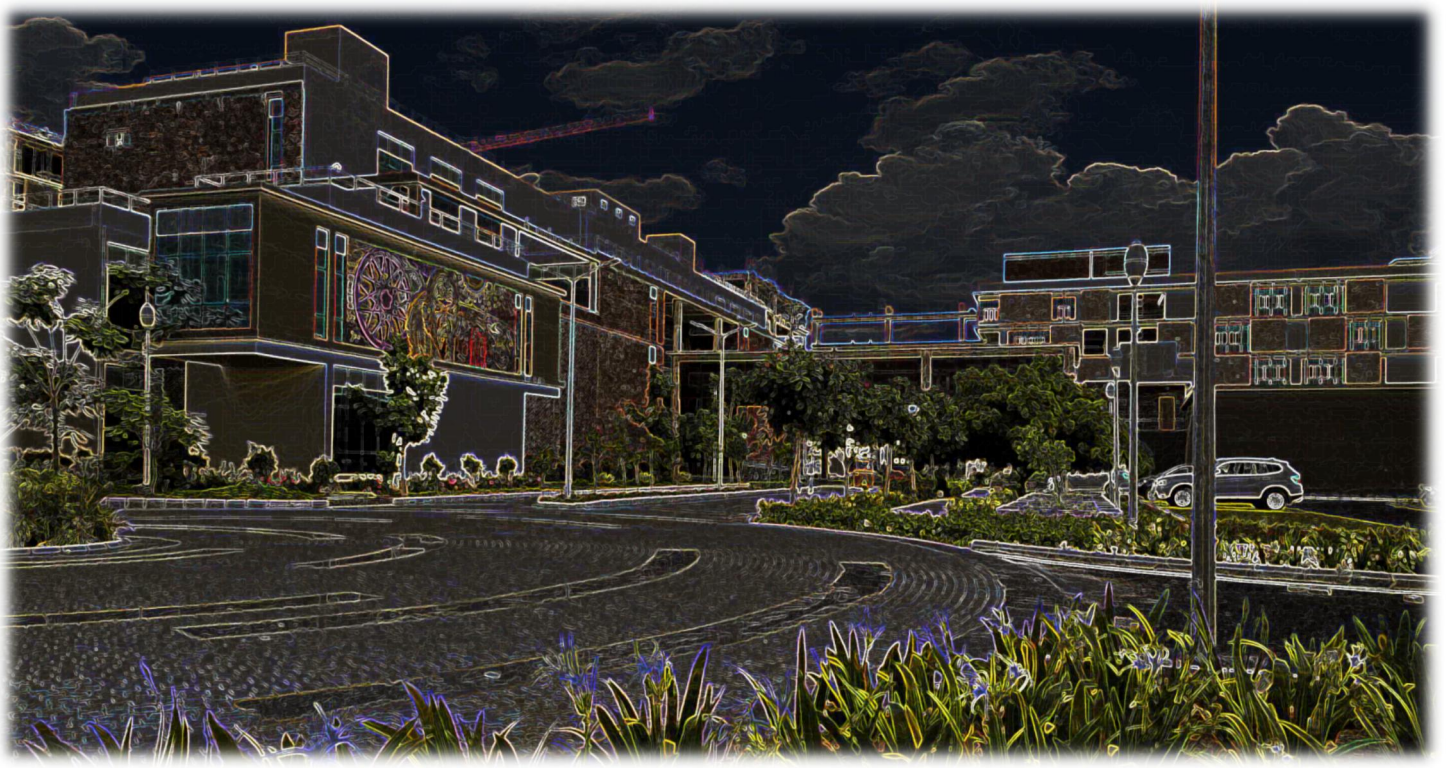
Computer Vision Project



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Plant(tomato) diesease detection using computer viison and deep learning

GROUP NUMBER-7

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ABSTRACT

India being an agricultural country, the agriculture serves more than 50% of its economy. After potato, tomato stands as most popular crop across the world. India ranks 2nd in the production of tomato. However, the quality and quantity of tomato crop goes down due to the various kinds of diseases. So the techniques used to detect those disease using computer vision and deep learning are discussed in this article.

KEYWORDS- image segmentation, plant village dataset, CNN.

CERTIFICATE

This is to certify that the report titled **Plant disease detection using computer vision and deep learning**,submitted by **, Venkata Anuhya Tummala, N Sree Dhyuti and M Sree Harshita members of Project 7**, to the Indian Institute of Information Technology, Design and Manufacturing Kancheepuram, for the award of the degree of **BACHELOR OF TECHNOLOGY** is a bonafide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Date: 03.12.2022

1. Introduction

Tomato being one of the most common plant, is not only grown by farmers but also by many gardeners.

The identification of the diseases in tomato should start from identifying the part of disease and then type of the disease.

As a first step to detect plants, we first need to know what are the plant diseases that are present and can be identified using leaves. After getting the list of diseases we need to find a data-set which contains those and we have to preprocess it before we train the computer using image processing techniques. Then we have to train the system to detect whether the leaf is healthy or not. If not healthy, we need to find about what disease it is infected with. We have to test and validate the model we create for better accuracy.

This work may help farmers to diagnose the disease faster instead of running behind plant scientists which in return increases the productivity of the crops and economy of the country.

2. Survey

a. **Plant diseases[1]-**

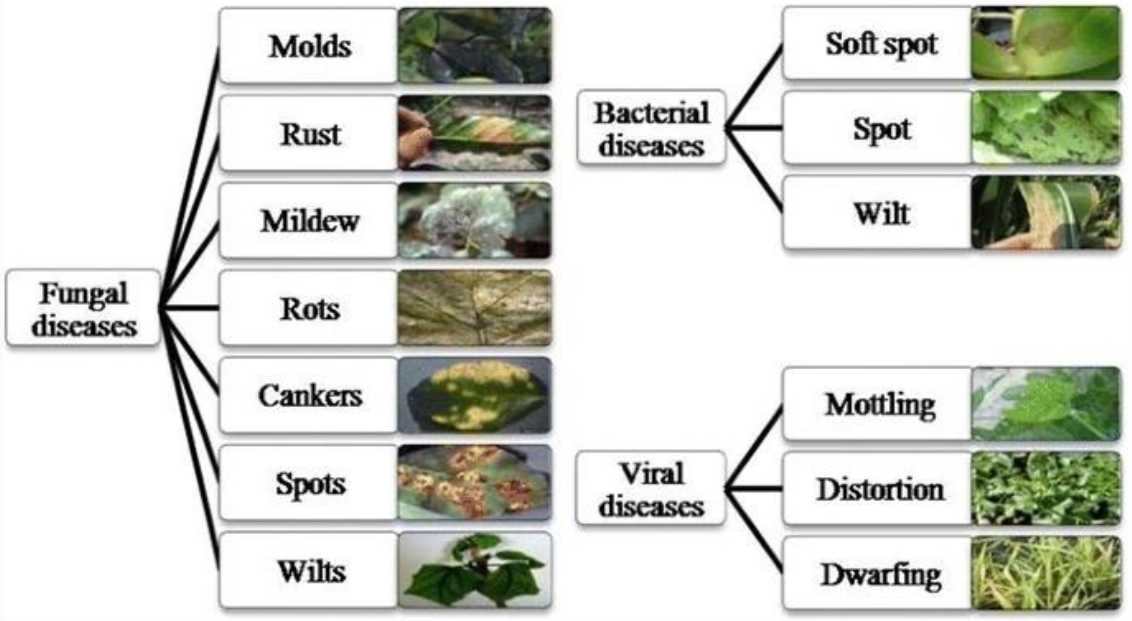
Plant disease can be classified into two different types based on its causes - biotic and abiotic.

Plant diseases originated from living organisms are *biotic*. Fungi, bacteria, and viruses are the main causes of different forms of *biotic* diseases. *Abiotic*, in

contrast, are produced by non-living ecological circumstances such as hail, spring frosts, weather conditions, burning of chemicals, etc .

Abiotic diseases are non-infectious, non-transmissible, less dangerous, and are mostly avoidable. So in this article will are focused on biotic diseases.

Fig. 1



Different categories of plant biotic diseases and their types in various cultures

[2]The early blight disease of tomato plants is caused by the fungus, which affects the plant leaves. If it affects the seedlings' basal stems, adult plant's stem, and fruits, it is called collar rot, stem lesion, and fruit rot, respectively.

Bacterial spot is a plant disease caused by bacteria. Molds are also a major cause of plant diseases. Late blight disease of tomato and potato plants is caused by mold. The appearance of dark uneven blemishes on leaves tips and plant stems are a few of the

symptoms. Tomato yellow leaf curl virus (TYLCV) is a devastating virus causing tomato disease.

Another viral disease that specifically affects tomato plants is caused by Tomato mosaic virus (ToMV). This virus is found worldwide and affects not only tomatoes but other plants as well. Symptoms of ToMV infection include twisting and fern-like appearance of leaves, damaged fruit with yellow patches, and necrotic blemishes.

b. **Dataset -**

SNO.	DATASET	DESCRIPTION	ARTICLES	REMARKS
1.	Plant Village	It contains healthy and infected leaves isolated on a uniform background.It has 38 crop-disease pairs, with 26 crop-disease categories for 14 crop plants. Note that, the data comes with predefined training and test subsets.	https://www.sciencedirect.com/science/article/pii/S016816991930056[124 citiations]	Very clean, huge variety of plants along with different diseases and a well-labeled dataset but the images are being taken in a controlled environment.
2.	IPM dataset	Has a variety of groups for agriculture crops, vegetable and fruits crops etc	list of articles	Unlike in PV, these test images are not limited to a controlled environment
3.	**Bing test datasets**	Bing Data is similar to Google Data. These data categories are commonly used for Search Engine Optimization (SEO) and Keyword Analytics.	https://www.sciencedirect.com/science/articl	Unlike in PV, these test images are not limited to a controlled environment

			e/pii/S01 6816991 9300560[124 citiations]	
4.	APS DATASET	The American Phytopathological Society processes thousands of scientifically peer-reviewed images showing disease symptoms, pests, and other disorders associated with plants and crops through its book- and journal-publishing programs. APS images are useful for teaching, training, and diagnostics.		Though we get a variety of images of diseased plants but we wouldn't get the leaf images in huge quantity

The dataset needs to have variety of images with different diseased tomato leaves which should be clean and realistic which should help in classification of the plant leaves .

c. **Methodology -**

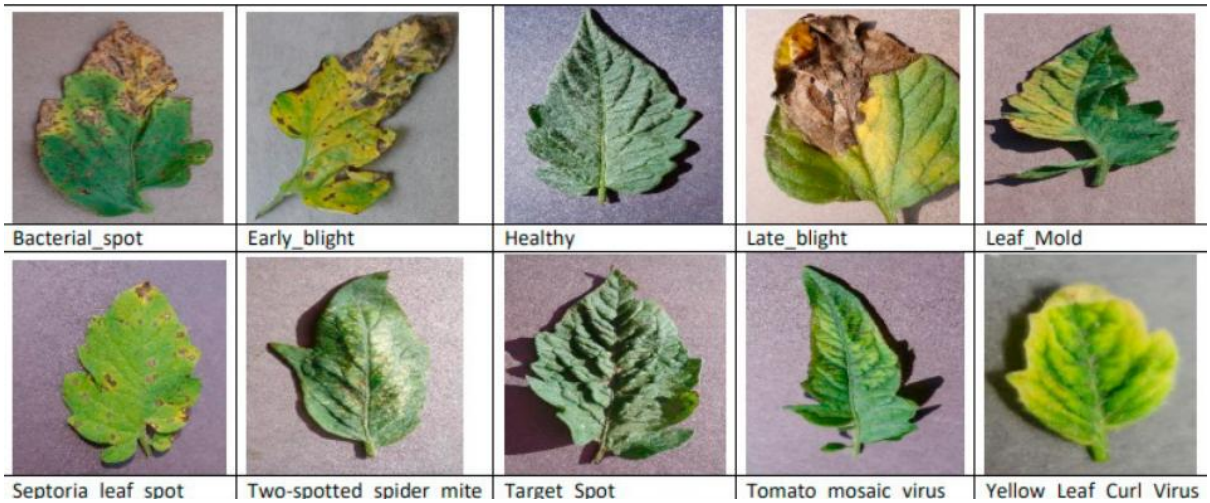
Year of Publication	Title	Methodology Adopted
2007	Detection and classification of plant leaf diseases using image processing techniques	More emphasis given to **Image Segmentation** using an algorithm names **Genetic Algorithm**
2011	An application of K-means clustering and artificial intelligence in pattern recognition for crop diseases	**K-means clustering** algorithm with neural networks for automatic detection of leaves diseases
2013	Agricultural plant Leaf Disease Detection Using Image Processing	Vision-based detection algorithm with **masking** the green-pixels and **color co-occurrence** method
2020	Image-Based Plant Disease Identification using Deep Learning	Using three meta-architectures: Single Shot MultiBox Detector (**SSD**), Faster Region-based Convolutional Neural Network (**RCNN**), and Region-based Fully Convolutional Networks (**RFCN**)
2022	Plant leaf disease detection using computer vision and	RGB conversion to gray, HE, **K-means clustering**, contour tracing to achieve 99% accuracy

	machine learning algorithms	

3. Proposal:

a. Plant village dataset exploration-

Images of Tomato disease have been taken from Plant Village dataset. The dataset includes over 50,000 images of 14 crops, such as tomatoes, potatoes, grapes, apples, corn, blueberry, raspberry, soybeans, squash and strawberry. We selected tomato as our target crop. The images of various classes of tomato are as follows



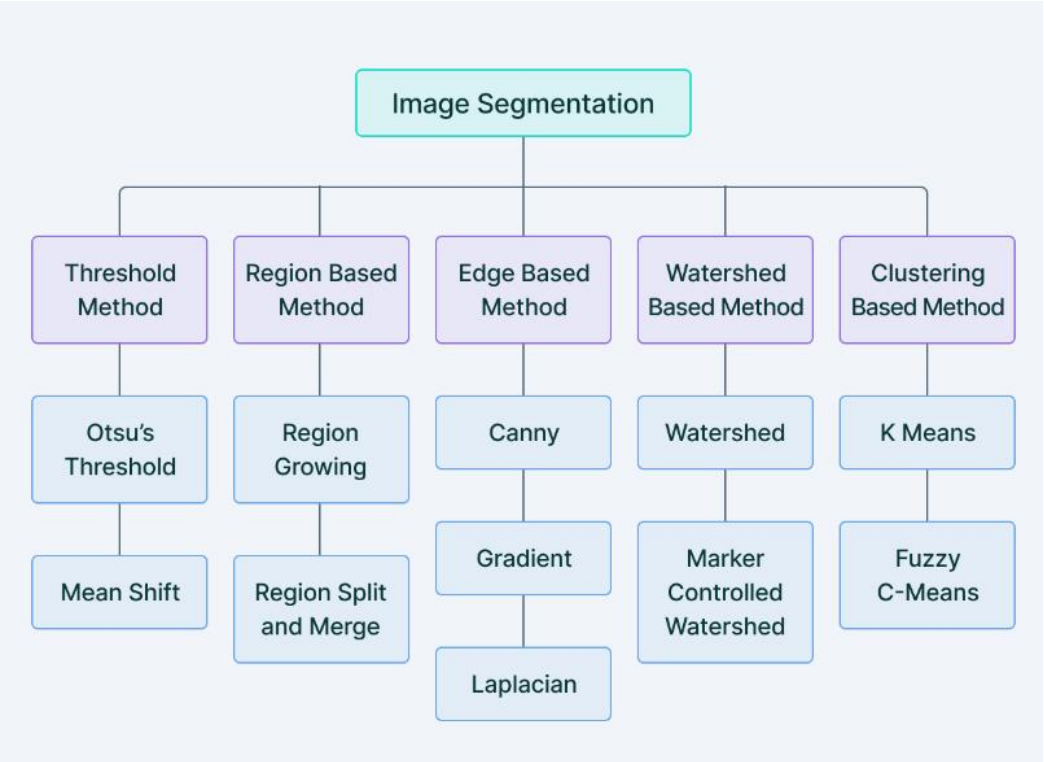
There are mainly nine types of diseases in tomato: 1) Target Spot, 2) Mosaic virus, 3) Bacterial spot, 4) Late blight, 5) Leaf Mold, 6) Yellow Leaf Curl Virus, 7) Spider mites: Two-spotted spider mite, 8) Early blight and 9) Septoria.

b. Methodology

- After going through the papers we realized that after acquiring the data they have passed it on to a model to classify but they took 100 epochs to reach and accuracy around 85%
- Hence if do preprocessing to the images before sending it to the model we can get a better accuracy at lower epochs.
- Therefore we have used image segmentation as a process prior to training the model.

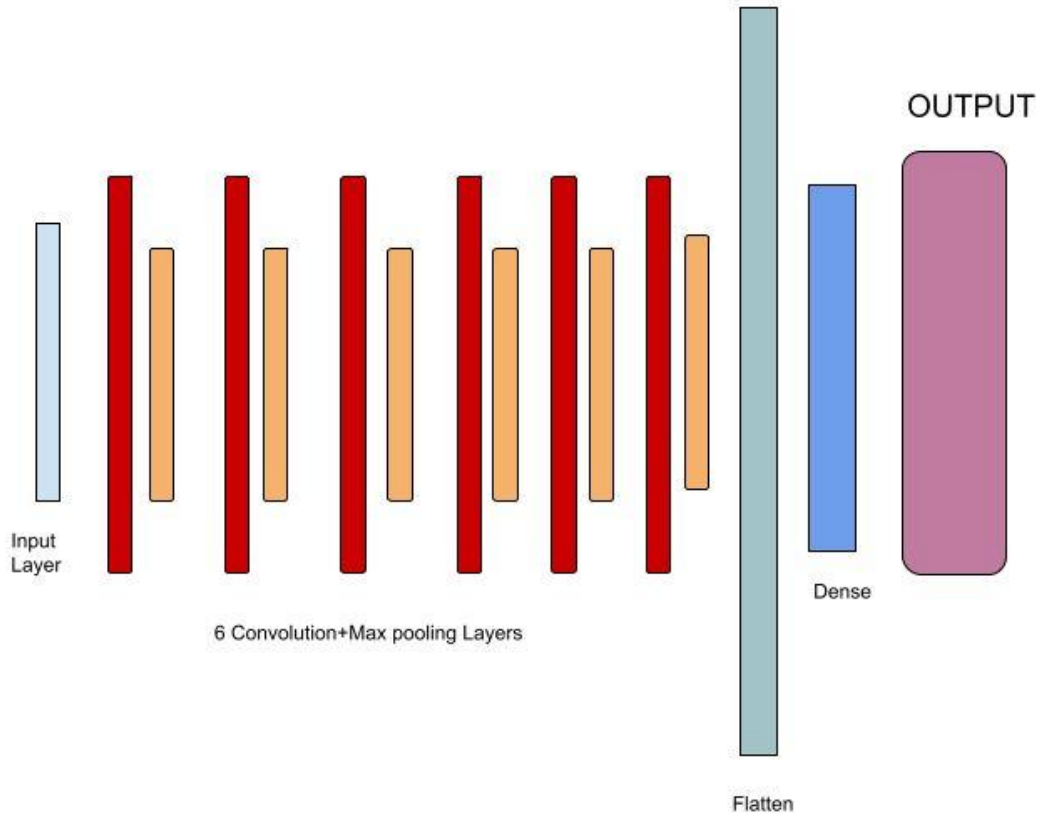
Image segmentation[11]

Image segmentation originally started from Digital Image Processing coupled with optimization algorithms. The following shows the ways in which we can do image segmentation



- Here the images from the dataset we have taken have a background and a foreground we have to eliminate the background.

- For that we followed the following process
    1. Doing the canny edge detection on the Grey scale image
    2. Reducing the noise using Gaussian blur
    3. Doing binary threshold on it using OTSU threshold
    4. We applied Sobel filter to smoothed the image.
    5. We did thresholding over it
    6. To reduce the gaps we did closing .
    7. Then thinned the boundary
    8. We then multiplied the original image to the above image and got a segmented image or leaf.
- Now we have the segmented image we will pass it on to the basic CNN model for training etc.



The given CNN architecture consists of an input layer followed by 6 Convolution layers followed by Max Pooling Layers. The resultant is then flattened and it passes through another dense layer to finally give the output.

Layer (type)	Output Shape	Param #
sequential (Sequential)	(16, 256, 256, 3)	0
sequential_1 (Sequential)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_3 (Conv2D)	(None, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_5 (Conv2D)	(None, 4, 4, 64)	36928
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 64)	0
flatten (Flatten)	(None, 256)	0
dense (Dense)	(None, 64)	16448
dense_1 (Dense)	(None, 10)	650

Structure of the CNN model

CNN

Convolutional neural networks are neural networks that are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are:

- Convolutional layer
- Pooling layer
- Fully-connected (FC) layer

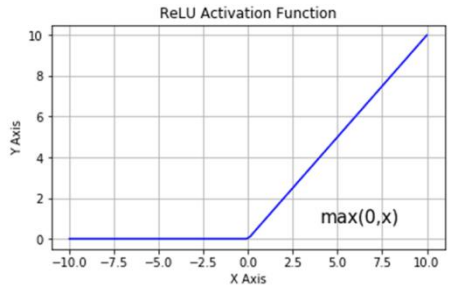
The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional

convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object.

4. Parameters of Evaluation:

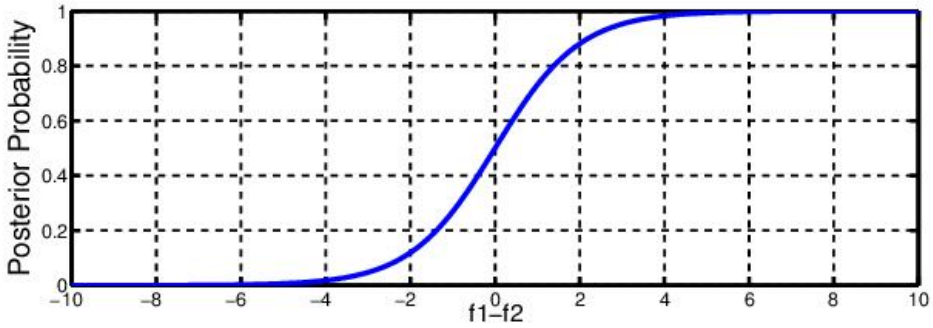
Activation Function used:

Rectified Linear Unit



For output, Softmax Activation used

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$



Optimiser

Adam

Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models. Adam

combines the best properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems

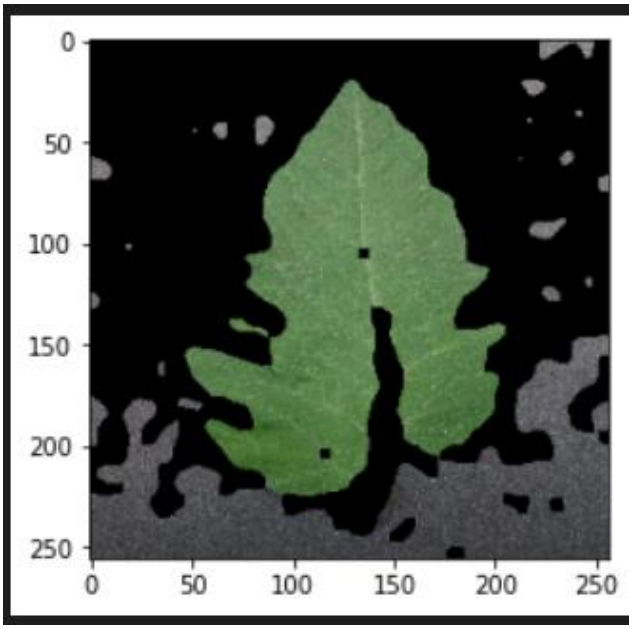
Loss Function

SparseCategoricalCrossentropy

$$\text{Loss} = -\frac{1}{\substack{\text{output} \\ \text{size}}} \sum_{i=1}^{\substack{\text{output} \\ \text{size}}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i)$$

5. Results:

Sample output from the segmentation we followed

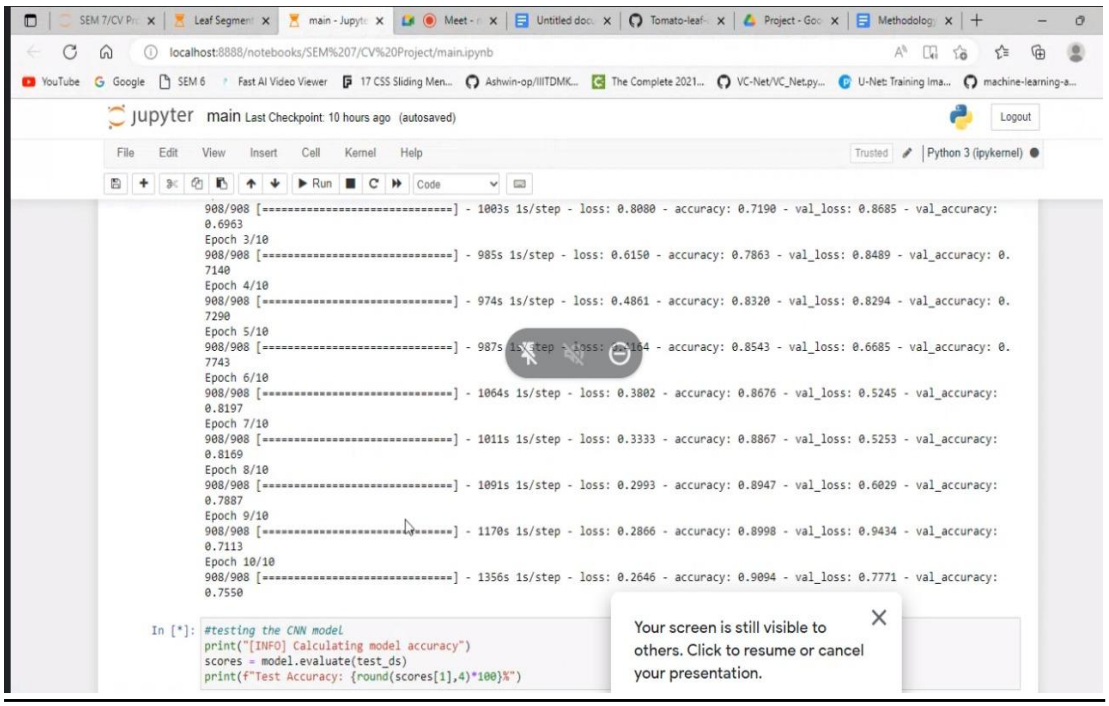


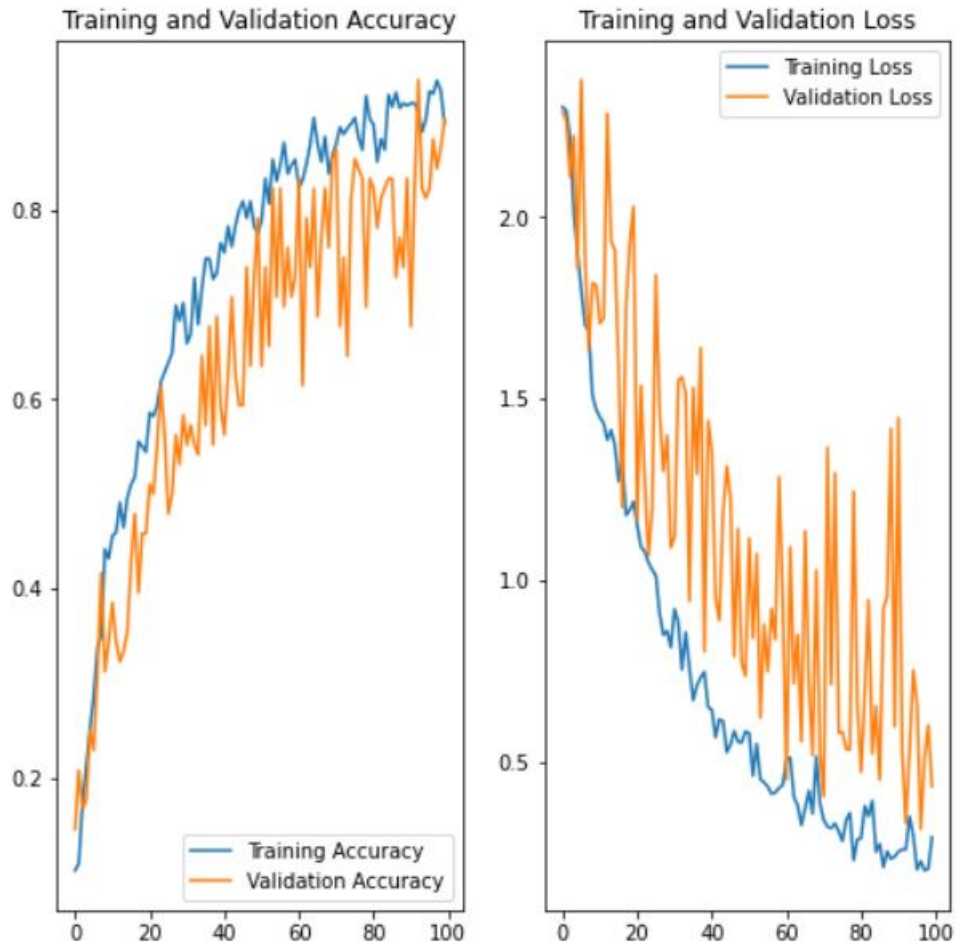
Without segmentation the accuracy of the CNN model

```
[INFO] Calculating model accuracy
7/7 [==============================] - 1s 8ms/step - loss: 0.3446 - accuracy: 0.8571
Test Accuracy: 85.71%
```

```
Epoch 91/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2542 - accuracy: 0.9129 - val_loss: 1.4474 - val_accuracy: 0.6771
Epoch 92/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2598 - accuracy: 0.9129 - val_loss: 0.5313 - val_accuracy: 0.8229
Epoch 93/100
50/50 [==============================] - 1s 22ms/step - loss: 0.2605 - accuracy: 0.9040 - val_loss: 0.3319 - val_accuracy: 0.9375
Epoch 94/100
50/50 [==============================] - 1s 22ms/step - loss: 0.3511 - accuracy: 0.8826 - val_loss: 0.5376 - val_accuracy: 0.8229
Epoch 95/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2971 - accuracy: 0.8952 - val_loss: 0.7532 - val_accuracy: 0.8125
Epoch 96/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2049 - accuracy: 0.9255 - val_loss: 0.6606 - val_accuracy: 0.8229
Epoch 97/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2280 - accuracy: 0.9230 - val_loss: 0.3162 - val_accuracy: 0.8750
Epoch 98/100
50/50 [==============================] - 1s 22ms/step - loss: 0.2023 - accuracy: 0.9369 - val_loss: 0.5113 - val_accuracy: 0.8438
Epoch 99/100
50/50 [==============================] - 1s 22ms/step - loss: 0.2073 - accuracy: 0.9268 - val_loss: 0.6017 - val_accuracy: 0.8646
Epoch 100/100
50/50 [==============================] - 1s 21ms/step - loss: 0.2938 - accuracy: 0.8914 - val_loss: 0.4335 - val_accuracy: 0.8958
```

Our accuracy with segmentation-





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6. Conclusion and Future scope:

i. Using CUDA programming we can reduce the time taken for the model
ii. Extending it to different plants.
iii. Increasing the accuracy of the segmentation we followed.

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