

**FERTILIZERS RECOMMENDATION SYSTEM FOR  
DISEASE PREDICTION  
PROJECT REPORT**

*Submitted by*

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# **1.INTRODUCTION**

Overview In this project, two datasets name fruit dataset and vegetable dataset are collected. The collected datasets are trained and tested with deep learning neural network named Convolutional Neural Networks (CNN). First, the fruit dataset is trained and then tested with CNN. It has 6 classes and all the classes are trained and tested. Second, the vegetable dataset is trained and tested. The software used for training and testing of datasets is Python. All the Python codes are first written in Jupyter notebooks supplied along with Anaconda Python and then the codes are tested in IBM cloud. Finally, a web-based framework is designed with help Flask a Python library. There are 2 html files are created in templates folder along with their associated files in static folder. The Python program 'app.py' used to interface with these two webpages is written in Spyder-Anaconda python and tested.

Purpose of this project is used to test the fruits and vegetables samples and identify the different diseases. Also, this project recommends fertilizers for predicted diseases.

## **2.LITERATURE SURVEY**

### **2.1 Cloud-Based AI to Identify Early Indicators of Water Stress**

Daniel, Shaurya Gupta, D. Hudson Smith. According to this paper, the critical need for sustainable water use in agriculture has prompted the EPA Strategic Plan to call for new technologies that can optimise water allocation in real-time. Demand for freshwater is rising while supply is remaining stagnant. This study evaluates the use of cloud-based artificial intelligence to spot early signs of water stress in six species of ornamental shrubs grown in containers. Earlier, modified Canon and MAPIR Survey II cameras that were flown by a small unmanned aircraft system (sUAS) at a 30 metre altitude collected near-infrared images. Cropped pictures of plants with no, low, and high levels of water stress were divided into four sets for cross-validation, and the Visual Recognition service from IBM Watson was used to train the models.

## 2.2 Detection of Cercospora leaf spot in okra using CNN

Rangarajan, Aravind Krishnaswamy, and Edwin Jayaraj Balu. Robotic agriculture powered by artificial intelligence (AI) is predicted to significantly disrupt the agricultural industry and offer profitable farming. However, there are significant obstacles to implementing such technologies in economically underdeveloped nations in a way that is both profitable and cost-effective. In this study, the disease Cercospora Leaf Spot (CLS), also known as lady's finger or *Abelmoschus esculentus* L., is identified in the okra plant. Deep learning models are used to detect the disease from images taken with a quadcopter that has been modified to be inexpensive and fitted with a camera. SqueezeNet and ResNet-18, two deep learning models with validation accuracy of 99.1% and 99%, respectively, were used in this study. The models' accuracy was tested using images obtained by the modified quadcopter, and the results were 92.3% and 94.6%, respectively.

## 3.THEORITICAL ANALYSIS

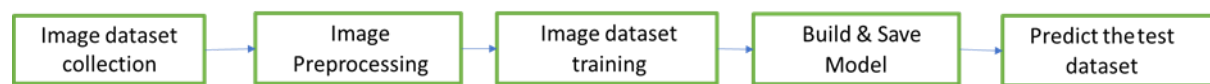


Fig 3.1 Block Diagram

The block diagram of the entire project is shown in Fig.3.1. First step is the image dataset collection followed by image preprocessing. The third step is the training of image datasets with initializing different hyper parameters. Then build the model and save the model file with .h5 format. The final stage is the testing of existing or new datasets using the trained model

## 4.HARDWARE/SOFTWARE DESIGNING

The software used for training and testing the dataset is Python. The Jupyter notebook (Notebook of IBM cloud also) is used for python programming. The neural network used for training and testing the model is Convolutional NeuralNetwork (CNN).

The CNN has following layers:

- Convolutional layer (32x32kernel (3x3))
- Flatten layer
- Dense layer (different layers with different size)
- Drop out layer(optional)

- Final output dense layer (size 6x1 for fruit dataset and 9x1 for Vegetable dataset)
- Max-pool layer (kernel(2x2))

In the preprocessing step, images are normalized to 1 and then resized to 128x128. The images are arranged in different batch sizes. Then train set and test set are formed from the collected datasets. In order to do the above steps in Python, the following Python libraries must be imported before starting the process:

- NumPy, Matplotlib
- TensorFlow, Keras.

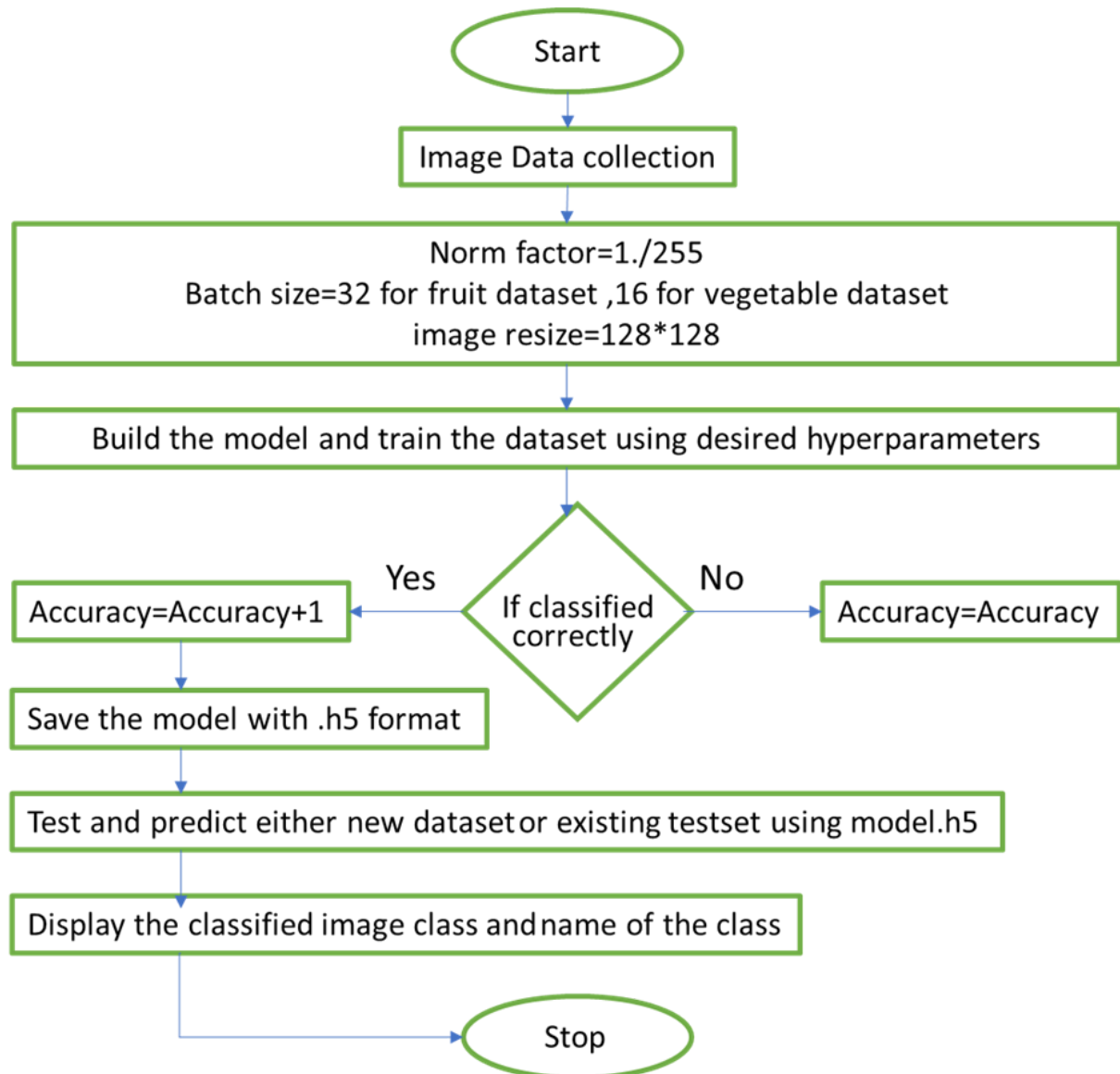
The following activation functions used in the CNN training:

- RELU at the end of convolution layer and Max Pool layer
- SoftMax at the end of output dense layer
- For testing the dataset argmax is used, it's an optional.

## 4. EXPERIMENT INVESTIGATION

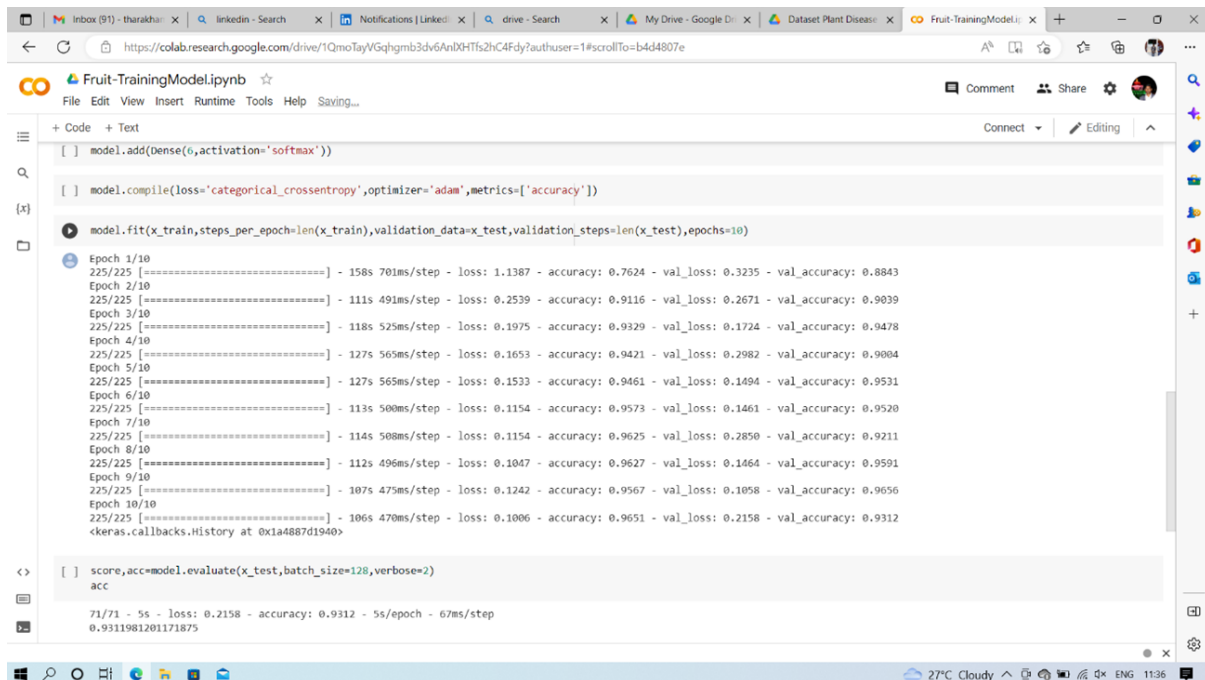
Analysis made while working on the solution The batch sizes are varied and tested. For different batch sizes, the CNN gives different accuracies. The batch size determines the number of iterations per epoch. Another important hyper parameter is the number of epochs. This determines accuracy and it has high influence on accuracy compared to other hyper parameters. The accuracy can be varied from 80% to 90% in vegetable dataset and 95% to 98% in the case of fruit dataset by increasing the number of epochs. The size of test dataset and train dataset also has very high influence on accuracies. The accuracy can be increased by using a greater number of images in train dataset. The computational time for model building is increased when the size of the train dataset increased and also number of epochs increased. The batch size of train dataset and test dataset also play a vital role in computational time. The Neural Network complexity is increased when a greater number of convolutional layers increased. If the number of layers increased, better accuracy result will obtain. At the same increasing the number of layers in CNN leads to more training time and also requires more time to build a model. The model .h5 size depends on the size of train datasets. But the memory requirement depends on the size of train dataset and CNN architecture complexity.

## 5.FLOW CHART



## 6.RESULTS

Final findings(output) of the project given below in the form of screenshot: Training and Testing of Fruit dataset



```
[ ] model.add(Dense(6,activation='softmax'))

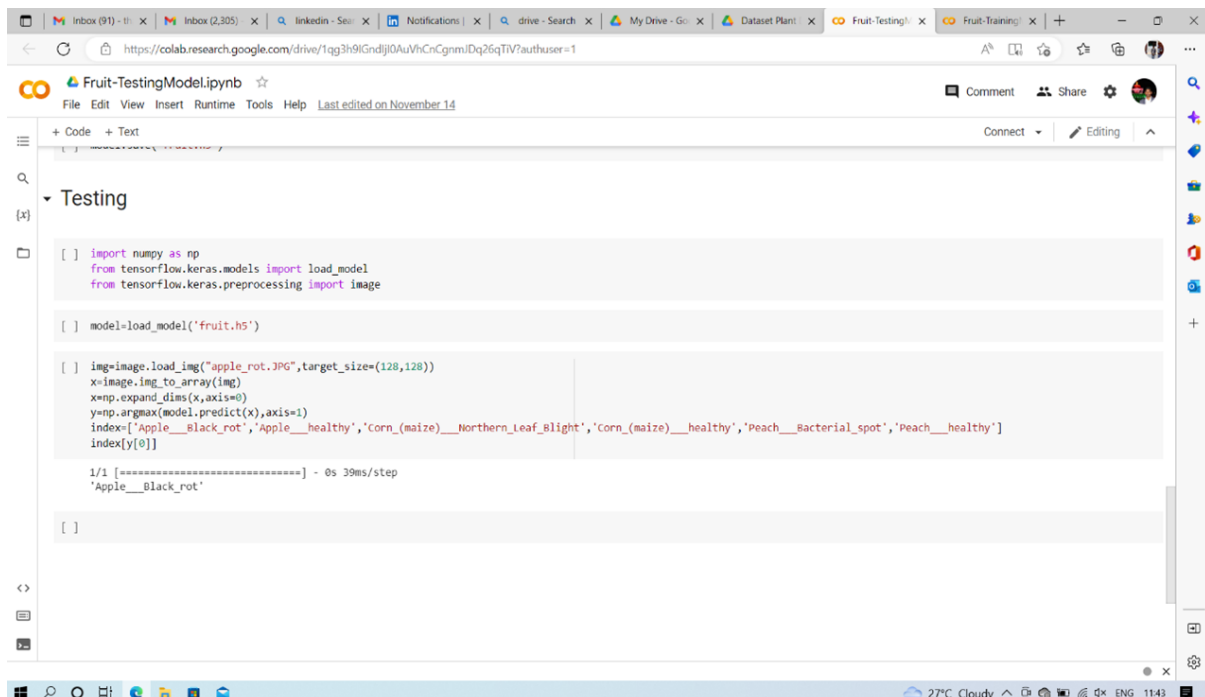
[ ] model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])

model.fit(x_train,steps_per_epoch=len(x_train),validation_data=x_test,validation_steps=len(x_test),epochs=10)

Epoch 1/10
225/225 [=====] - 158s 701ms/step - loss: 1.1387 - accuracy: 0.7624 - val_loss: 0.3235 - val_accuracy: 0.8843
Epoch 2/10
225/225 [=====] - 111s 491ms/step - loss: 0.2539 - accuracy: 0.9116 - val_loss: 0.2671 - val_accuracy: 0.9039
Epoch 3/10
225/225 [=====] - 118s 525ms/step - loss: 0.1975 - accuracy: 0.9329 - val_loss: 0.1724 - val_accuracy: 0.9478
Epoch 4/10
225/225 [=====] - 127s 565ms/step - loss: 0.1653 - accuracy: 0.9421 - val_loss: 0.2982 - val_accuracy: 0.9004
Epoch 5/10
225/225 [=====] - 127s 565ms/step - loss: 0.1533 - accuracy: 0.9461 - val_loss: 0.1494 - val_accuracy: 0.9531
Epoch 6/10
225/225 [=====] - 113s 500ms/step - loss: 0.1154 - accuracy: 0.9573 - val_loss: 0.1461 - val_accuracy: 0.9520
Epoch 7/10
225/225 [=====] - 114s 508ms/step - loss: 0.1154 - accuracy: 0.9625 - val_loss: 0.2850 - val_accuracy: 0.9211
Epoch 8/10
225/225 [=====] - 112s 496ms/step - loss: 0.1047 - accuracy: 0.9627 - val_loss: 0.1464 - val_accuracy: 0.9591
Epoch 9/10
225/225 [=====] - 107s 475ms/step - loss: 0.1242 - accuracy: 0.9567 - val_loss: 0.1058 - val_accuracy: 0.9656
Epoch 10/10
225/225 [=====] - 106s 470ms/step - loss: 0.1006 - accuracy: 0.9651 - val_loss: 0.2158 - val_accuracy: 0.9312
<keras.callbacks.History at 0x1a4887d1940>

[ ] score,acc=model.evaluate(x_test,batch_size=128,verbose=2)
acc
71/71 - 5s - loss: 0.2158 - accuracy: 0.9312 - 5s/epoch - 67ms/step
0.9311981201171875
```

Figure 6.1 Training of Fruit data



```
[ ] import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

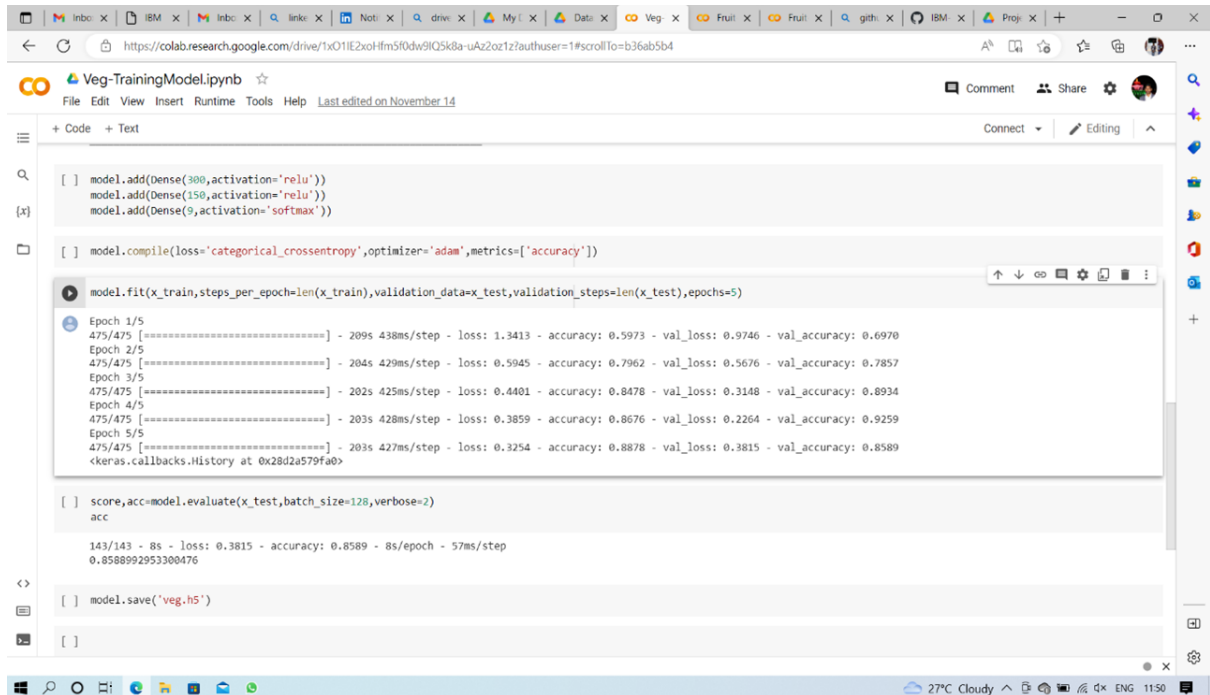
[ ] model=load_model('fruit.h5')

[ ] img=image.load_img("apple_rot.JPG",target_size=(128,128))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=["Apple__black_rot",'Apple__healthy','Corn_(maize)__Northern_Leaf_Blight','Corn_(maize)__healthy','Peach__Bacterial_spot','Peach__healthy']
index[y[0]]

1/1 [=====] - 0s 39ms/step
'Apple__black_rot'

[ ]
```

Figure 6.2 Testing of Fruit data



```
[ ] model.add(Dense(300,activation='relu'))
model.add(Dense(150,activation='relu'))
model.add(Dense(9,activation='softmax'))

[ ] model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])

model.fit(x_train,steps_per_epoch=len(x_train),validation_data=x_test,validation_steps=len(x_test),epochs=5)

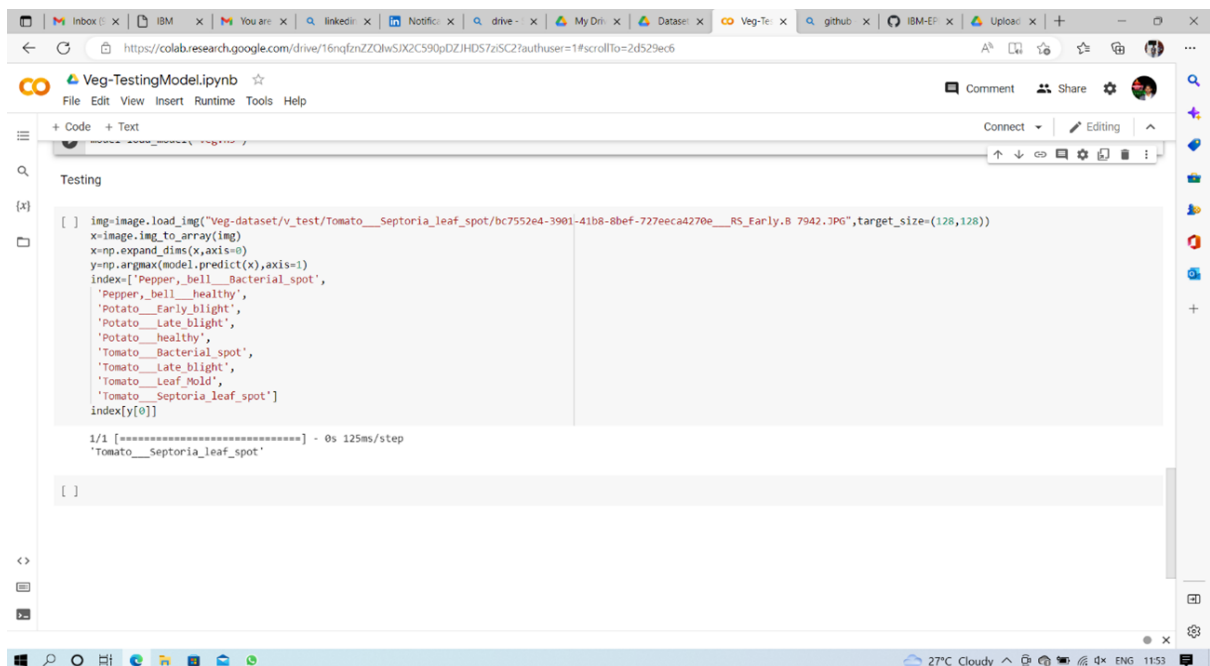
Epoch 1/5
475/475 [=====] - 209s 438ms/step - loss: 1.3413 - accuracy: 0.5973 - val_loss: 0.9746 - val_accuracy: 0.6970
Epoch 2/5
475/475 [=====] - 204s 429ms/step - loss: 0.5945 - accuracy: 0.7962 - val_loss: 0.5676 - val_accuracy: 0.7857
Epoch 3/5
475/475 [=====] - 202s 425ms/step - loss: 0.4401 - accuracy: 0.8478 - val_loss: 0.3148 - val_accuracy: 0.8934
Epoch 4/5
475/475 [=====] - 203s 428ms/step - loss: 0.3859 - accuracy: 0.8676 - val_loss: 0.2264 - val_accuracy: 0.9259
Epoch 5/5
475/475 [=====] - 203s 427ms/step - loss: 0.3254 - accuracy: 0.8878 - val_loss: 0.3815 - val_accuracy: 0.8589
<keras.callbacks.History at 0x28d2a579fa0>

[ ] score,acc=model.evaluate(x_test,batch_size=128,verbose=2)
acc
143/143 - 8s - loss: 0.3815 - accuracy: 0.8589 - 8s/epoch - 57ms/step
0.8588992953300476

[ ] model.save('veg.h5')

[ ]
```

Figure 6.3 Training of Vegetable Data.



```
Testing

[ ] img=image.load_img("Veg-dataset/v_test/Tomato__Septoria_leaf_spot/bc7552e4-3901-41b8-8bef-727eecca4270e__RS_Early.8_7942.JPG",target_size=(128,128))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['Pepper__bell__Bacterial_spot',
'Pepper__bell__healthy',
'Potato__Early_blight',
'Potato__Late_blight',
'Potato__healthy',
'Tomato__Bacterial_spot',
'Tomato__Late_blight',
'Tomato__Leaf_Mold',
'Tomato__Septoria_leaf_spot']
index[y[0]]

1/1 [=====] - 0s 125ms/step
'Tomato__Septoria_leaf_spot'

[ ]
```

Figure 6.4 Testing of Vegetable Data

# OUTPUT

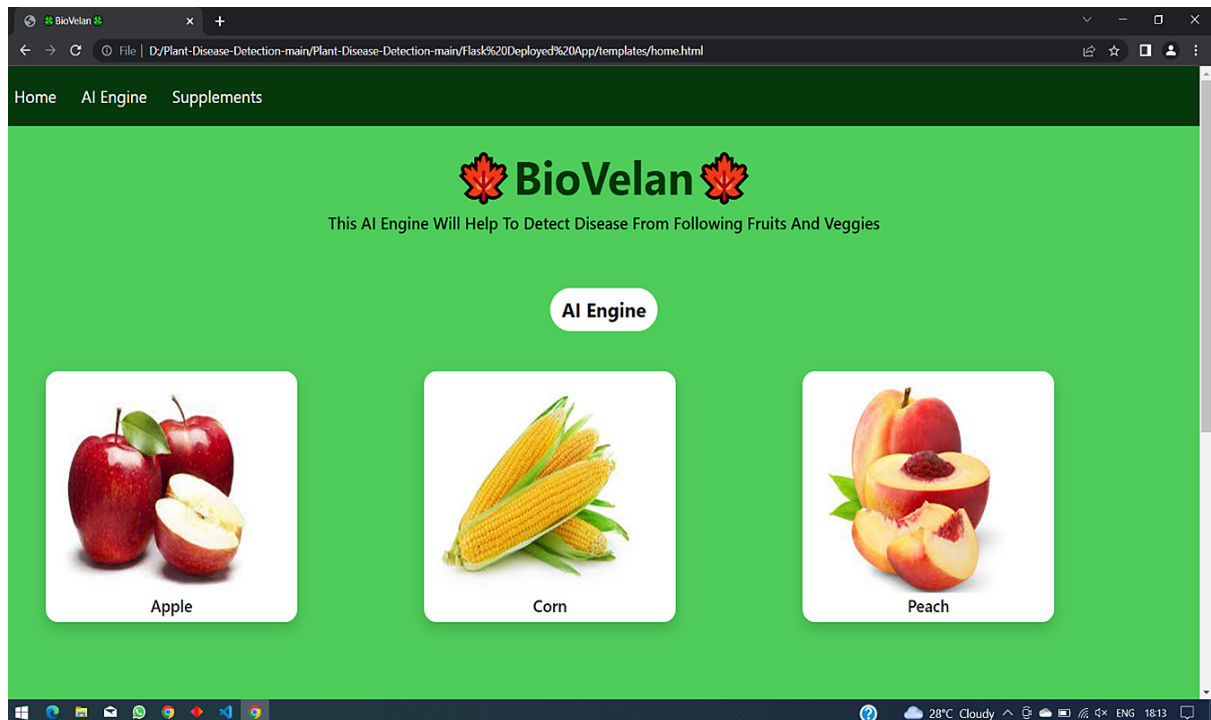


Figure 6.5 Home Page

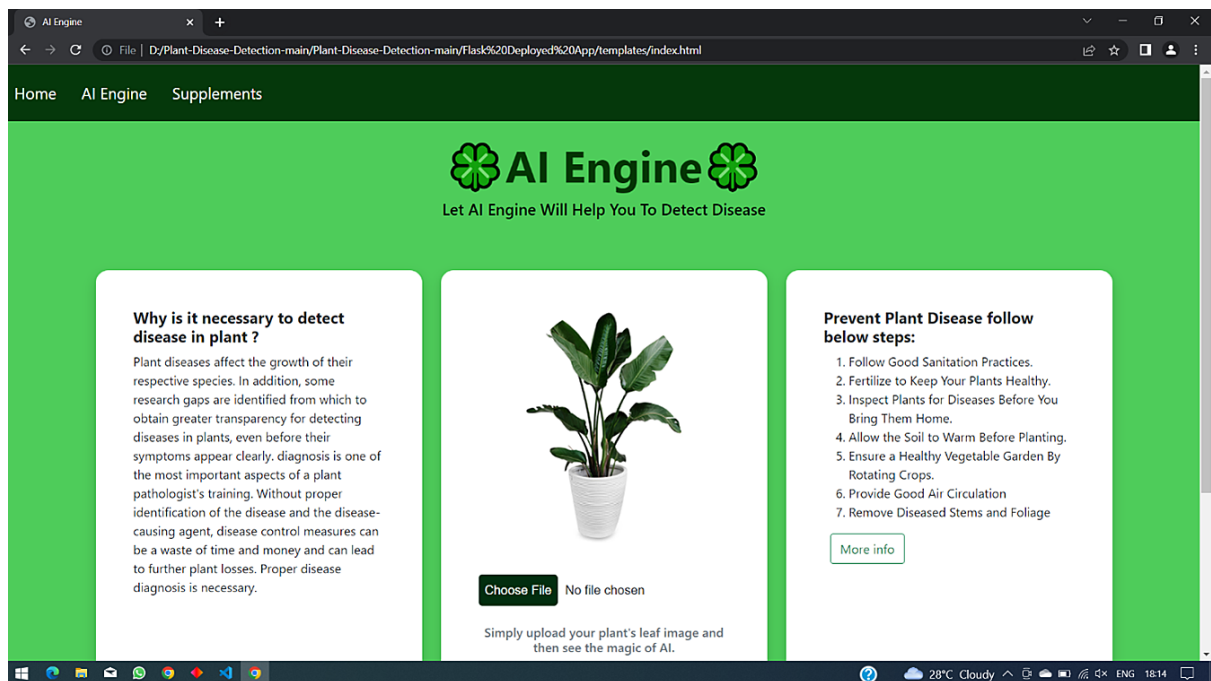


Figure 6.6 Image Upload Page



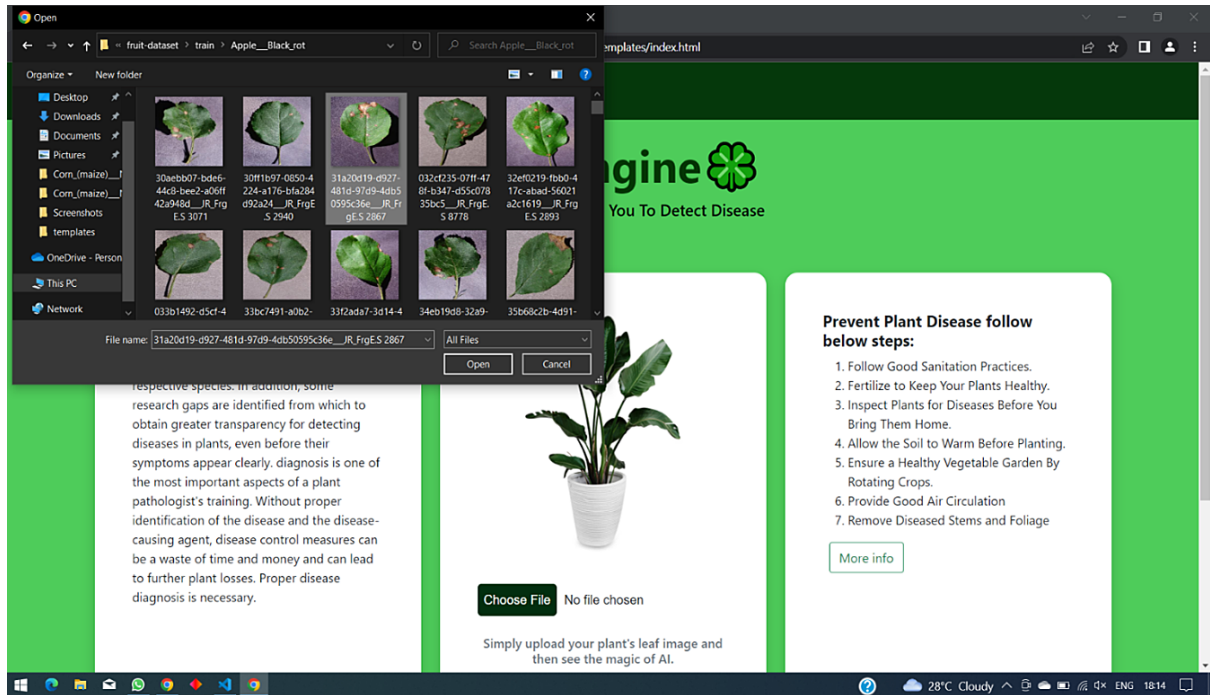


Figure 6.7 Upload the Image of Diseased Leaf

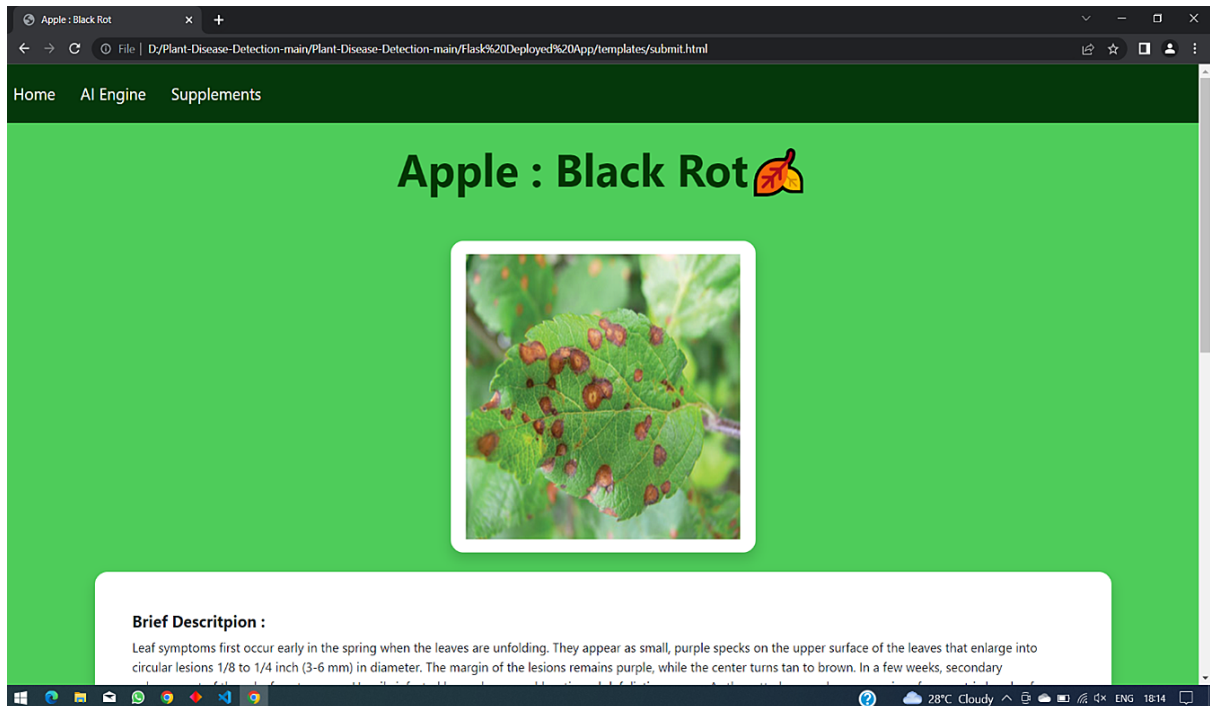


Figure 6.8 Disease Information

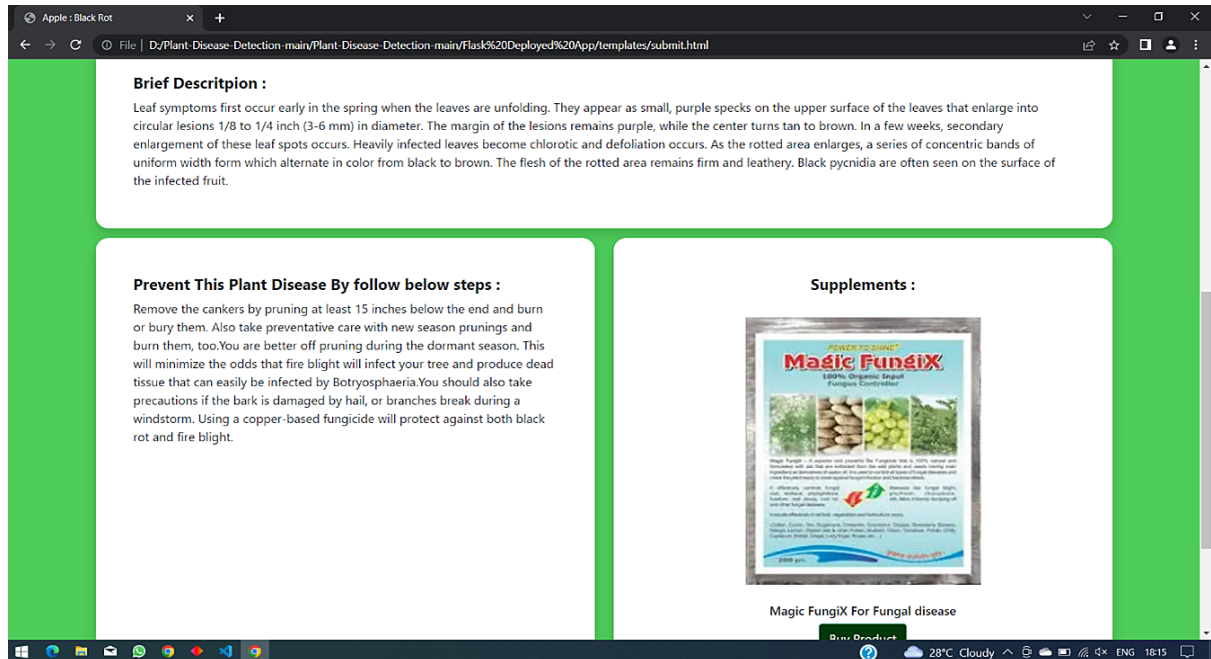


Figure 6.9 Fertilizer Recommendation

## 7. ADVANTAGES & DISADVANTAGES

### List of advantages

- The proposed model here produces very high accuracy of classification.
- Very large datasets can also be trained and tested.
- Images of very high can be resized within the proposed itself.

### List of disadvantages

- For training and testing, the proposed model requires very high computational time.
- The neural network architecture used in this project work has high complexity.

## 8. APPLICATIONS

- The trained network model used to classify the image patterns with high accuracy.
- The proposed model not only used for plant disease classification but also for other image pattern classification such as animal classification.
- This project work application involves not only image classification but also for pattern recognition.

## 9.CONCLUSIONS

The model proposed here involves image classification of fruit datasets and vegetable datasets. The following points are observed during model testing and training:

- The accuracy of classification increased by increasing the number of epochs.
- For different batch sizes, different classification accuracies are obtained.
- The accuracies are increased by increasing more convolution layers.
- The accuracy of classification also increased by varying dense layers.
- Different accuracies are obtained by varying the size of kernel used in the convolution layer output.
- Accuracies are different while varying the size of the train and test dataset.

## 10.FUTURE SCOPE

The proposed model in this project work can be extended to image recognition. The entire model can be converted to application software using python to exe software. The real time image classification, image recognition and video processing are possible with help of OpenCV python library. This project work can be extended for security applications such as fingerprint recognition, iris recognition and face recognition.

## 11.BIBLIOGRAPHY

- [1]. Clemente, Andressa Alves, Gabriel Mascarenhas Maciel, Ana Carolina Silva Siquieroli, Rodrigo Bezerra de Araujo Gallis, Lucas Medeiros Pereira, and Jéssyca Gonçalves Duarte. "High-throughput phenotyping to detect anthocyanins, chlorophylls, and carotenoids in red lettuce germplasm." International Journal of Applied Earth Observation and Geoinformation 103, 2021
- [2]. Kerkech, Mohamed, Adel Hafiane, and Raphael Canals. "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach." Computers and Electronics in Agriculture 174, 2020.

## 12. APPENDIX

### A. Source Code (Jupyter notebook python code)

```
"""Fruit-TestingModel.ipynb"""  
from tensorflow.keras.preprocessing.image import ImageDataGenerator  
  
train_datagen=ImageDataGenerator(rescale=1./255, zoom_range=0.2, horizontal_flip=True, vertical_flip=Fa
```

```

lse)

test_datagen=ImageDataGenerator(rescale=1./255)

x_train=train_datagen.flow_from_directory('fruit-dataset/f_train',
                                          target_size=(128,128),batch_size=24,class_mode='categorical')
x_test=test_datagen.flow_from_directory('fruit-dataset/f_test',
                                       target_size=(128,128),batch_size=24,class_mode='categorical')

x_train.class_indices

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Convolution2D,MaxPooling2D,Flatten

model=Sequential()

model.add(Convolution2D(32,(3,3),input_shape=(128,128,3),activation='relu'))

model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.summary()

model.add(Dense(300,activation='relu'))
model.add(Dense(150,activation='relu'))
model.add(Dense(6,activation='softmax'))

model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])

model.fit(x_train,steps_per_epoch=len(x_train),validation_data=x_test,validation_steps=len(x_test),epochs
=10)

score,acc=model.evaluate(x_test,batch_size=128,verbose=2)
acc

model.save('fruit.h5')

"""#Testing"""

import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

model=load_model('fruit.h5')

```

```

img=image.load_img("apple_rot.JPG",target_size=(128,128))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['Apple___Black_rot','Apple___healthy','Corn_(maize)___Northern_Leaf_Blight','Corn_(maize)___healthy','Peach___Bacterial_spot','Peach___healthy']
index[y[0]]

```

```

"""Veg-TestingModel.ipynb"""

from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen=ImageDataGenerator(rescale=1./255,zoom_range=0.2,horizontal_flip=True,vertical_flip=False)
test_datagen=ImageDataGenerator(rescale=1./255)

x_train=train_datagen.flow_from_directory('veg-dataset/v_train',
                                         target_size=(128,128),batch_size=24,class_mode='categorical')
x_test=test_datagen.flow_from_directory('veg-dataset/v_test',
                                         target_size=(128,128),batch_size=24,class_mode='categorical')

x_train.class_indices

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Convolution2D,MaxPooling2D,Flatten

model=Sequential()

model.add(Convolution2D(32,(3,3),input_shape=(128,128,3),activation='relu'))

model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.summary()

model.add(Dense(300,activation='relu'))
model.add(Dense(150,activation='relu'))
model.add(Dense(9,activation='softmax'))

model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])

```

```

model.fit(x_train,steps_per_epoch=len(x_train),validation_data=x_test,validation_steps=len(x_test),epochs
=5)

score,acc=model.evaluate(x_test,batch_size=128,verbose=2)
acc

model.save('veg.h5')


import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

model=load_model('veg.h5')

"""Testing"""

img=image.load_img("Veg-dataset/v_test/Tomato___Septoria_leaf_spot/bc7552e4-3901-41b8-8bef-
727eeca4270e___RS_Early.B_7942.JPG",target_size=(128,128))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['Pepper,_bell___Bacterial_spot',
'Pepper,_bell___healthy',
'Potato___Early_blight',
'Potato___Late_blight',
'Potato___healthy',
'Tomato___Bacterial_spot',
'Tomato___Late_blight',
'Tomato___Leaf_Mold',
'Tomato___Septoria_leaf_spot']
index[y[0]]

```