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Transfer Learning Approaches for Leaf Diseased Portion Detection

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***Abstract*—Overview - In this study, The difficulties in identifying and classifying diseased areas on leaves prompted us to create a deep block attention solid-state drive (SSD) for identifying diseased areas on leaves and classifying their severity. We propose a novel leaf disease portion method. Squeeze- and-excitation SSD (Se-SSD), and DBA-SSD approaches are recommended for finding plant leaves.SSD feature extraction network and channel attention mechanism are coupled by Se SSD, VGG feature extraction network is enhanced by DB SSD, and channel attention mechanism is coupled by DBA SSD. Convolutional layers trained on Image Net images using the VGG model are transferred to this model, reducing training time and speeding up the training process. On the other hand, the collected images containing plant leaves are randomly split into a training set and a test setup .1:1 ratio. After careful consideration, we chose the Leaf Village dataset because it contains imagery relevant to the study area. This collection contains leaf images, including images of cotton leaves. Image data is enhanced using data enhancement techniques such as horizontal flipping and histogram equalization. In this study, we examine and contrast the enhanced performance of VGG16 and RCNN with that of the more conventional Faster RCNN and Single Shot target identification approaches operating in the same setting. Comparing its performance with that of other target identification algorithms, we find that SSD and faster RCNN outperforms other algorithms in terms of algorithm.**

***Index Terms*—VGG16 Architecture, SSD Algorithm, Faster-RCNN Algorithm,Leaf diseased portion**

I. Introduction

India is a developing country. Agriculture has historically been the backbone of India's economic standing. Currently, India ranks second in the world in terms of agricultural production. The economic contribution of agriculture to India's GDP has steadily declined as the country's overall economic growth has increased. Agriculture currently plays a significant role in India's economic growth. Cotton has become an essential part of human life. Cotton, like many other plants, is susceptible to various diseases in its early stages. These diseases are caused by one or more fungi, pathogens that can cause stunting. However, by following the right precautions, these diseases can be avoided and the plant is disease-free. Soil quality, environmental temperature, water level, irrigation quality, seed type and other factors play a role in cotton production. Pesticides and fertilizers that are used to reduce the effect of insect attacks on the plant can worsen the situation if used in excessive amounts. Much research is being done to prevent insect attacks and to identify insect attacks at an early stage to prevent further losses. The traditional method of detecting a diseased part of a plant requires a considerable amount of work and time to analyze the disease. By the time a cure for the disease is developed, the disease has spread and is causing crop damage. Our main goal is to segment part of the disease using different transfer learning techniques and distinguish different types of disease in cotton plants by observing their form and structure using image processing and machine learning. Plants are susceptible to various diseases. This can be caused by several factors, such as changing environmental conditions, infestation by pests and insects, lack of nutrition .

CNNs have been integrating more and more in recent years. Phenotype of a plant. They have great success. Due of its strength, when simulating complicated systems Recognize patterns in the data and draw regularities. Examples include seeds and the identification of cultivars in seeds. to complete leaves on plants. some of the most recent Plant disease classification utilised a network model. The orchard kiwi Target identification algorithm was proposed by Longsheng Fu. depending on the type of kiwifruit pictures with 3x3 and 1x1 folds DY3TNet model proposed, R-CNN, YOLOv2, and Compare YOLOv3-tiny are installed in the YOLOv3 Tiny model. The improved DY3TNet model is smaller and taller of efficiency, according to test results. Guoxu Liu and others Tomatoes were identified using the YOLOv3 model, which is based on a highly interconnected network structure for feature extraction. C-Bbox in place of the traditional R-Bbox, tomato form, and less characteristics Faster RCNN and YOLOv2 were contrasted. Based on Mobilenev2 and a lightweight YOLOv3 network model, the Tomato grayspot detection method. This approach enhances Detection of tomato pits accurately through introduction the ing-GIOU Function for Regression Loss and Pretraining How to mix transitional learning with hybrid training Boost the generalisation of models. literature In order to identify undernutrition symptoms based on thoroughly documented nutritional deficiencies in sugar beets, we analysed the performance of five networks: AlexNet for VGG-16, ResNet-101, DenseNet-161, and SqueezeNet.

To ascertain the effectiveness of plant disease detection, it is important to construct a quick and high classification accuracy model. The YOLO series, Faster RCNN, SSD [18], and FPN are some of the most popular target recognition networks right now. The SSD target detection network extracts many levels of visual features, including low-level and high-level semantic information, using an end-to-end strategy for regressing features. Previous research has established the speed of the SSD network. However, the high accuracy standards in agricultural production cannot be satisfied by directly applying SSD methods to identify plant disease. A fusion residual network and a module for extracting features from a 1- by-1 convolution are suggested in this paper. It improves SSD's ability to extract features and its location and identi- fication precision for identifying plant illness. Additionally, we apply spatial transformation and pixel modification to images utilising data-enhancement, which not only boosts the algorithm's feature count, detection efficiency, and accuracy, but also lowers labour costs for the detection of agronomic plant diseases. Images were also captured using cameras that work in the visible region of the electromagnetic spectrum for analysis (400–700 nm). As a result, there is no need for costly equipment or highly experienced labour to collect the input data [19]. Therefore, the protocol's future users can gather data quickly, easily, and cheaply using portable (and thus in situ) devices.

A. Faster R-CNN Network

The following figure depicts the Faster R-CNN architecture. There are two modules in it: RPN: To develop proposals for regions. Fast R-CNN: For finding objects in the suggested areas.Producing region proposals is the responsibility of the RPN module. It uses neural networks to implement the idea of attention, which directs the Fast R-CNN detection module where to look for objects in the image. This is how the Faster R-CNN operates: RPN produces regional proposal ideas. The ROI Pooling layer is used to extract a fixed-length feature vector from each of the image's region proposals. The extracted feature vectors are then classified using the Fast R-CNN. The detected objects' class scores are returned together with their bounding-boxes.

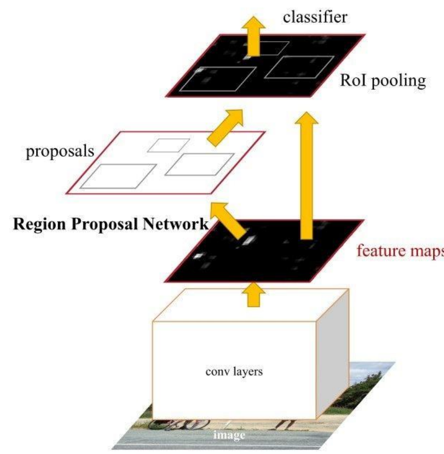

Fig. 1. Caption

B. The System Of Leaf Disease Detection

Li et al. expanded the regional proposition frame of the Faster R-CNN and used the ResNet50-based feature pyramid network (FPN) to study five distinct diseases that affect bitter gourd leaves. According to the study's findings, Once the feature pyramid network was included, the developed model's average accuracy increased to 86.39 percent., the prior model's 7.54% accuracy to the new model's 16.56% accuracy at detecting grey spots. Each picture is detected in 0.322 seconds, guaranteeing detection in real time.

Li et al. [1]to overcome the challenges of real-time apple leaf disease identification in pictures, We enhanced the Faster R-CNN with a feature pyramid network (FPN) and focused region-of-interest pooling (PROI Pooling). The research revealed that the enhanced model successfully identified Even though the single-photo detection time was reduced by 43ms, the mean average accuracy rose by 5.81 percent, 13.92 percent, and 4.86 percent when compared to Faster R-CNN, YOLOv3, and Mask R-CNN, respectively.five apple leaf diseases in their native environments with an average mean accuracy of 82.28%.Even though the detection time for a single photo was decreased by 43ms, the mean average accuracy rose in comparison to Faster R-CNN, YOLOv3, and Mask R-CNN by 5.81%, 13.92%, and 4.86%, respectively.

The deep learning-based customised backbone video detection architecture Li et al[2] propose may more precisely depict the success of video detection in trials. When testing recognition of untrained rice movies, the proprietary backbone system outperformed the VGG16, ResNet50, ResNet101, and YOLOv3 backbone systems. Rice sheath blight and rice stem borer signs were detected with exceptional sensitivity according to the unique DCNN architecture, such as wilting leaves. Also employed was a detection rate of 30 frames per second (FPS).

To address the issue of conventional convolutional neural networks' poor segmentation accuracy in images of crop disease leaves, Wang et al. [3] modified a standard VGG16 model to create a regional disease detection network (RD-net), replacing the fully linked layer with a global pooling layer. A regional segmentation network (RS-net) was created based on the Encoder-Decoder model structure, and the multi-scale convolution kernel was utilised to enhance the original convolution kernel's local receptive field and precisely segment the lesion area. The datasets of the cucumber target spot disease, cucumber brown spot, wheat stripe rust, and anthracnose, as well as corn leaf spot and corn round spot, were field photographed and subjected to segmentation tests. The recall rate was 78.31% while the segmentation accuracy was 87.04%. The single picture segmentation time was 0.23 seconds, and the total evaluation index value was 88.22 percent.

Ozguven and Adem [4] updated the Faster R-CNN to create a system for automatically detecting and recognising leaf spot disease for sugar beet disease, there are three tiers of seriousness (mild, moderate, and severe).The newly developed Faster R-CNN outperforms the existing Faster R-92.89 CNN with an accuracy of 95.48%.

Yu et al. [5] To address the problem of the classification model's insufficient accuracy in ranking the harmfulness of insect and disease attacks on crops,To do this, they propose a new version of ResNet50 (CDCNNv2) and combine it with deep transfer learning to create a classification scheme for the severity of agricultural illnesses & insect infestation. The system performs a range of auxiliary tasks, such as completely automated real-time crop pest and disease detection, management and prevention suggestions, and medicine recommendations.

The WEB application was finished when Li et al. [6] developed the PARNet model by fusing the focus mechanism that makes use of leftover data. The platform's average accuracy for five illnesses affecting tomato leaves was 96.84%, which is rather remarkable. When compared to other vehicles in its class, it was 2.25 to 11.58 percent greater (VGG16, ResNet50, and SENet).

For the purpose of recognising ginger illness, Jiang et al. developed a convolutional neural network system used data from four distinct natural environments to classify ginger diseases [7].They improved upon the standard LeNet-5 network's convolutional neural network architecture. The diagnostic accuracy for four distinct ginger diseases was 96%.

Using transfer learning and the Faster R-CNN, Zhou [8] discovered five unique apple leaf diseases and created an Android-based system to diagnose them. For illnesses of apple leaves, the detection method's average identification accuracy was 76.55 percent.

Using a mobile phone and the MobileNet network, Liu et al. found an average identification accuracy of 87.5% for six different types of sick grape leaves collected in the field, with an average computation time of 134 ms per picture.

Esgario et al. [10]developed a method using the ResNet50 architecture to identify and assess the impact of biological agents on coffee leaf stress. The algorithm successfully classified biological stress on coffee leaves with a 95.24 percent accuracy rate and predicted the severity with an 86.51 percent accuracy rate.

C. SSD Network

The SSD algorithm model, which was also shown with the YOLO series, performs one-stage real-time target detection. By using VGG as the primary tool for feature extraction, SSD takes the idea of one-stage regression prediction from the YOLO series and combines it with the Anchor Box method from the Faster RCNN. Six progressively smaller feature layers are retrieved from the deepest to the shallowest layer as the features for the regression prediction. The benefit of SSD is that it can significantly speed up algorithmic operations while preserving detection accuracy. It is also taken into consideration to identify both big and minor targets. The organisation of the SSD backbone network is depicted in Figure 2.

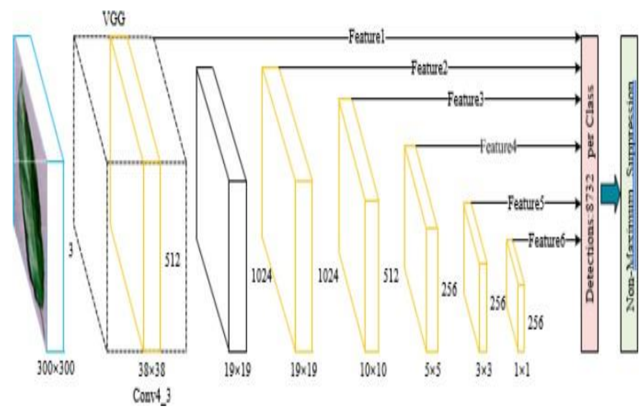

Fig. 2.

Smooth L1 for regression and log loss for classification are both part of SSD's loss function. Additionally, it regulates the proportion of positive to negative data, which may facilitate quicker optimization and more stable training outcomes. All classification and regression failures are added together to form the loss function. N is the sum of the default boxes that match their Ground Truth equivalents. You may adjust the ratio of confidence loss to location loss using this. Assume a value of 1 by default. The loss of location information is a common smooth L1 loss, whereas the loss of trust is a common soft - max loss.

Due to the use of complete convolution for direct regression prediction and the removal of candidate frame generation, the SSD network is now significantly better at detecting things. But there are rare times when the accuracy of identification falls short as to what we expect. SSD will miss and make errors when the surface features of two leaves are identical and whenever two leaves are hard to tell apart, which happens often when leaf disease is being found. So, SSD needs to be improved so that it can better identify features.

D. Squeeze-and-Excitation SSD Single Network

Well with supporting structure "Squeeze- and Excitation (SE)" module, that changes the function regression coefficients of each channel and the internal interdependence's between channels, Se Block [35] concentrates on the connection between channels and can expressly model the interdependence's for both feature channels. In Figure 3, you can see how the Se Block components interact.At first, the feature map's spatial dimension is reduced, and each of the map's two-dimensional feature channels is transformed into a real number representing some fraction of the world's perceptual space. Input feature channels map 1:1 to output dimensions. The importance of the each feature channel then is shown by a weight that would be calculated for each feature channel based on the relationship between both the feature channels.In the next step of the propagation process, the initial features are re-calibrated by multiplying by the channel weights.

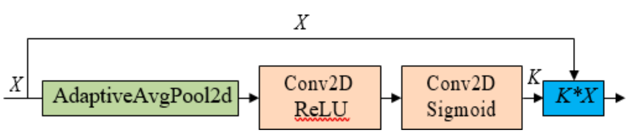

Fig. 3.

The research builds on top of the previous six beneficial feature layers by adding a module based on a Se Block focus mechanism that is employed in a regression prediction model based on an SSD model. This is done to improve the SSD model's ability to extract features and pay more attention to the most important feature layers. The dimension of the channel is used to change the size of the feature layers. Figure 3 shows how the Se SSD network is put together.

E. Experimental Environment

A dataset of 3000 plant leaves was used in this study's deep neural network, which also used transfer learning. Both the types of leaf organisms and the severity of leaf disease are recognised by the output data prediction window. On an HP laptop with an i7 9th Gen, an NVIDIA Ge-Force GTX 1650 graphics card, and 16GB RAM, the tests were conducted. The deep learning platform we employ is called Tensorflow.

After much deliberation, we settled on the PlantVillage dataset [36] because it has a lot of disease species and a lot of leaf species. In this study, we utilise Labelimg to annotate the dataset and get VOC-formatted training data. Labelimg's simplicity is appreciated by those working with both label files (stored as xml files) and image files (stored as jpg files). The 3000 photos in the experiment's dataset are divided into five main groups: chilli, potatoes, strawberries, and tomatoes. The severity of leaf disease is used to divide each main category into three subcategories: better and healthier, general, and severe. There are 15 subgroups listed, and the size of the picture is about 255x470x3. Over the whole dataset, the split between test and train and validation data is 1:8:1. A schematic representation of the data set's construction is shown in Figure 4.

Four experiments were made so that the improved algorithm could be tested more thoroughly. Se SSD with a channel

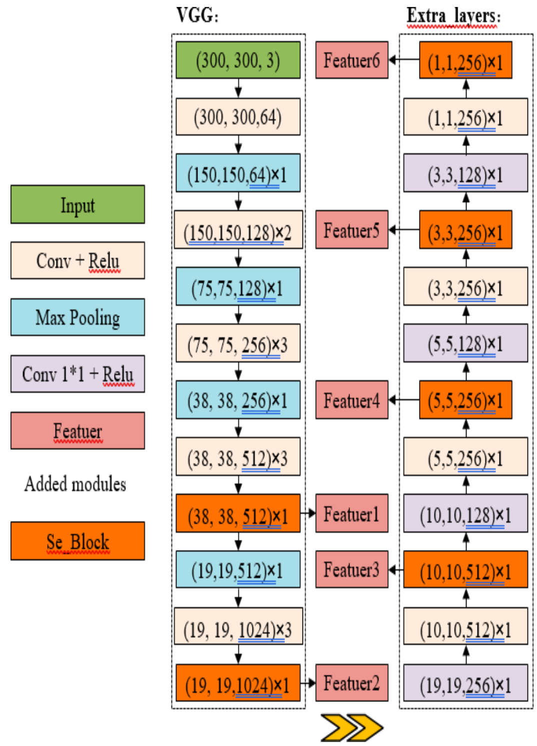

Fig. 4.

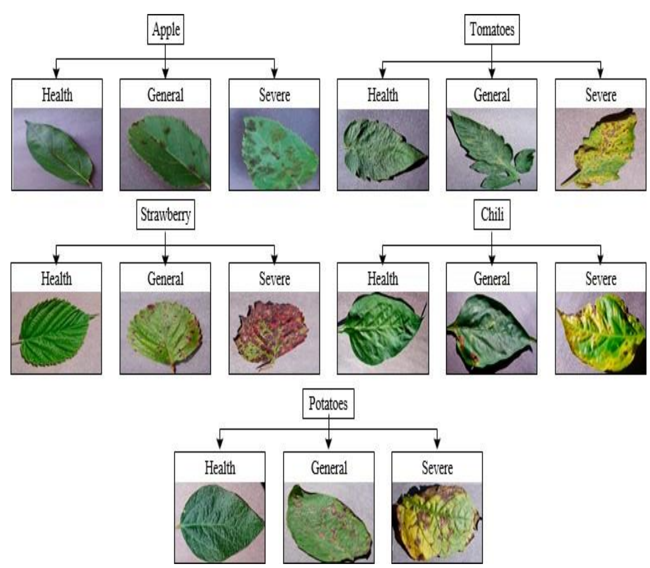

Fig. 5.

learning algorithm added at the end of the feature based network, In the first experiment, we train a Se SSD network that includes a Se Block channel attention mechanism and then evaluate its performance in locating plant leaves. Each of the four studies, 1500 random photos were used. The studies were trained using 15,000 sets of plant leaves. The experimental studies followed the experimental flow shown in Figure 5,

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which is a pattern of experiment, comparison, optimization, and experiment.This was carried out so that the model's mean accuracy (mAP) could be determined and compared to that of other models.

F. Performance Evaluation Metrics

By holding steady some of the network layer weights, eight images were used to train each batch over the first 50 epochs. The complete network was trained using data from the preceding 50 epochs, after which the frozen layers were thawed. The original learning rate of 5104 increased to 104 after being unfrozen. The model's settings were adjusted to perfection. In Figure 6, the vertical coordinate represents the loss value at the conclusion of training for each Epoch, while the horizontal coordinate represents the total number of training epochs. Different improvement algorithms are indicated by different line shapes.As the number of iterations rises, the model's loss value falls. Around 90–100 Epoch, the loss numbers in the training log progressively stop changing.

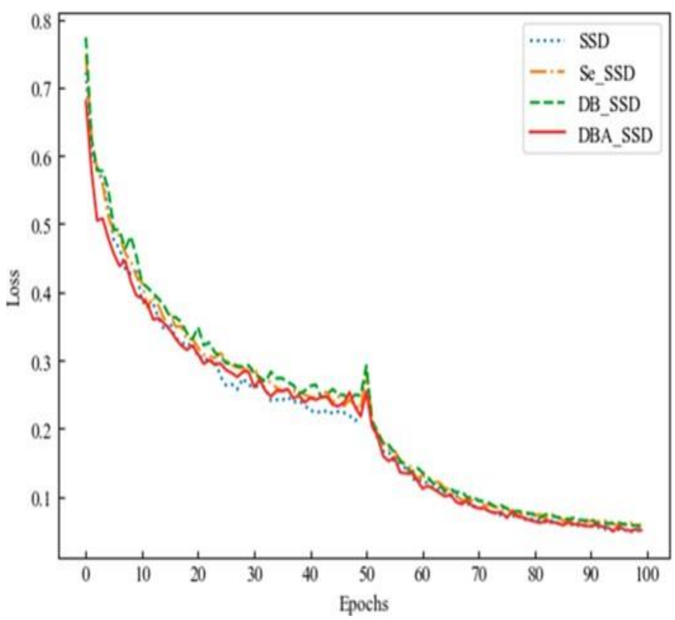

Fig. 6.

Se_SSD, on the other hand, has the highest accuracy as it contains a channel attention mechanism that speeds up network training. This forces the network to focus on informative channels for feature learning. The comparison of his SSD and the enhanced system for illness prediction in various kinds of fruits and vegetables is shown in Fig. 7. Se_SSD's prediction accuracy is relatively high among most categories, with Se_SSD's mAP value of 90.77%, while SSD's mAP value of his is 89.96 %. Increase the input plane from he 3232 pixels to he 600600 pixels.

Observe further the experimental results' data distribution in Figure 8. Points on the triangle indicate the mean, the thin solid line in the centre of the rectangle represents the median, and the horizontal coordinates reflect the various kinds

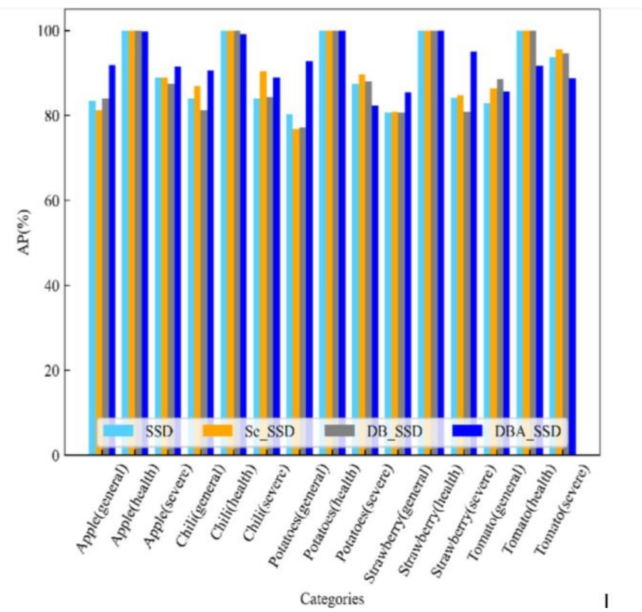

Fig. 7.

of enhanced algorithms. The distribution of anticipated AP values for the 15 categories is represented by the vertical coordinates. Figure 12 shows that among the four methods SSD, Se SSD, the DBA's accuracy in SSD prediction is more focused.. Additionally, the mean and median are the greatest. The SeSSD technique outperforms other improved algorithms in terms of performance.

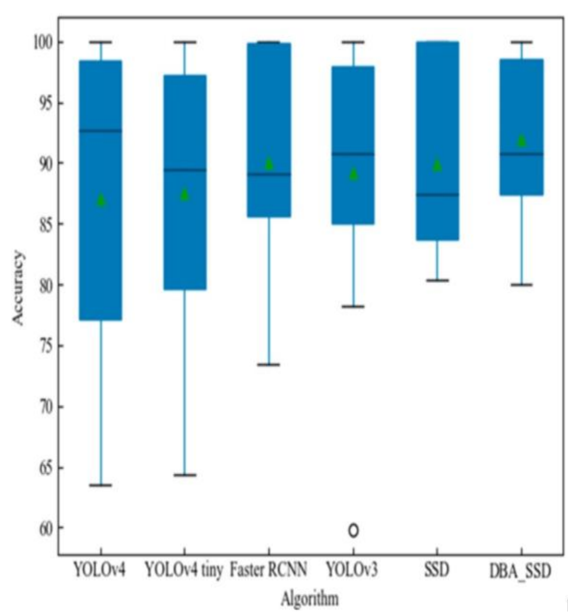

Fig. 8.

G. Conclusion

In this paper we have tried to compare various deep learning algorithms and provide a review of the research work which is done recently in plant leaf disease detection. If sufficient data is available for training, then these techniques will be very useful in recognizing plant diseases with higher accuracy. Collecting large datasets and performing data pre-processing techniques such as data augmentation and data annotation is also very important for the model to achieve high accuracy.

There are few inadequacies in the model. Most of the deep learning architecture work very well on their datasets but are not very efficient in accurate prediction on other datasets. The model is very poor in terms of robustness, so better model needs to develop in the future which can adapt and are efficient in adapting to various different types of disease datasets.In few researches we have discussed the, the size of the datasets is quite large but it was taken in the laboratory. It is anticipated to take the diseased leaf in real time conditions

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