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A REVIEW OF EXISTING DISEASE DETECTION TECHNIQUES IN INFECTED PLANT LEAVES

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Abstract: Agriculture is actually a basis of economy and agricultural production. It is an important factor for economic development not only in India but almost throughout the world. As such, the yield factor and also quality and quantity of agricultural production are obviously playing very crucial part in the development of economy. Over the years, plant diseases and pests have become a very important determining factor for such yields because such diseases in plants stand as a major threat and hindrance in the way of higher yield or production in agriculture sector.

Hence, it becomes the prime task to properly monitor the plants from the very initial stage and detect the diseases thoroughly and find out the ways and means for controlling or removing those plants diseases, pests etc for obtaining better rate of growth of production and minimum damages of crops.

It is a fact that traditional methods are generally followed for motoring of plants as well as detection of plant diseases in particular. This process is no doubt very much time consuming, expensive and requires involvement of lot of expertise too. Hence, there is a need to speed up the process and automate the system of plant disease detection. It may be rather useful to develop an effective disease detection system by using image processing techniques or machine vision equipments based on deep learning method as well as feature extraction and classification tools. Different researchers have developed and applied various techniques for plant disease and pest detection and the potential of those methods has been reviewed in current trends and possible process of using computer vision and advanced image processing technique for detection of plant diseases.

INTRODUCTION

Deep learning is a branch of machine learning which is completely based on artificial neural networks, deep learning is also a kind of mimic of human brain because the neural network can mimic the human brain. It's on hype nowadays because earlier we had lot of data and not enough processing power. A formal definition of deep learning is- neurons Deep learning is a particular kind of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones. In human brain approximately there are 100 billion neurons, all together this is a picture of an individual neuron and each neuron is connected through thousands of their neighbors. The question here is how it recreates these neurons in a computer. So, it creates an artificial structure called an artificial neural net where we have nodes or neurons. It has some neurons for input value and some for output value and in between, there may be lots of neurons interconnected in the hidden layer.

The matter of detection of plant disease is not only an art but also a science and a very interesting field of study especially in our country. In-fact, the process of diagnosis or in other words, recognition of symptoms, signs etc. requires very intuitive judgments and use of scientific methods. India being basically an agricultural economy where about 70% of total population directly or indirectly depends on agriculture. Naturally, disease on plants play a crucial role in damaging crops and thus reducing agricultural products both in terms of quality and quantity rather significantly. The plant diseases are generally bacteria, viruses and fungus related diseases that not only restrict the growth of the plants but also destroy the crops.

Any study on plant diseases covers the areas of studying visually observable aspects of the plants, monitoring of different diseases as well as their remedies. In early days, mostly the tasks of monitoring, detecting as well as analyzing the leaf and plant diseases need to be undertaken manually exclusively by persons who are experts in these fields. As such, these required huge volume of work, long processing time and considerable expenses. In-fact, accurate detection and proper classification of leaf diseases can prevent it and minimize agricultural losses. Different plant leaf bears different types of diseases and there are a list of methods needs to be applied for detecting plant leaf diseases of various natures. For an example, image processing technique may be used for detection of plant leaf diseases.

In this research work, different methods used for detection of leaf diseases have been explained and compared. Section 2 describes the basic concept of the symptoms of leaf diseases, Section 3 shows literature reviews, Section 4 highlights the key challenges and Section 4 is the concluding part of the study.

LEAF DISEASES AND SYMPTOMS

The leaf disease are mainly caused by bacteria, viruses and fungal and symptom of a plant disease is quite visible or having rather visible effect on the plant itself. Actually, symptoms may include a clear detectable change in color, shape and (or) function of the plant as it generally responds to the pathogen. It should be kept in mind that very low growth of plants reveals some sort of symptom of disease. Different disease symptoms have been mentioned below:

a) Viral Disease Symptoms

   Among all the diseases of plant leaf, these diseases which are caused by viruses are most difficult for diagnosis. Since no signs of tell-tale are produced and observed due to viruses, it is rather difficult to detect readily and mostly it is confused with cases like deficiencies of nutrients as well as herbicide injuries. The common carriers of viral led diseases are Aphids, Leafhoppers, whiteflies, cucumber beetles insects etc. For example, yellow or green stripes and spots on foliage on the plant leaves are normal signs or symptoms of mosaic virus attack and the leaves also get wrinkled, curled and growth gets stunted.

b) Bacterial Disease Symptoms

Many serious diseases of vegetables are caused by pathogenic bacteria. Such bacteria don't generally penetrate into the plant tissues directly but enter through wounds or natural openings of the plants. Wounds are caused by insects and other pathogens that damage the plant leaf. It is also caused by the tools that are used for pruning and picking operations.

Bacterial diseases are featured by tiny pale green spots which soon and easily come into view as water soaked one. Moreover, the lesions get enlarged and then disappear leaving dead dry spots on the leaves of the plants.

c) Fungal Disease Symptoms

The main symptom of plant leaf diseases caused by fungus is the late blight that is generally visible on the lower, older leaves in the form of gray-green spots, water-soaked. With the gradual maturity of fungal disease, these spots become darker and then white fungal growth is formed on the lower sides of the plant leaves.

LITERATURE REVIEW

Jasim & Tuwaijari (2020)have given a system to classify and detect plant leaf diseases using convolution neural network with training and testing accuracy were 98.29% and 98.029% for all datasets. This work is related to specific types of plants i.e. tomatoes, pepper, and potatoes from plant village dataset which contains 20636 images of plants and 15 classes of plant leaf diseases are classified.

Nagaraju & Chawla(2019) described automatic identification of diseases through hyperspectral images using deep learning models. Also identified some **challenging issues such as**: Adapting new computer vision technologies are not enough standard for automatic disease detection, Environmental conditions while acquiring the input data can also impact on analyzing the disease classification, Disease symptoms are not well defined and making challenging to set healthy and diseased portions and Visual similarities in the disease symptoms can force the existing methods to rely on variations to discriminate.

Saleem *et al.* (2019) described a review of deep learning models used to identify various plant diseases. Some of the **research gaps** are: Using hyperspectral/multispectral imaging with efficient DL architectures plant diseases can be detected in early stage. DL models should be improved/modified to detect and classify diseases. An empirical comprehensive study is needed to detect the plant diseases, like the classes and size of datasets, learning rate and illumination etc.

Amara *et al*. (2017) proposed a deep learning based approach to classify banana leaf diseases such as banana sigatoka and banana speckle using LeNet architecture of Convolutional Neural Network. The result was effective in terms of illumination, complex background,different resolution, pose, size and orientation of real images.

Arsenovic *et al.*(2019) presented the current limitations and shortcomings of existing plant disease detection models. They provided a new dataset of 79265 images of leaf in real environment. Researchers proposed a novel two – stage neural network based architecture for plant disease classification with 93.67% accuracy.

Guo *et al.* (2020) proposed a deep learning based model to detect plant diseases (i.e. black rot, bacterial plaque and rust) which improves accuracy, generality and training efficiency. This model mainly emphasized on usage of region proposal network(RPN) on diseased leaves dataset to recognize and localizes the leaves; then extracted features through Chan – Vese (CV) algorithm. The final accuracy of disease detection using transfer learning model was 83.57%.

Hruska *et al.* (2018) presented machine learning classification methods on hyperspectral data processing for agricultural applications. This study advocated that hyperspectral sensors are currently available for unmanned aerial vehicle through which high volume of data can be generated and also proved to be effective in producing accurate results.

Bai *et al.* (2017) proposed and improved Fuzzy C-means (FCM) algorithm for extraction of cucumber leaf spot disease against a complex background. This algorithm is based on neighbor hood gray scale information that improves the noise - filtering and overcomes the under use of image pixel spatial information by FCM.

Barbedo (2016) provided an analysis of important challenges such as: presence of complex backgrounds that could not be easily separated, boundaries of the symptoms often are not well defined, uncontrolled capture conditions may present characteristics that make the image analysis more difficult etc. The author also proposed possible solutions to overcome some of the challenges.

Brahimi*et al.* (2017) used large dataset containing 14828 images of tomato leaves infected with nine diseases. CNN was used as learning algorithm that automatically extracted the features from raw images and achieved 99.18% accuracy. Comparison was also presented between the results of deep learning models (AlexNet and GoogleNet) and shallow models based on hand crafted features.

Cruz *et al.* (2017) proposed a vision based approach for disease detection of Olive Quick Decline Sindrome (OQDS) on leaves of Oleaeuropaea L. infected by Xylella fastidiosa with 98.6% accuracy.The proposed algorithm was based on Transfer learning, the application of deep learning, deals with lack of lack of sufficient training examples using plant village dataset whereas their previous work used pre-trained AlexNet and GoogLeNet network.

DeChant *et al.* (2017) demonstrated a system to identify northern leaf blight (NLB) lesions of maize plants through images with 96.7% accuracy. In this approach, computational pipeline of Convolutional neural networks (CNNs) was used.

Durmus *et al.* (2017)performed the disease detection on the leaves of tomato plants by using deep learning models. The work was implemented through algorithm coded robots in real time or from close up photographs of leaves by fabricated sensors in green house. In this work, AlexNet and SqueezeNet architectures were tested with accuracy of 95.65% and 94.3% respectively. It was also found that size of SqueezeNet model was 80 times smaller than AlexNet model.

Ferentinos (2018) developed convolutional neural network models for disease detection in plants using simple leaves images of healthy and diseased plants. Model training was done with 87,848 numbers of images from open database using 25 different plants in 58 unique classes of [plant, disease] combinations. After training several model architectures, 99.53% success rate was achieved.

Fuentes *et al.* (2017) proposed a deep learning detector for diseases and pests detection in tomato plants using images captured from camera with various resolutions. Total nine classes were targeted to identify and used three families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD). They used VGG net and Residual Network (ResNet) extractors for combining deep features. To increase the accuracy and reduce the false number of false positives during training, they proposed a method for class annotation and data augmentation.

SUMMARY OF LITERATURE REVIEW

S.No.	**Author**	**Sample**	**Findings**	**Used Architecture(CNN)**
1	Jasim & Tuwaijari (2020)	Plant Village dataset was used for 20636 images of plants and 15 classes of plant leaf diseases. Types of used plants were tomatoes, pepper, and potatoes.	The accuracy for training and testing with CNN was 98.29% and 98.029% respectively.	ConvNets
2	Nagaraju & Chawla(2019)	Hyperspectral images dataset.	He has done exhaustive literature review and identified various chanllenges.	NA
3	Saleem *et al.* (2019)		Discussed exhaustive review using hyperspectral/multispectral imaging so that platn diseases can be detected in early stage.	NA
4	Amara *et al*. (2017)	Real dataset of banana leaves of 3700 images. Out of these 1643 healthy leaves, 240 leaves of black sigatoka and 1817 images of black speckle.	Effective result in terms of illumination, complex background,different resolution, pose, size and orientation of real images.	LeNet
5	Arsenovic *et al*.(2019)	Training with PlantVillage datasetn and testing with PlantDisease dataset.	Proposed a novel two – stage neural network based architecture for plant disease classification with 93.67% accuracy. Also found a new dataset of 79265 images of leaf in real environment.	AlexNet, VGG-19, Inception version 3, DenseNet 201, ResNet 152

6	Guo *et al.* (2020)	1000 leaves from the plant photo bank of China (PPBC).	Used region proposal network(RPN) on diseased leaves dataset to recognize and localizes the leaves; then extracted features through Chan – Vese (CV) algorithm.The final accuracy of disease detection using transfer learning model was 83.57%.	VGG-16 & RPN algorithm
7	Hruska *et al.* (2018)	Remote sensed dataset i.e. Hyperspectral images of agriculture	Hyperspectral sensors are currently available for unmanned aerial vehicle through which high volume of data can be generated and also proved to be effective in producing accurate results.	NA (Survey Paper)
8	Bai et al. (2017)	129 cucumber disease images for vagetable disease database	Improves the noise - filtering and overcomes the underuse of image pixel spatialinformation by FCM.	Fuzzy C- means
9	Barbedo (2016)	Leaf analysis for segmentation under humidity, exposoure to sunlight, wind, temperature	With the help of digital images more trustworthy , more powerful and accurate image analysis can be done.	NA (Review)
10	Brahimi *et al.* (2017)	Dataset of 14828 images of tomato leaves infected with nine diseases	CNN automatically extracted the features from raw images and achieved 99.18% accuracy. Comparison was also presented between AlexNet ,GoogleNet and shallow models based on hand crafted features.	AlexNet, GoogLeNet
11	Cruz *et al.* (2017)	PlantVillage dataset of 100 healthy leaves, 99 X. fastidiosa-positive leaves and 100 X. fastidiosa-negative leaves	True positive rate of Olive Quick Decline Syndrome (OQDS) detection on leaves of Olea europaea L. infected by Xylella fastidiosa is 98.60 ± 1.47% in testing. Also proposed algorithm is based on Transfer learning, deals with lack of sufficient training examples.	Convolutional neural network trained with the stochastic gradient descent method.
12	DeChant *et al.* (2017)	Self captured 1796 leaf images (infected and non-infected) of maize plant through Sony a6000 camera at 78 dpi.	The accuracy of identification of Nothern leaf blight (NLB) lesions in maize plant using CNN is 96.7%.	Computational pipeline of CNN
13	Durmus et al. (2017)	PlantVillage dataset for tomato leaf images.	Ten different classes of tomato plant diseases were used. As per result AlexNet showed better results than SqueezeNet. Accuracy results are based on Caffe test model.	AlexNet and SqueezeNet

14	Ferentinos (2018)	Open database of 87,848 images that contains 25 different plants in a set of 58 distinct classes of plant-disease combinations, including healthy plants.	During testing dataset for the identification for [plant, disease] classes using different CNN models, the highest success rate was achieved by the VGG and AlexNetOWTBn architectures. These two models were further trained using original images , the final highest classification percentage of 99.53% was achieved by VGG model, which was the final model for plant disease detection.	AlexNetOWTBn and VGG
15	Fuentes et al. (2017)	Plant dataset of 5000 images under different environment for tomato disease	Deep learning architecture with feature extractor (proposed here) is able to successfully recognize nine different categories of diseases and pests, including complex intra and inter - class variations. Also technique based data annotation and augmentation results in better performance.	Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN) and Single Shot Multibox Detector (SSD)
16	Mindhe et al. (2020)	Plant Village dataset of 54,444 images with PyTorch as deep learning platform.	Using ResNet 34 neural network, the achieved accuracy is 96.21%. This model is capable of detecting 14 crop species and 26 common diseases. Along with UI app , a web application is also develped for easy accessibility.	ResNet 34
17	Kawasaki et al. (2015)	800 cucumber leaf images	The average accuracy for classificaiton of cucumber into diseased and non-diseased classes is 94.9% using CNN based model.	Caffe framework of CNN
18	Lu et al. (2017)	Dataset of 500 images of healthy and diseased leaves of rice and stems.	Total 10 common rice diseases are identified with 95.48% accuracy.	Multistage CNNs configuration
19	Ferreira et al. (2017)	Database of approx 15000 images of the soil , soybean, broadleaf and grass weeds. Images were taken from professional drone.	Using ConvNets, the achieved accuracy was above 98% in detection of broadleaf and grassweeds in relation to soybean and soil.	CaffeNet architecture for training and ConvNets for detection.
20	Oppenheim & Shani (2017)	2465 images of potatoes	Using Deep Convolutional Neural Network algorithm , the potato diaseases classified in four diseases classes and a healthy potato class. The accuracy of classification ranges from 83% to 96% as per the trained models.	Visual Geometry Group (VGG) architecture
21	Sladojevic et al. (2016)	4483 self acquired filed images of apple , pear , grape, cherry, peach	Accuracy (96.3%)	CaffeNet (AlexNet)
22	Barbedo JGA (2019)	1575 self-acquired field images	Accuracy (94%)	GoogLeNet
23	Nachtigall et al. (2016)	1450 self-acquired lab images of apple	Accuracy (96.6%)	AlexNet

24	Liu et al. (2018)	1053 self-acquired lab images of apple leaf	Accuracy (97.62%)	Custom CNN (AlexNet precursor with cascade inception)
25	Brahimi et al. (2018)	PlantVillage dataset for 14 crops	Accuracy (99.76%)	AlexNet, DenseNet169, Inceptionv3, ResNet34, SqueezeNet, VGG13
26	Mohanty et al. (2016)	PlantVillage dataset for 14 crops and 26 diseases	F1-score (0.9934), Precision (0.9935), Recall (0.9935), Accuracy (0.9935)	AlexNet, GoogLeNet
27	Ozguven et al. (2018)	155 self-acquired images (38 healthy, 20 mild, 35 severe, 62 mixed mild and severe infection of sugar beet	Sensitivity (95.48%), Specificity (95.48%), Accuracy (95.48%)	Faster R-CNN (modified)
28	Elhassouny et al. (2019)	Plant Village dataset for tomato	Accuracy (90.3%)	MobileNets
29	Castelao et al. (2019)	300 high resolution field images divided into 3000 superpixel images of soyabean leaves	Accuracy (99.04%), Learning error (0.049	Inceptionv3, ResNet-50, VGG19, Xception
30	Fuentes et al. (2018)	8927 self-acquired images representing 9 anomalies and one class for background of tomato leaves	mAP (96%)	Faster R-CNN with VGG16 feature extractor
31	Jiang et al. (2019)	2029 lab and field images of apple leaves.	mAP (78.8%) Detection speed (23.13 FPS)	INAR-SSD
32	Wang et al. (2017)	PlantVillage (healthy & black rot images) of apple	Accuracy (90.4%)	Custom CNN
33	Wallelign et al. (2018)	PlantVillage dataset of soyabean plant	Accuracy (99.21%), Recall (0.99), Precision (0.99) F1-Score (0.99	Custom CNN

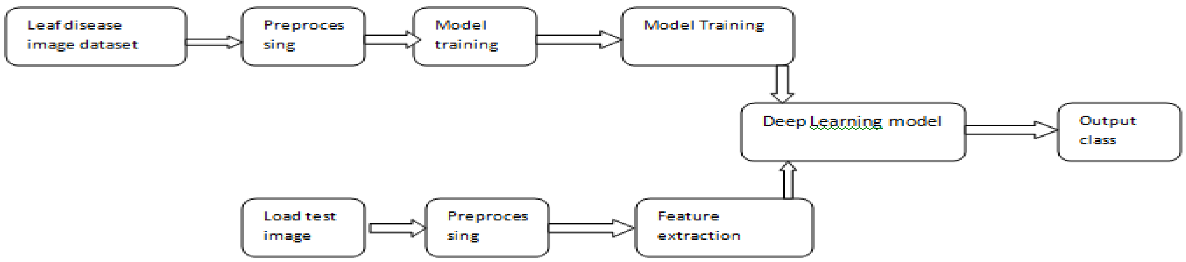
Mindhe *et al.* (2020) created an application for easily detection of plant diseases using deep learning so that everyone can use it. The neural network model was built for detecting 14 crop species and 26 common diseases. ResNet 34 of neural network was used with accuracy of 96.21%.

Kawasaki et al. (2015) presented a novel plant disease detection model based on Convolutional neural network. For training 800 cucumber leaf images were used. Using 4 fold cross validation strategy, this model classified into disease classes and non-disease classes with 94.9% accuracy.

Lu et al. (2017) proposed a novel approach for disease identification in leaves or stems of rice plants using deep Convolutional neural network (CNNs). The dataset of 500 images of healthy or diseased rice plants were used for training CNN to identify 10 common rice diseases. Using 10-fold cross-validation, this model achieved 95.48% accuracy which is more effective and accurate than Convolutional machine learning model.

Ferreira et al. (2017) demonstrated weed detection in soybean crops using Convolutional neural network. As weeds are undesirable plants that resist the growth of soybean plants, so removing these is necessary. Initially image dataset was created using professional drone to collect fifteen thousand images of the soil, saybean, grass weeds and broad leafs. CaffeNet architecture was used for the training of neural network. For comparing the results of ConvNets, support vector machines, AdaBoost and Random Forest were used with shape, color and texture feature extraction techniques. For the detection of broadleaf and grass weeds w.r.to soil and soybean using ConvNets the achieved accuracy was 98%.

Oppenheim & Shani (2017) presented an algorithm for potato disease classification using deep Convolutional neural network.After training the algorithm, it classifies the tubers into five classes such as four diseased classes and a healthy potato class. The accuracy varies as per Train – Test set division. The highest accuracy achieved 96.85% with 90% train – 10% test model and lowest 83.21% with 10% train – 90% test model.



Proposed Architecture of Plant disease prediction using Deep Learning model

Challenges and future trends: A study on the major challenge or problems faced in the process of detection of plant diseases reveal the fact that many researchers have expresses different views on this particular aspect.

Khitthuk *et al.*, in 2018 proposed analysis of different features of the plants and diagnosis of plant leaf diseases through application of varied statistics, classification process as well as use of co-occurrence matrix and artificial intelligence technology.

Vaishnnave *et al.*, in 2019, emphasized on early detection of plant leaf disease (mainly for groundnut plant leaves) by using KNN classifier method.

Jhuria *et al.*, in 2013, proposed image processing and also use of K-mean and Random forest classifier methods for cluster information and classification of different types of fungal diseases like Bacterial blight, Carcospora Leaf spot etc. respectively.

Dhakate and Ingole in 2015, proposed use of Neural Network as well as K-mean clustering methods basically for detection of plant diseases in case of Pomegranate fruit plants through cluster formation of the images that have been used.

Anand *et al.* in 2016, emphasized on pre- processing of plant leave images and detection of diseases in plant leaf (mainly in case of Brinjal plant) by means of using K-mean clustering, image processing techniques and co-occurance methods. They focused largely on use of various parameters for identification of area, diameter, perimeter and centroid etc for determination leaves.

Islam *et al*. in 2017 advocated application of Machine Learning, SVM methods along with image processing system manly for detecting presence of diseases in Potato plant leaves mainly at the early stage.

It was widely accepted by most of the researchers that for the purpose of reducing the quantum of losses the yields of output of agricultural productions, a very important and useful step involves detection of diseases in the plants at an early stage. In this context, Gaikwad and Musande in 2017, emphasized on developing methods for very early detection of plant diseases (mainly wheat plants) by using image processing as well as K-mean clustering methods. Emphasis was given on extraction of basic features involving texture, colour and shape and use of Neural Network classification method for detecting presence of fungal diseases on plants and plant leaves.

It has been observed that the basic problem or main challenge is this approach relates to practical use of sensors in both present and future stages. Padol and Jadav in 2016, recommended use of SVM classification techniques for plant diseases (mainly for Grape leaf diseases) to be performed in training and testing phases.

The very need for developing and effective system for early detection of fungal diseases (mainly for cotton plants) was felt due to huge loss in case of yield of cotton crop caused by plant diseases. In this context, Bhimte and Thool in 2018, proposed use of image processing system along with Support Vector Machine (SVM) classifier for rather early detection of disease on leaves of cotton plants.

Further, Pawar and Jadav in 2017, proposed use of a novel method for the purpose of identification of diseases and its classification based on application of K-mean clustering algorithm and KNN method specially for Pomegranate plant leaves through extraction of features like colour, texture, edges, morphology etc.

Apart from the above mentioned research studies and different views of the researchers towards overcoming the challenges and (or) problems faced, it may be worth mentioning that compared to the use of traditional methods like image processing, Deep learning algorithm has no doubt provided much better results in the task of detection of plant diseases and pests but this method too have higher level of computational complexities.

Conclusion

Basically, detection of plant diseases involves three different phases like feature extraction, segmentation and classification. In most of the cases, different machine learning techniques have been applied for feature extraction and classification along with deep learning methods have been widely used for segmentation and prediction of diseases accurately.

Though these techniques provided much better results in the task of detecting plant diseases compared to the traditional methods like image processing but these methods are also having limitations such as computational complexity, higher execution time and costs etc.

As such, there is a great need for developing a more effective and efficient method for detection of plant diseases at early stage with less execution time and expenses too.

Although in recent times, the plant diseases and pests detection technology is developing very rapidly and infact it is moving from the area of academic research to wide application in agricultural sector but still there remains certain distance from mature and effective application in real natural environment altogether.

Hence, in future time much more work is required to be done in this field for solving the existing problems and at the same time enhancing the present work and developing more efficient and robust system for early and automatic tracing and detection of such plant diseases which as a matter of fact can very well be extended for identifying all possible diseases related to plants and plant leaves. There is obviously enough scope for extending future studies and developing future work in this particular field of interest.

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