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Plant Leaf Disease Detection using Image Processing and Deep Learning

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Abstract: *Agriculture is regarded as the backbone of the Indian economy, with 70% of the people employed in agriculture and related industries. Therefore, it is crucial that we make an effort to support the health of plants. Plant diseases are one of the issues causing plants' health to deteriorate. It is difficult to diagnose these illnesses by sight alone. The goal of this project is to identify plant diseases earlier and more conveniently by employing a convolutional neural network. This paper presents an overview of different types of classification techniques used for detecting diseases in plants.*

Keywords: Plant Disease, Detecting Disease, Convolutional Neural Network, Machine Learning, Deep Learning, Classification, AlexNet, ResNet

I. INTRODUCTION

In India, agriculture is of utmost importance as seventy percent of the population are employed in related sectors. It is the basis of food and nutrition, a foundation for human existence. Diseases in plants impair its health as well as a negative effect on the economy generated by it. The existing method for plant disease detection is simply naked eye observation by experts. For doing so, a large team of experts as well as continuous monitoring is required, which is costly for large farms. The aim of this system is to ease the process of identifying and detecting the diseases in plants by analyzing spots on its leaves. For this project we will be using the image dataset of 12 economically and environmentally beneficial plants of India, namely Mango, Arjun, Alstonia Scholaris, Guava, Jamun, Jatropha, Pongamia Pinnata, Pomegranate, Lemon, and Chinar. For detection, we have used the input images and applied deep learning techniques to obtain maximum accuracy. The following section will talk about classification of various diseases in plants

II. TYPES OF PLANT DISEASES

One of the major challenges is to accurately analyze the spot and not mistake a certain innocuous spot as a disease. Therefore it is essential that we understood what certain spots and patches meant. Fig. 1-6 illustrates the different types of patches/spots visible when a plant is diseased. [6]

Fig.1 Black Spot on Rose

Black spot is one of the most commonly found spots on roses and some other garden plants. It mostly occurs when the leaves are left wet for more than 6 hours or more.

Fig.2 Fungal Leaf Spots on Pepper

Fungal Leaf spot diseases can be found in plants that are indoor as well as outdoor. As the spots keep on getting enlarged, they start to appear like blotches.

Fig.3(a) Powdery Mildew on Grape leaves **Fig.3(b)** Powdery Mildew on Grapes

Powdery Mildew type of fungal disease is easy to identify with the white powder-like substance on the upper leaf surface. But it can even occur on the fruit or the stem of the plant.

Fig.4 Downy Mildew on Sunflower **Fig.5** Blight on Potato

It is important to identify the nuances between Fig.3 Powdery Mildew and Fig.4 Downy Mildew. The latter is more closely related to algae and produces grayish fuzzy spores on the lower part of the leaf. Blight mostly affects potatoes and tomatoes. It is a wind borne disease and can spread rapidly. Therefore it is important to prevent blights. This disease killed a million people during the Ireland potato famine in 1845.

Fig.6 Canker on Citrus Plants

Canker looks like an open wound, some of them are lethal while others are benign. It mostly occurs on leaves that are subjected to cold weather, insects or drought conditions. The aforementioned types are the most common types of diseases affecting the important plants. However there are other kinds as well, namely mottle(Viral Diseases); Rust, Wilt, Rot (Fungal Disease), etc. In today's time when the population is growing rapidly and capricious weather changes are impacting the agricultural harvest, plant disease also adds to the poor production and quality of food. Thus, it becomes necessary to take firm steps toward identifying these beforehand.

II. LITERATURE SURVEY

Numerous studies have been conducted employing Deep Learning techniques to classify healthy and unhealthy plants based on images of their leaves.

For detection, Prof. Dhanashri. H. Gawali and Shivani K. Tichkule applied SVM Classifier for Soybean leaves, KNN on Cotton, PCA Morphological features on Wheat, and BPNN, K-means on grape leaves [1]. Aanis Ahmad, Dharmendra Saraswat, & AlyEl Gamala [2] have used a variety of plants collected from different datasets like PlantVillage, Digipathos, PlantDoc, RoCoLe etc. They have also studied various ways for image acquisition and have discussed various techniques for identification. By employing different techniques on different leaves and comparing accuracies, they have concluded the best algorithm for those specific plants. Aravindhan Venkataramanan, Deepak Kumar P Honakeri, & Pooja Agarwal [4] have used 32 thousand images of 8 different plants, and 8 different CNN classifiers are trained to identify each of these plants. They also used YOLOv3 Object Detector to suit the use-case and identify the leaf in the image. Mr. Ashish Nage, and Prof. V.R. Raut has also used CNN but a different way to pre-process the image dataset to remove the noise by following RGB to Gray Converter, Resizing the image, CLAHE , and Gaussian blur and finally applying CNN.

III. DATASET

For this project, we have chosen the plants that are economically important to India, in export and commercial sense. The dataset used is obtained from 'PlantVillage', a very common source for projects that use image dataset of plants, both healthy and diseased. We have implemented and trained our model using 13 different plants namely: Tomato, Grape, Orange, Soybean, Potato, Corn(Maize), Squash, Strawberry, Cherry, Raspberry, Peach, Apple, and Pepper Bell. Each of these is represented in the dataset and has images of its healthy state and diseased state. There are a total of 70,295 images. Here's the distribution of all images along with their class name:

Plant	Disease	Images
Tomato	Healthy	1926
	Late Blight	1851
	Early Blight	1920
	Septoria Leaf Spot	1745
	Yellow Leaf Curl	1961
	Mosaic Virus	1790
	Bacterial Spot	1702
	Target Spot	1827
	Leaf Mold	1882
	Spider Mite	1741
	Bacterial Spot	1702
Grape	Healthy	1692
	Leaf Blight	1722
	Black Rot	1888
	Black Measles	1920
Orange	Huanglongbing	2010
Soybean	Healthy	2022
	Black Rot	1888
Squash	Powdery Mildew	1736
Potato	Healthy	1824
Late	Blight	1939
Early	Blight	1939
Corn(Maize)	Healthy	1859
	Northern Leaf Blight	1908
	Gray Leaf Spot	1642
	Northern Leaf Blight	1908
	Common Rust	1907
Strawberry	Healthy	1824
	Leaf Scorch	1774

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Peach	Healthy	1728
	Bacterial Spot 1838	1838
Apple	Healthy	2008
	Apple Scab	2016
	Black Rot	1987
	Rust	1760
Blueberry	Healthy	1816
Raspberry	Healthy	1781
Cherry	Healthy	1826
	Powdery Mildew	1683
	Gray Leaf Spot	1642
	Northern Leaf Blight	1908
Pepper Bel	Healthy	1988
	Bacterial Spot	1913
	Apple Healthy	2008

Fig. 7(a) and (b) shows a sample of a healthy and diseased strawberry leaf from the dataset.

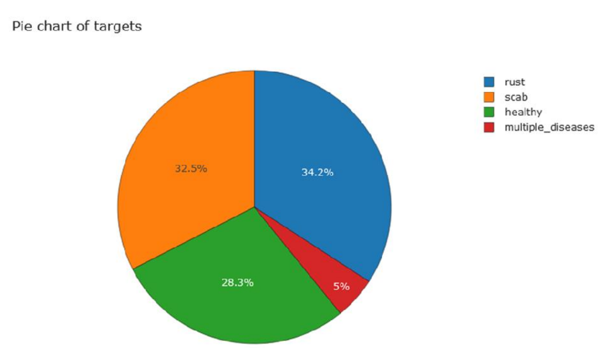
Fig.7(a) Healthy Strawberry

Fig. 7(b) Leaf Scorch in Strawberry

For preparation of second model, which will give generalized results, we have used another dataset which contains 4 types of classifications:

1. Healthy
2. Rust
3. Scab
4. Multiple Diseases

The dataset contains around 3600 images of leaves of different shapes and sizes, with a mixture of classes. The distribution can be seen as below.



V. METHODOLOGY

After preparing the dataset, followed the cleaning, resizing, and augmentation of the image dataset. Here, we zoomed in on the images and sheared. Basically, this step was essential in further stages of the project, wherein if an input image was not clicked in a similar fashion to the dataset, it could still accurately predict the plant as well as its disease.

In a practical environment, the input image cannot always be focused on the diseased leaf. Thus, it was crucial that we identified the leaf and removed the unnecessary background which would hasten the process of prediction. Thus, we used OpenCV Grabcut, which provides accurate foreground extraction and segmentation. It accepted the image in the dataset, and iteratively estimated colour distribution of background and foreground; constructed a Markov random field over background and foreground and finally applied a graph cut optimization to get the final segmentation. The final one will contain the image of the diseased plant on a black background.

Fig.8 Before and after applying Grabcut Algorithm

After processing our dataset completely, the next step involved training suitable models for an accurate prediction of diseases. We have used 3 models based on their precision and flexibility, the explanation of which follows:

5.1 Convolutional Neural Network (CNN)

A Convolutional Neural Network is a Deep Learning algorithm which is widely used for classification of images. After providing an input image, the algorithm allocates significance to the learnable parameters which are weights and the biases to the different aspects/objects in the image which in fact helps us to classify or separate the images from one other. A CNN has the ability to notice the spatial and temporal dependencies in an image with the help of different filters.

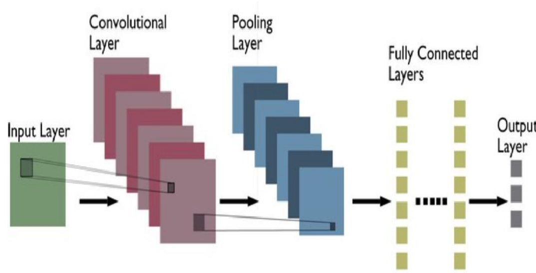


Fig.10 CNN architecture

5.2 AlexNet

CNN is hard to apply for images of high resolution. And the dataset we used in the project consists of high resolution images. AlexNet was thus chosen as the next model based on its capability of achieving high accuracies on challenging image datasets. The architecture of AlexNet consists of eight layers: five convolutional layers and three fully-connected layers. It also has special features like ReLU, Multiple GPUs and Overlapping Pooling

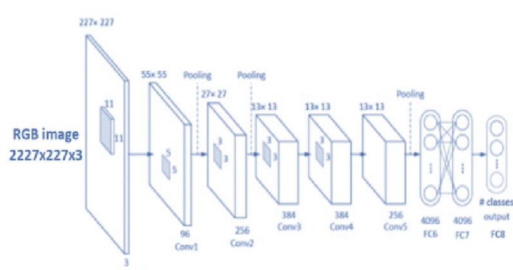


Fig.11 AlexNet architecture

5.3 ResNet

To overcome the drawbacks of VGG and go deeper without losing its generalization capabilities, we worked with ResNet. It solved the problem of "Vanishing Gradient"- when the network goes deeper, the loss function truncates to zero and thus results in a no learning stage. ResNet allows gradients to skip connections from forward layers to initial layers. The logic applied here is simple: the input of the first layer of the model is bypassed to the last layer and the network then predicts the function it was learning before with the input that was recently added to it.

$$f(x) + x = h(x)$$

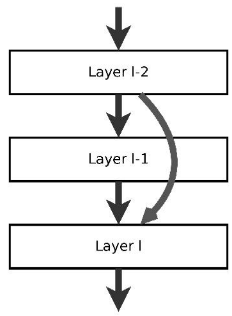


Fig.12 A very basic view of ResNet architecture

After training the models successfully, followed the development of the interface. We developed an app which allowed the users to take an input of the image by clicking an image or by uploading an image from the gallery. The front-end connected to our back-end model accurately identified the plant and its disease and displayed the same with the accuracy with which it was predicted.

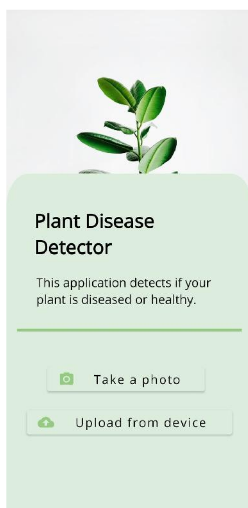


Fig.13(a) Front-end Interface: Accepting Image **Fig.13(b)** Front-end Interface: Displaying Result

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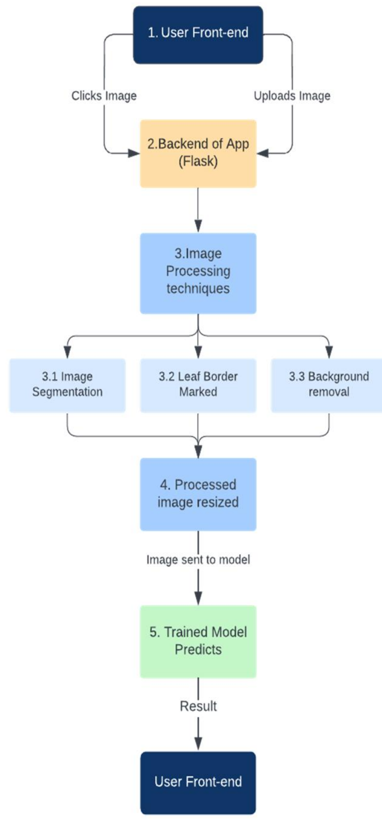

Fig.14 Pipeline Flowchart

VI. RESULTS

We have experimented with the above mentioned architectures and as we can see from the below tables we have achieved maximum accuracy in Resnet architecture in both the datasets. Also we found that segmenting the image to remove the background and then feeding these images to the architectures results in a better accuracy as compared to normal non-preprocessed images from the dataset. After fine tuning the models and changing the hyperparameters we got the best result.This increase was around 8% to 10% which is considered to be significant.

Table 1: Result Table (Without Image Processing and Hyperparameter Tuning)

Algorithms	Dataset1	Dataset2
Convolutional Neural Network	79.36 %	68.39%
AlexNet	81.29 %	70.42%
ResNet	83.45%	73.12%

Table 2: Result Table (Without Image Processing)

Algorithms	Dataset1	Dataset2
Convolutional Neural Network	82.28 %	70.25%
AlexNet	85.31 %	75.64%
ResNet	89.80%	78.14%

TABLE 3.

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Table 3: Result Table (of both the datasets)

Algorithms	*Dataset1*	*Dataset2*
Convolutional Neural Network	92.28 %	80.25%
AlexNet	94.53 %	85.64%
ResNet	97.90%	88.14%

VII. CONCLUSION

We can conclude with our experiments that segmenting the images to remove the background noise and providing them as an input results in better performing models as compared to non-segmented images. With the help of our app we can easily identify the plant and check whether it is suffering from a disease or not . So the overall system would act as an important use case in the agricultural sector.

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