



KUMARAGURU
college of technology
character is life

Department of Information Science and Engineering

U18ISE0001 – IMAGE AND VIDEO ANALYTICS

**Project Report on Plant Disease Classification into healthy, powdery
or rust using Tensorflow and Keras**

SUBMITTED BY

Jahfiyathul Firthous A 21BIS011

Nithyashree A 21BIS020

Nivethika R 21BIS022

CODE:

```
import os
```

```
def total_files(folder_path):
```

```
    num_files = len([f for f in os.listdir(folder_path) if  
os.path.isfile(os.path.join(folder_path, f))])
```

```
    return num_files
```

```

train_files_healthy = "Dataset/Train/Train/Healthy"
train_files_powdery = "Dataset/Train/Train/Powdery"
train_files_rust = "Dataset/Train/Train/Rust"

test_files_healthy = "Dataset/Test/Test/Healthy"
test_files_powdery = "Dataset/Test/Test/Powdery"
test_files_rust = "Dataset/Test/Test/Rust"

valid_files_healthy = "Dataset/Validation/Validation/Healthy"
valid_files_powdery = "Dataset/Validation/Validation/Powdery"
valid_files_rust = "Dataset/Validation/Validation/Rust"

print("Number of healthy leaf images in training set",
total_files(train_files_healthy))

print("Number of powder leaf images in training set",
total_files(train_files_powdery))

print("Number of rusty leaf images in training set", total_files(train_files_rust))

print("=====
==")

print("Number of healthy leaf images in test set", total_files(test_files_healthy))
print("Number of powder leaf images in test set", total_files(test_files_powdery))
print("Number of rusty leaf images in test set", total_files(test_files_rust))

print("=====
==")

```

```
print("Number of healthy leaf images in validation set",  
total_files(valid_files_healthy))  
  
print("Number of powder leaf images in validation set",  
total_files(valid_files_powdery))  
  
print("Number of rusty leaf images in validation set", total_files(valid_files_rust))
```

```
from PIL import Image  
import IPython.display as display
```

```
image_path = 'Dataset/Train/Train/Healthy/8ce77048e12f3dd4.jpg'
```

```
with open(image_path, 'rb') as f:  
    display.display(display.Image(data=f.read(), width=500))
```

```
image_path = 'Dataset/Train/Train/Rust/80f09587dfc7988e.jpg'
```

```
with open(image_path, 'rb') as f:  
    display.display(display.Image(data=f.read(), width=500))
```

```
from keras.preprocessing.image import ImageDataGenerator
```

```
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2,  
zoom_range=0.2, horizontal_flip=True)
```

```
test_datagen = ImageDataGenerator(rescale=1./255)
```

```
train_generator = train_datagen.flow_from_directory('Dataset/Train/Train',  
                                                    target_size=(225, 225),  
                                                    batch_size=32,  
                                                    class_mode='categorical')
```

```
validation_generator =  
test_datagen.flow_from_directory('Dataset/Validation/Validation',  
                                 target_size=(225, 225),  
                                 batch_size=32,  
                                 class_mode='categorical')
```

```
from keras.models import Sequential  
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
```

```
model = Sequential()  
model.add(Conv2D(32, (3, 3), input_shape=(225, 225, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Conv2D(64, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Flatten())  
model.add(Dense(64, activation='relu'))  
model.add(Dense(3, activation='softmax'))  
  
model.compile(optimizer='adam', loss='categorical_crossentropy',  
metrics=['accuracy'])
```

```
history = model.fit(train_generator,  
                    batch_size=16,  
                    epochs=5,  
                    validation_data=validation_generator,  
                    validation_batch_size=16  
                    )
```

```
from matplotlib import pyplot as plt  
from matplotlib.pyplot import figure
```

```
import seaborn as sns  
sns.set_theme()  
sns.set_context("poster")
```

```
figure(figsize=(25, 25), dpi=100)
```

```
plt.plot(history.history['accuracy'])  
plt.plot(history.history['val_accuracy'])  
plt.title('model accuracy')  
plt.ylabel('accuracy')  
plt.xlabel('epoch')  
plt.legend(['train', 'val'], loc='upper left')  
plt.show()
```

```
model.save("model.h5")
```

```
from tensorflow.keras.preprocessing.image import load_img, img_to_array  
import numpy as np
```

```
def preprocess_image(image_path, target_size=(225, 225)):  
    img = load_img(image_path, target_size=target_size)  
    x = img_to_array(img)  
    x = x.astype('float32') / 255.  
    x = np.expand_dims(x, axis=0)  
    return x
```

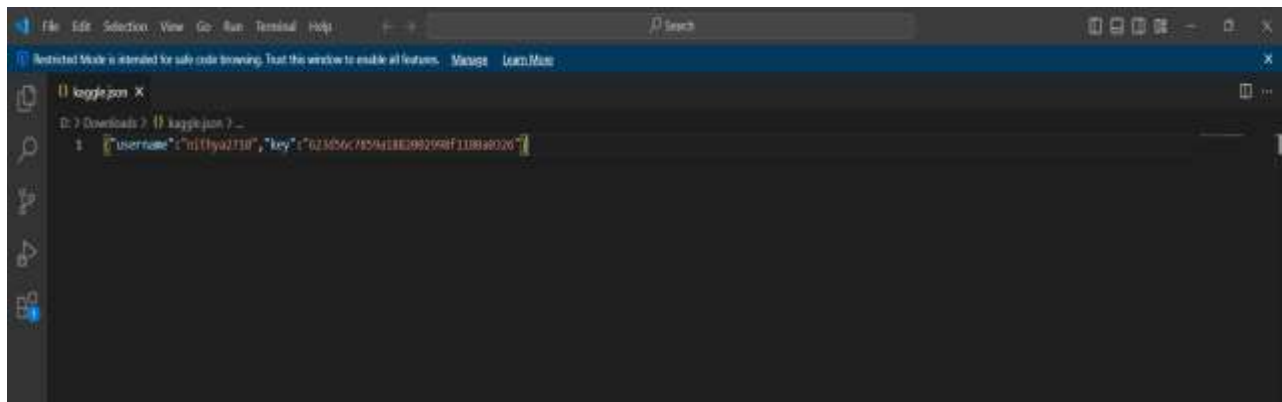
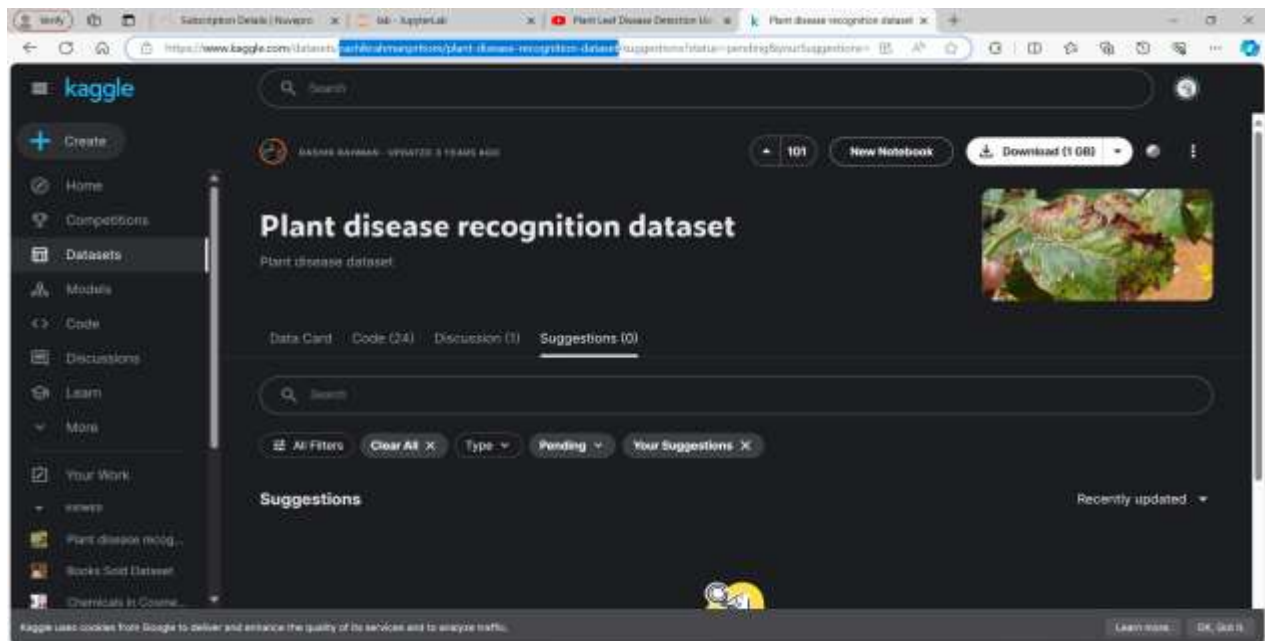
```
x = preprocess_image('Dataset/Test/Test/Rust/82f49a4a7b9585f1.jpg')
```

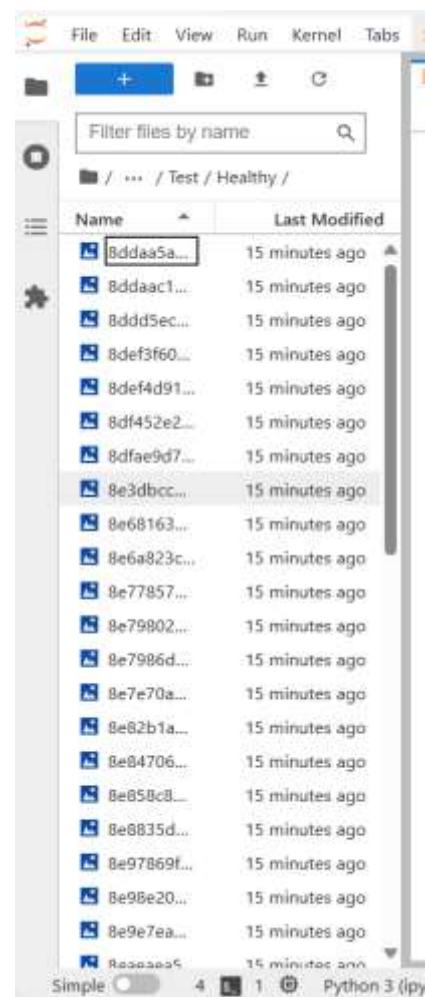
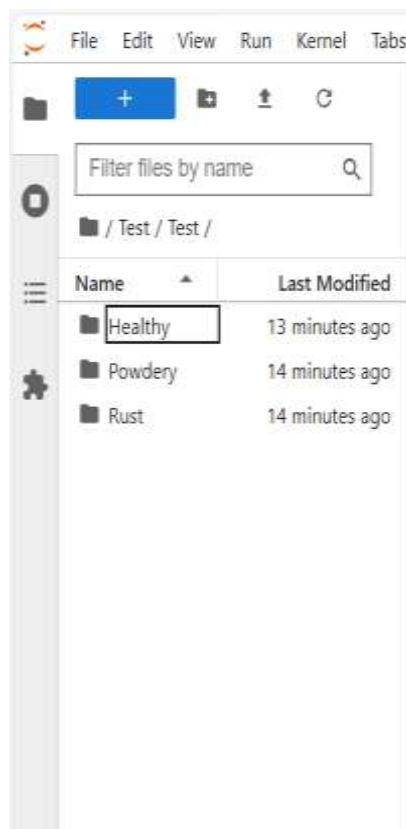
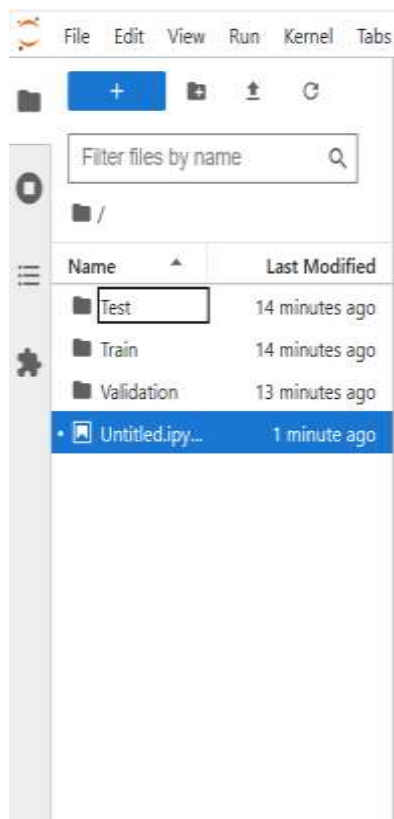
```
predictions = model.predict(x)  
predictions[0]
```

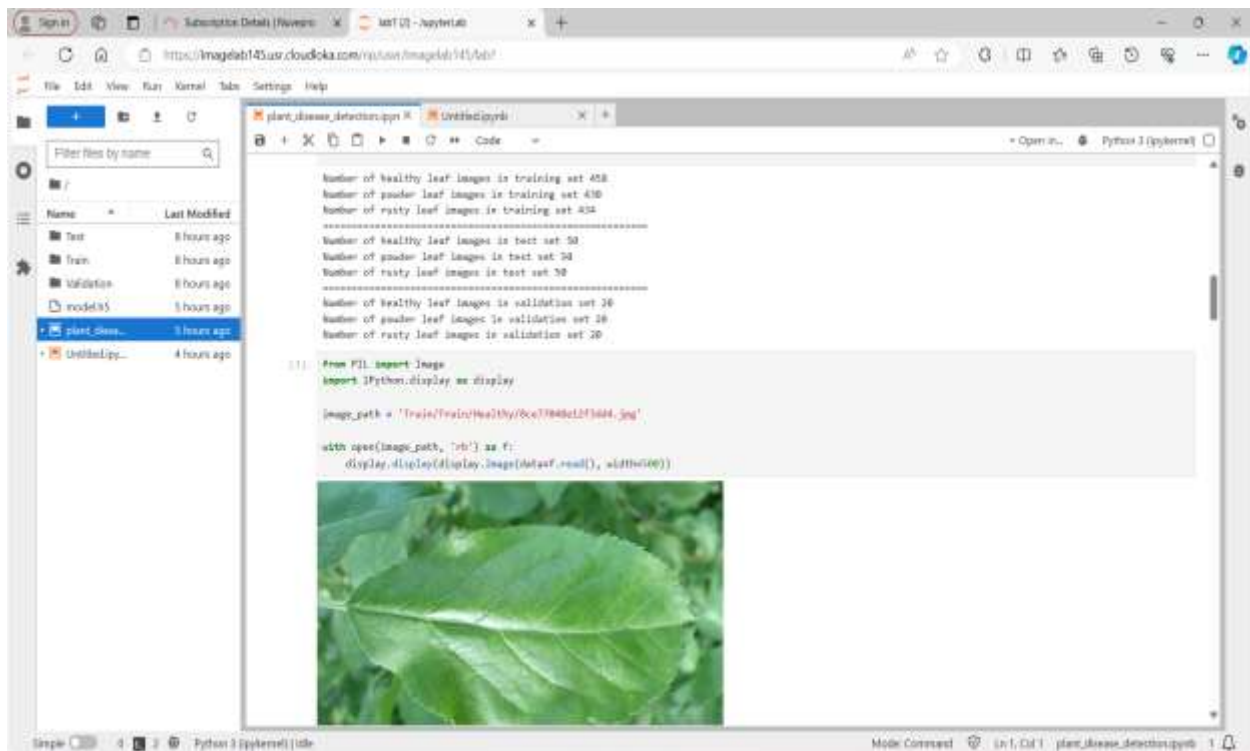
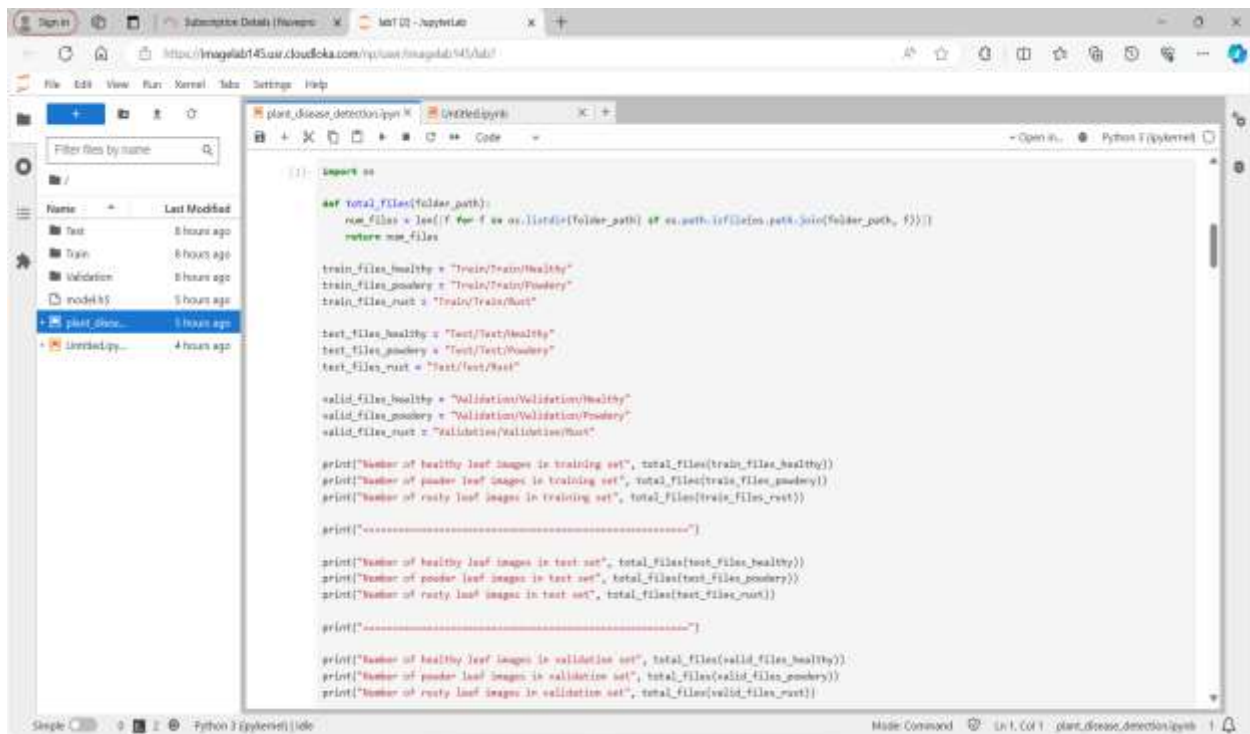
```
labels = train_generator.class_indices  
labels = {v: k for k, v in labels.items()}  
labels
```

```
predicted_label = labels[np.argmax(predictions)]  
print(predicted_label)
```

SCREENSHOTS :







plant_disease_detector.py

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

history = model.fit(train_generator,
                    batch_size=32,
                    epochs=5,
                    validation_data=validation_generator,
                    validation_batch_size=32
                )

epoch 1/5
2024-06-18 09:31:56.388255: W external/local_tsl/tsl/framework/ops_allocator_impl.cc:83] Allocation of 203689984 exceeds 10% of free system memory.
2024-06-18 09:31:59.462889: W external/local_tsl/tsl/framework/ops_allocator_impl.cc:83] Allocation of 203689984 exceeds 10% of free system memory.
1/42 [.....] - ETA: 6.18s - loss: 1.8929 - accuracy: 0.4862

2024-06-18 09:32:02.575532: W external/local_tsl/tsl/framework/ops_allocator_impl.cc:83] Allocation of 203689984 exceeds 10% of free system memory.
2024-06-18 09:32:05.545492: W external/local_tsl/tsl/framework/ops_allocator_impl.cc:83] Allocation of 203689984 exceeds 10% of free system memory.
2/42 [.....] - ETA: 4.86s - loss: 1.3021 - accuracy: 0.4531

2024-06-18 09:32:06.884325: W external/local_tsl/tsl/framework/ops_allocator_impl.cc:83] Allocation of 203689984 exceeds 10% of free system memory.
42/42 [=====] - 256s 60s/step - loss: 1.3195 - accuracy: 0.5597 - val_loss: 0.4750 - val_accuracy: 0.6557

epoch 2/5
42/42 [=====] - 241s 60s/step - loss: 0.4675 - accuracy: 0.7996 - val_loss: 0.4155 - val_accuracy: 0.8361

epoch 3/5
42/42 [=====] - 243s 60s/step - loss: 0.4288 - accuracy: 0.8263 - val_loss: 0.4006 - val_accuracy: 0.8535

epoch 4/5
42/42 [=====] - 244s 60s/step - loss: 0.3053 - accuracy: 0.8807 - val_loss: 0.4671 - val_accuracy: 0.8535

epoch 5/5
42/42 [=====] - 246s 60s/step - loss: 0.2568 - accuracy: 0.9134 - val_loss: 0.4209 - val_accuracy: 0.8535

[[[]]]

!pip install matplotlib

Collecting matplotlib
  Downloading matplotlib-3.8.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.8 kB)
Collecting contourpy>=1.0.1 (from matplotlib)
  Downloading contourpy-1.2.1-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.8 kB)
Collecting cycler>=0.10 (from matplotlib)
  Downloading cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
```

plant_disease_detector.py

```
Downloading fonttools-4.51.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (231 kB)
135.3/135.3 kB 2.9 MB/s eta 0:00:01

Collecting kinkooler>=1.3.1 (from matplotlib)
  Downloading kinkooler-1.6.5-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.4 kB)
Requirement already satisfied: numpy>=1.21 in /opt/conda/lib/python3.11/site-packages (from matplotlib) (1.26.4)
Requirement already satisfied: packaging>=20.0 in /opt/conda/lib/python3.11/site-packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=8 in /opt/conda/lib/python3.11/site-packages (from matplotlib) (10.2.8)
Collecting pyparsing>=2.3.1 (from matplotlib)
  Downloading pyparsing-3.1.2-py3-none-any.whl.metadata (5.1 kB)
Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python3.11/site-packages (from matplotlib) (2.8.2)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-packages (from python-dateutil>=2.7->matplotlib) (0.12.1)
Downloading matplotlib-3.8.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (11.6 MB)
11.6/11.6 MB 20.4 MB/s eta 0:00:00:01

Downloading contourpy-1.2.1-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (198 kB)
198.8/198.8 kB 4.3 MB/s eta 0:00:01

Downloading cycler-0.12.1-py3-none-any.whl (8.5 kB)

Downloading fonttools-4.51.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (4.9 MB)
4.9/4.9 MB 14.4 MB/s eta 0:00:00:01

Downloading kinkooler-1.6.5-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.4 MB)
1.4/1.4 MB 15.8 MB/s eta 0:00:00:01

Downloading pyparsing-3.1.2-py3-none-any.whl (103 kB)
103.2/103.2 kB 2.8 MB/s eta 0:00:00:01

Installing collected packages: pyparsing, kinkooler, fonttools, cycler, contourpy, matplotlib
Successfully installed contourpy-1.2.1 cycler-0.12.1 fonttools-4.51.0 kinkooler-1.6.5 matplotlib-3.8.4 pyparsing-3.1.2
Note: you may need to restart the kernel to use updated packages.

[[[]]]

!pip install seaborn

Collecting seaborn
  Downloading seaborn-0.13.2-py3-none-any.whl.metadata (5.4 kB)
Requirement already satisfied: numpy>=1.24.0; >=1.20 in /opt/conda/lib/python3.11/site-packages (from seaborn) (1.26.4)
Requirement already satisfied: pandas>=1.2 in /opt/conda/lib/python3.11/site-packages (from seaborn) (2.2.0)
Requirement already satisfied: matplotlib>=3.5.2, >=3.4 in /opt/conda/lib/python3.11/site-packages (from seaborn) (3.8.4)
Requirement already satisfied: contourpy>=1.0.1 in /opt/conda/lib/python3.11/site-packages (from matplotlib>=3.5.2, >=3.4->seaborn) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-packages (from matplotlib>=3.5.2, >=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /opt/conda/lib/python3.11/site-packages (from matplotlib>=3.5.2, >=3.4->seaborn) (4.51.0)
Requirement already satisfied: kinkooler>=1.3.1 in /opt/conda/lib/python3.11/site-packages (from matplotlib>=3.5.2, >=3.4->seaborn) (1.6.5)
```

plant_disease_detector.py

```
Requirement already satisfied: contourpy>1.0.1 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (1.2.1)
Requirement already satisfied: cycler>0.10 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>4.22.0 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (4.51.0)
Requirement already satisfied: kiwisolver>1.3.1 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (1.4.5)
Requirement already satisfied: packaging>20.0 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (23.2)
Requirement already satisfied: pillow>8 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (10.2.0)
Requirement already satisfied: pyparsing>2.5.1 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (3.1.2)
Requirement already satisfied: python-dateutil>1.7 in /opt/conda/lib/python3.11/site-packages (from matplotlib>3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>2018.1 in /opt/conda/lib/python3.11/site-packages (from pandas>1.2->seaborn) (2023.1.post1)
Requirement already satisfied: tzdata>2022.7 in /opt/conda/lib/python3.11/site-packages (from pandas>1.2->seaborn) (2024.1)
Requirement already satisfied: six>1.5 in /opt/conda/lib/python3.11/site-packages (from python-dateutil>1.7->matplotlib>3.6.1,>=3.4->seaborn) (1.16.0)
Downloading seaborn-0.13.2-py3-none-any.whl (284 kB)
298.6/298.6 KB 4.1 MB/s eta 0:00:00
Installing collected packages: seaborn
Successfully installed seaborn-0.13.2
Note: you may need to restart the kernel to use updated packages.
```

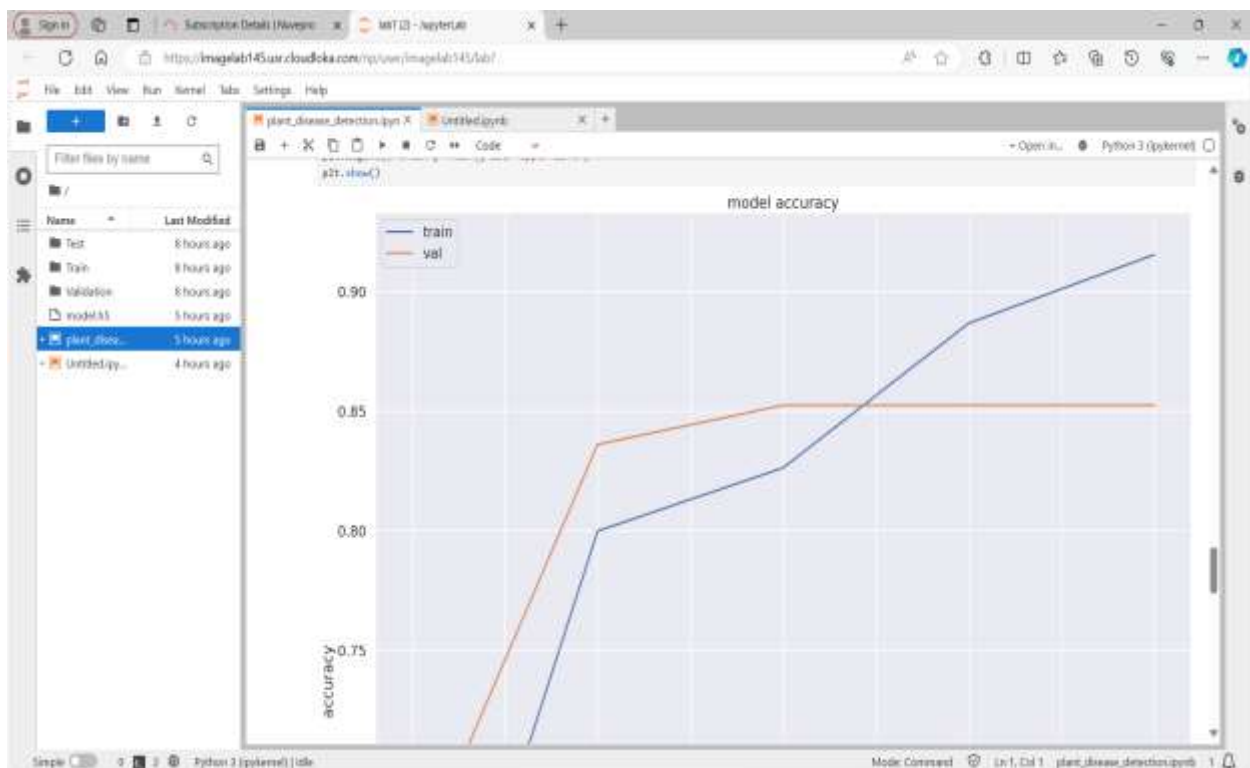
```
from matplotlib import pyplot as plt
from matplotlib.pyplot import figure

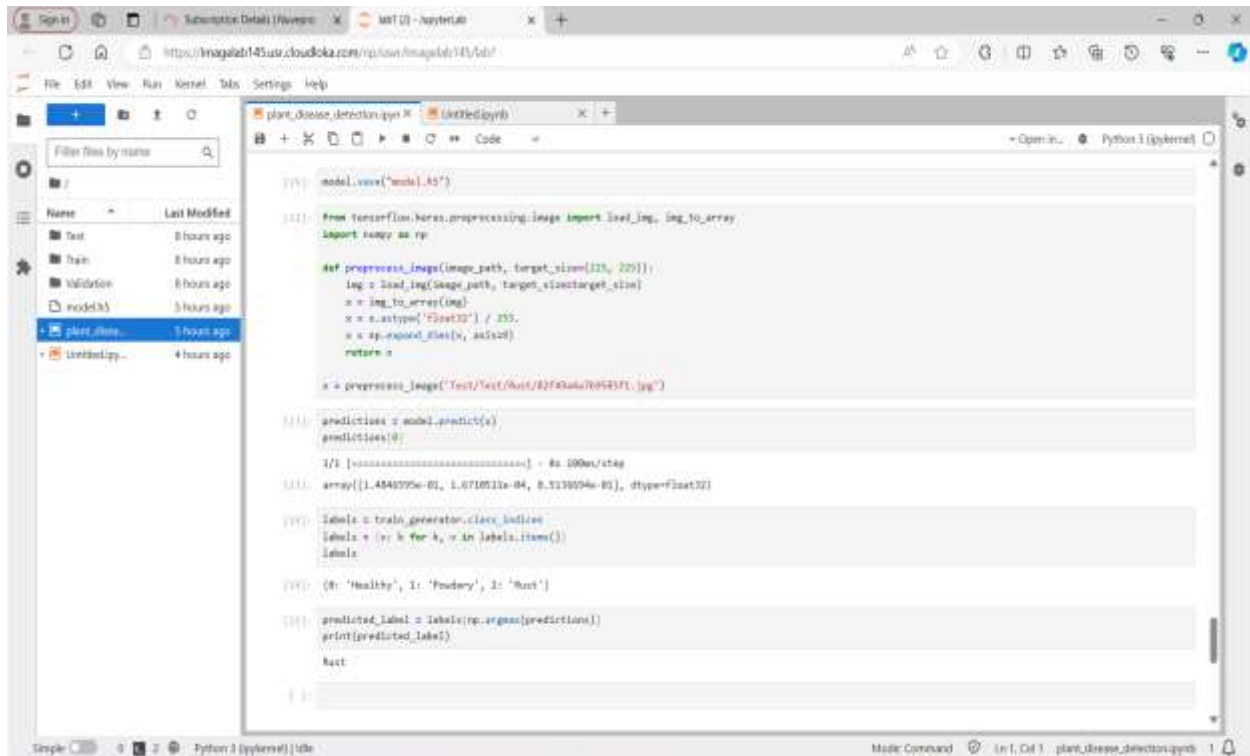
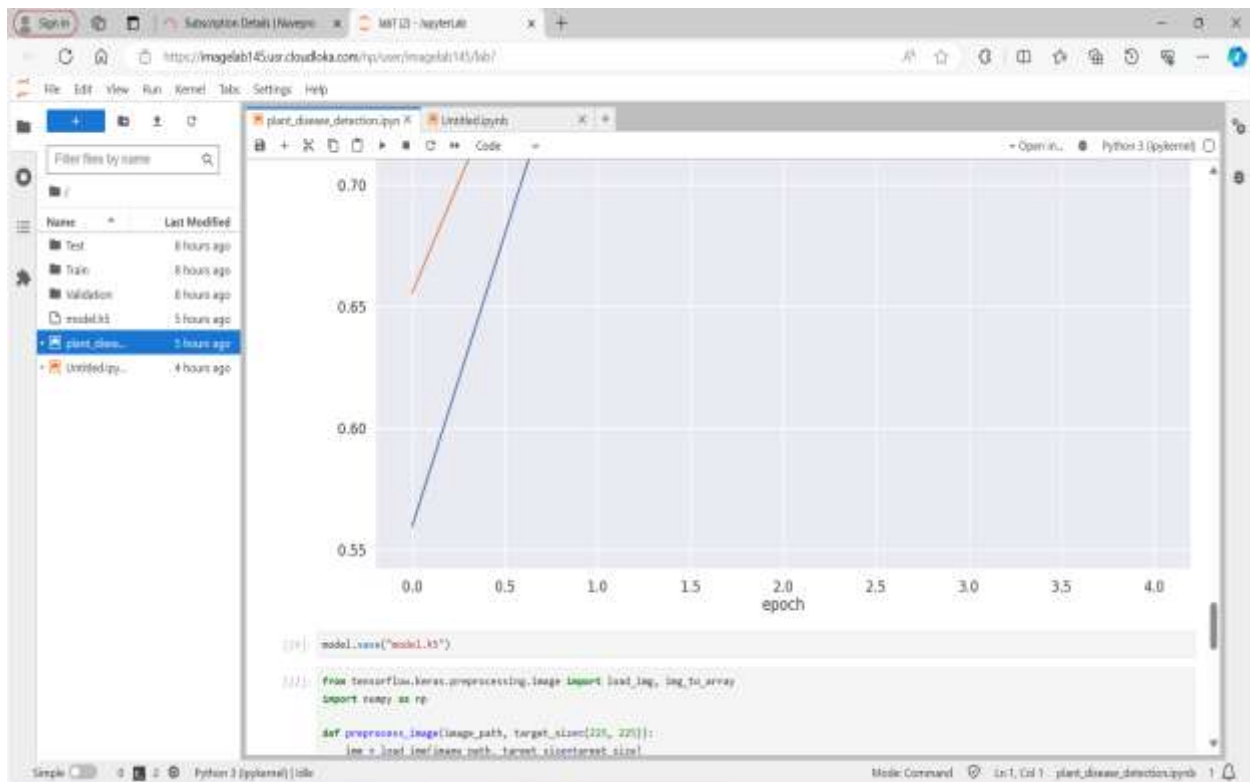
import seaborn as sns
sns.set_theme()
sns.set_context("poster")

figure(figsize=(20, 25), dpi=100)

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

model accuracy





CODE EXPLANATION:

1. Importing Libraries:

- `os`: Provides functions for interacting with the operating system, used for file and directory operations.
- `PIL.Image`: Used for image manipulation.
- `IPython.display`: Allows displaying images within the Jupyter Notebook.
- `keras.preprocessing.image`: Provides utilities for image data preprocessing.
- `keras.models`, `keras.layers`: Used to define and build the neural network model.
- `matplotlib.pyplot`, `seaborn`: Libraries for data visualization.
- `numpy`: Library for numerical operations.

2. Defining Functions:

- `total_files`: Counts the total number of files (images) in a given folder path.

3. Defining File Paths:

- Paths to the training, testing, and validation folders for each category of leaf images.

4. Printing Number of Files:

- Prints the number of files (images) in each category for training, testing, and validation sets.

5. Displaying Sample Images:

- Displays sample images from the training set using `IPython.display`.

6. Image Data Generators:

- ImageDataGenerator is configured for data augmentation and normalization for training and testing images.

7. Creating Data Generators:

- flow_from_directory method creates directory iterators for both training and validation data, generating batches of augmented images.

8. Defining the Convolutional Neural Network (CNN) Model:

- A sequential model is created with convolutional layers, max pooling layers, flattening layer, and dense layers with ReLU activation functions.
- Output layer has softmax activation for multiclass classification.

9. Compiling the Model:

- Configures the model for training with optimizer, loss function, and metrics.

10. Training the Model:

- fit method trains the model using data generated by the data generators.
- Training history is stored in history object.

11. Visualizing Training History:

- Plots model accuracy over epochs for both training and validation sets.

12. Saving the Model:

- The trained model is saved to a file named "model.h5".

13. Image Preprocessing Function:

- preprocess_image function loads and preprocesses an image for model prediction.

14. Making Predictions:

- A sample image is preprocessed and fed to the trained model to make predictions.
- Predicted label is obtained by mapping the index with the class labels.

15. Printing Predicted Label:

- Prints the predicted label for the sample image.

EXPLANATION OF PROJECT:

1. Data Collection:

- The project involves collecting a dataset of images of plant leaves, each labeled with the type of disease present (e.g., healthy, powdery mildew, rust).

2. Data Preprocessing:

- The collected dataset is likely to undergo preprocessing steps such as resizing images to a uniform size, splitting them into training, testing, and validation sets, and possibly augmenting the data to increase its diversity and robustness.

3. Model Architecture:

- A Convolutional Neural Network (CNN) architecture is chosen for this image classification task. CNNs are widely used for image classification tasks due to their ability to automatically learn features from images.

4. Model Training:

- The model is trained using the training dataset. During training, the model learns to classify images into different disease categories by adjusting its parameters based on the provided training data.

5. Model Evaluation:

- The trained model's performance is evaluated using the validation dataset. This step helps to assess how well the model generalizes to unseen data and whether it is overfitting or underfitting.

6. Visualizing Training History:

- The training history, including metrics such as accuracy and loss, is visualized using plots. This allows monitoring the model's performance over epochs and helps in identifying any issues such as overfitting or training convergence.

7. Model Deployment:

- Once the model achieves satisfactory performance on the validation set, it can be deployed for inference. This involves making predictions on new, unseen images to classify them into the appropriate disease categories.

8. Application:

- The trained model can be used in various applications, such as agricultural systems for automated disease detection in plants. It can help farmers and

researchers identify diseased plants early, enabling timely intervention to prevent crop losses.