analyzed after import, the data is summarized, all zero values are removed, and finally the data is converted to the format required by the CNN algorithms used. The following diagram shows how the analysis is done. Here the tomato leaf disease detection dataset is taken from Kaggle in that normal and 10 types of diseases data containing around 10,000 images. It contains tomato leaf diseases like Tomato_mosaic_virus

- Target_Spot
- Bacterial_spot
- Tomato_Yellow_Leaf_Curl_Virus
- Late_blight
- Leaf_Mold
- Early_blight
- Spider_mites Two-spotted_spider_mite
- Tomato___healthy
- Septoria_leaf_spot

Modules:

1. Image Acquisition
2. Image pre-processing
3. Image Segmentation
4. Feature Extraction
5. Classification

6. Disease Detection

1. Image Acquisition:

It is a method of recording objects and events using various technologies such as photographic equipment, scanners and detectors. Image acquisition is the first step in the overall image analysis workflow in artificial intelligence and image processing. The accuracy and reliability of subsequent processing are greatly affected by the resolution and characteristics of the resulting image. The camera originally took pictures of the leaves of plants. The captured image is in RGB format representing red, green and blue. This is the beginning stage. This will be used as a data source.

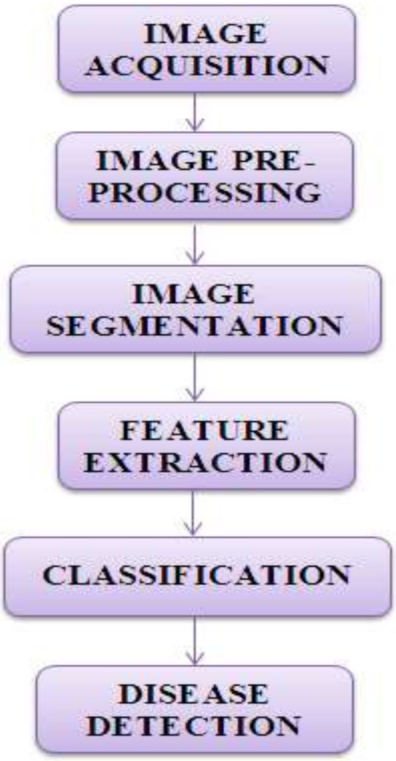


Fig1: Proposed Methodology

2. Image preprocessing:

A. Null value handling
B. Categorical handling
C. Scaling

The specified data set for this data preparation module is missing some values, which may lead to inaccurate predictions. Remove missing values using Python. Also, to get correct results, the replicated data should be removed from the data set. Normalization is the process of scaling data to a specific range.

3. Image Segmentation:

The method of splitting an image into multiple components or parts of similar quality or features such as colour, appearance, form, and so on is known as image segmentation. Image segmentation methods include thresholding, edge detection, clustering, range growing, and watershed segmentation. These approaches can be used for both grayscale and color photographs. The RGB image is transformed to create a HIS model for classification using boundary and point detection techniques. This procedure helps identify the affected part of the leaf. Eight connectivity of pixels are tested for edge detection and line detection method is used.

4. Feature Extraction:

The process of translating the unprocessed information into a set of significant and pertinent features that can be employed in additional analysis and modelling is known as feature extraction. It entails extracting and translating the most critical and necessary details from the source data into a more manageable format.

5. Classification:

A. Model training with classifier
B. Accuracy
C. Save model

In this module classification will done and accuracy of the model will be explained. CNNs are great tools for separation and classification, but they are not the only technique to achieve these goals. CNN structures fall into two types according to his are segmentation and networks. CNNs that recognize regions in images from any number of semantically understandable classes of objects, and classification CNNs that classify each pixel into any number of categories based on a set of convenient element classifications.

6. Disease Detection:
A. Input test data
B. Preprocess
C. Load model
D. Classification
E. View result

MACHINE LEARNING ALGORITHMS:
Convolutional Neural Network:

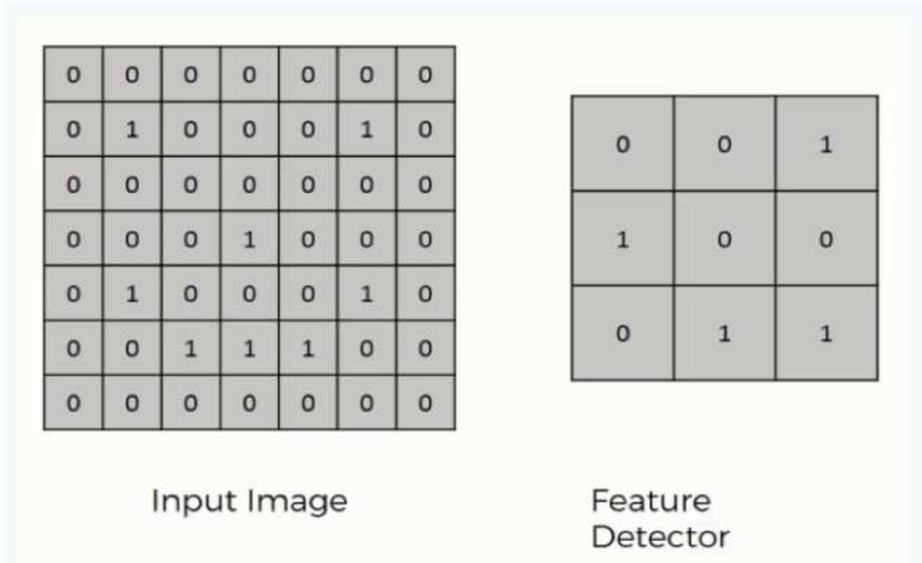
Step1: convolutional operation
Convolutional operations serve as the first stepping stone for our strategy. This phase provides a brief introduction to neural network filters or feature detectors. In addition, we discuss functional maps, their parameters, detection levels, how patterns are detected, and how results are presented.

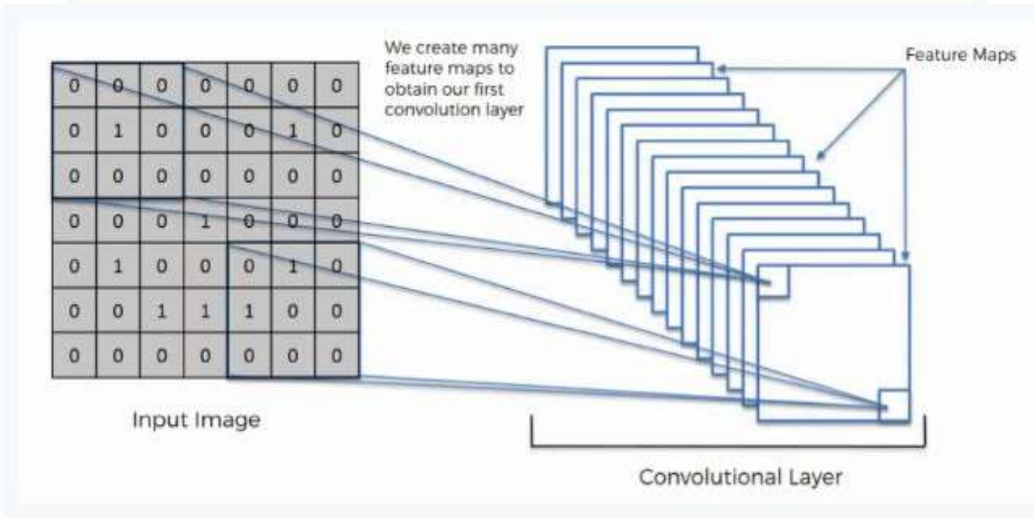
Step 2: Pooling Layer
This section describes pooling and helps you understand how pooling usually works. However, in this case, a particular type of pooling (max pooling) plays a central role. However, consider different tactics, such as medium (or full) pooling. This part ends with a presentation using visual interactive tools.

Step 3: Flattening
Here, we provide an overview of the flattening process and how to move from pooling to flattened layers in convolutional neural networks.

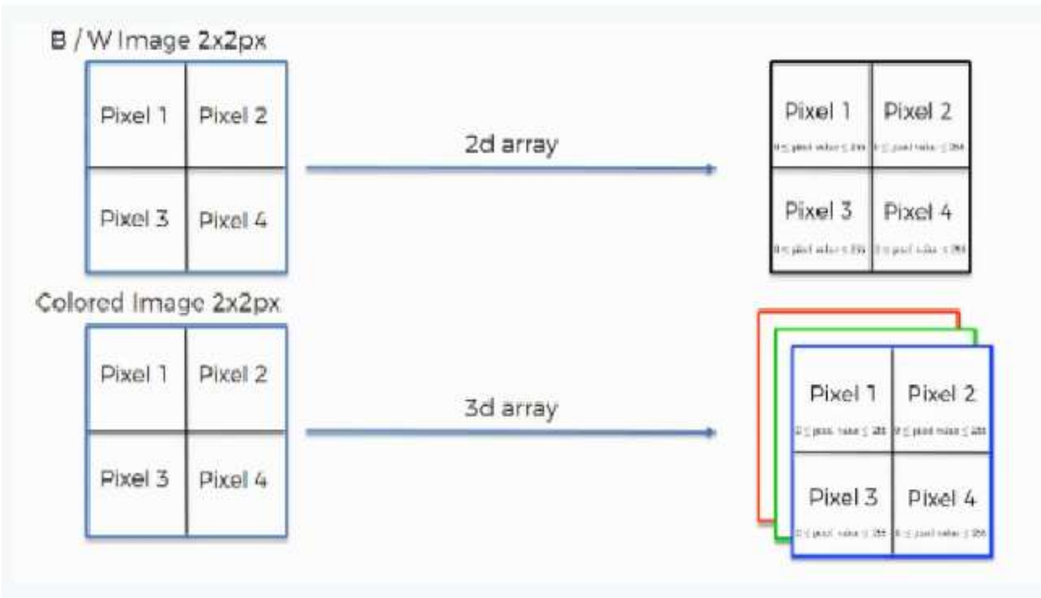
Step 4: Full Connection
This part summarizes everything that was explained in the previous section. Understanding this helps us understand how a convolutional neural network works and how the "neurons" it generates classify photos.

The Convolution Operation





Convolutional Neural Networks Scan Images



RESULTS:

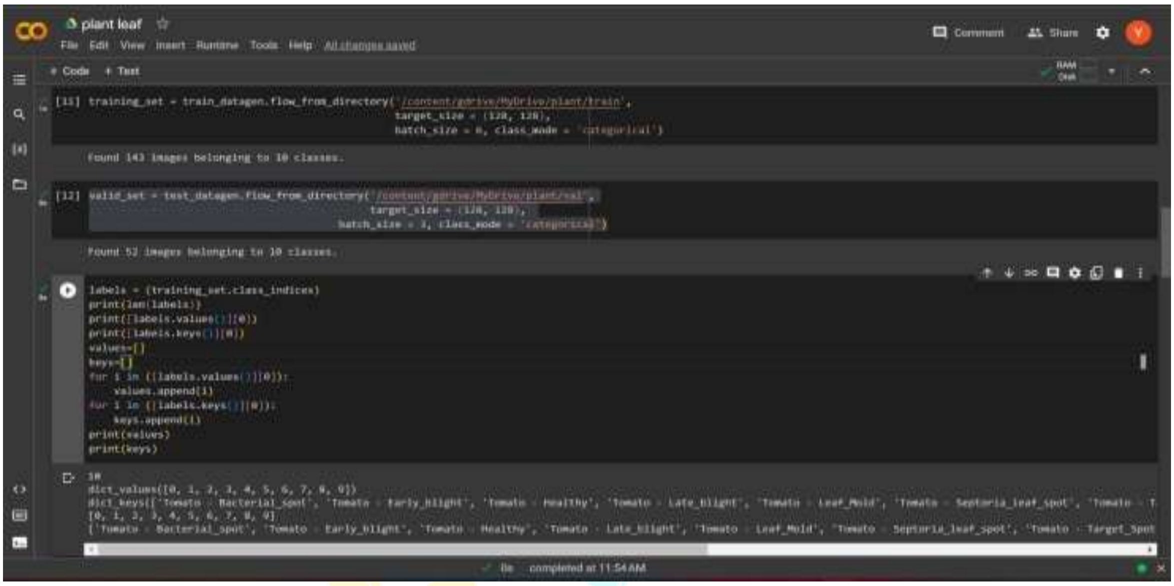


Fig2: leaf diseases

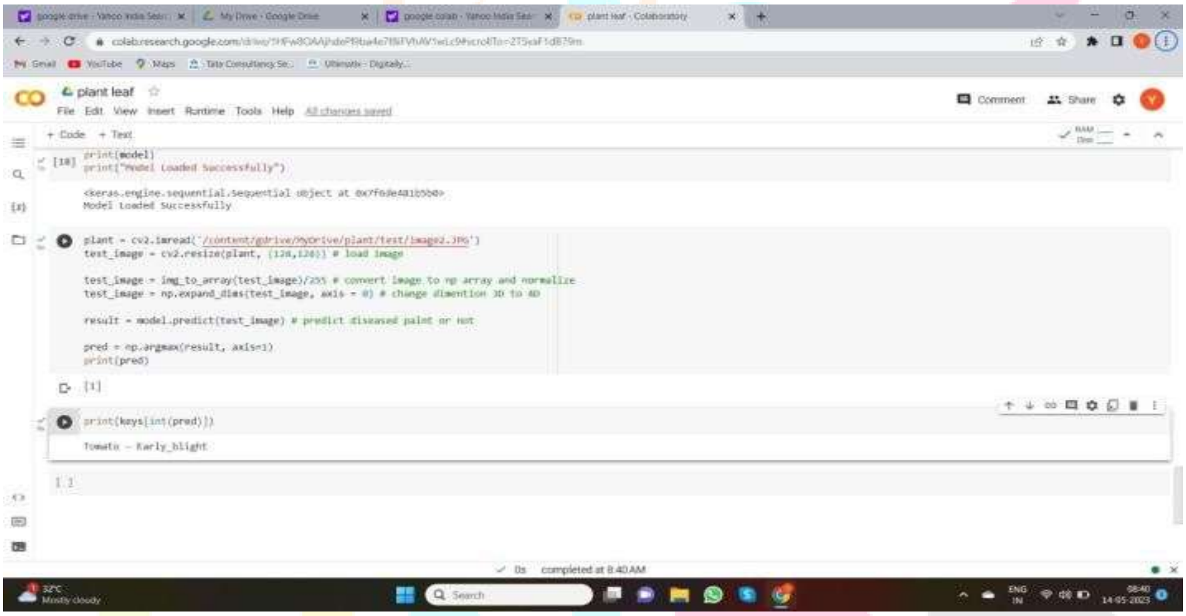


Fig3: Tomato Early Blight

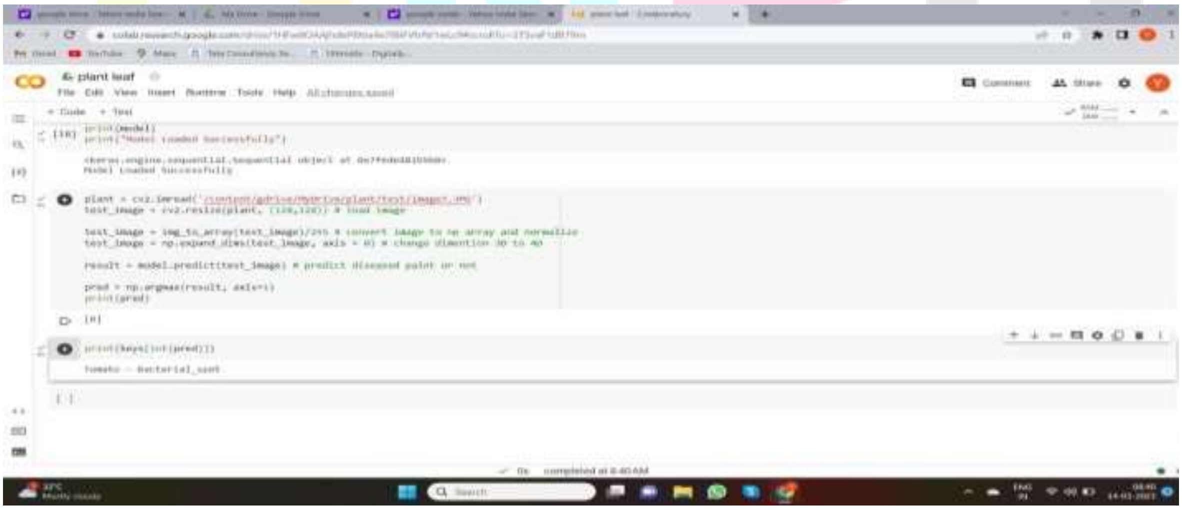


Fig4: Tomato Bacterial Spot

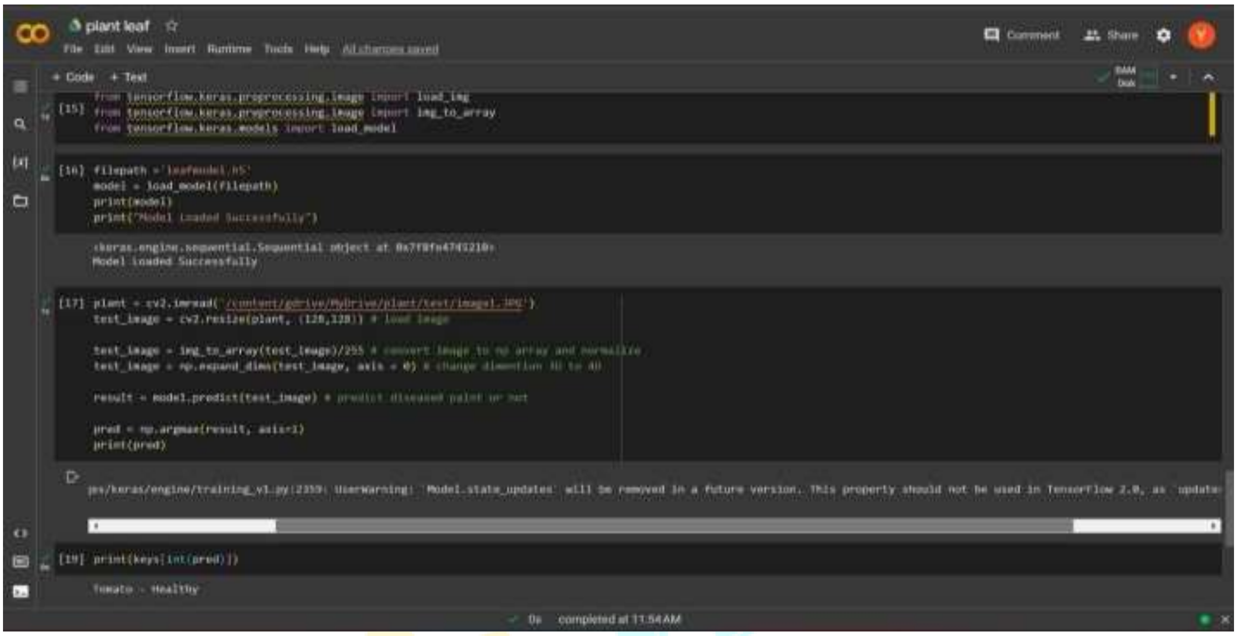


Fig5: Healthy Tomato Leaf

CONCLUSION:

This article provided a complete overview of previous work on leaf disease detection using deep learning and focused on the fundamentals of deep learning and focused learning. Given enough data for training, the DL method can identify leaves very accurately. Leaf infections. Advantages of detecting plant leaf diseases in small samples, to improve classification accuracy, while emphasizing the value of collecting large datasets with a lot of variable data for expansion. We emphasize the importance of CNN activation map visualization and hyperspectral imaging for early detection of leaf infections. All diseases have been studied, but they have some drawbacks. Most of the DL systems published in research perform well in terms of identifying the dataset for which they are designed, but perform poorly when used with different datasets, and their algorithms are not robust. It has been shown that it should be modified to accommodate different disease records. . Using DL models is essential. This dataset contains a large number of images of various plant species and their diseases, but since the images were all taken in the laboratory, hyperspectral imaging can be used to visualize the plant in its real environment. Can be expected to create an extensive collection of diseases. There are several obstacles to early diagnosis of plant diseases. One of the biggest challenges is getting tagged datasets to train machine learning models. Describing many hyperspectral images is a long and tedious task requiring expertise. In addition, even experienced professionals, even when labeled datasets are available, can accurately determine where to look for symptoms of unnoticed disease, and discover completely invisible diseases. Describing pixels in is still an obstacle.

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