Presented by: Team Project Title: Tomato Plant Disease Detection

Members Name :

1. Disha Mathankar

   Rollno: MPIITDCV30988

2. Anurag Gupta

   Rollno: MPIITDCV53525

3. Pooja kushwaha

   Rollno: MPIITDCV66985

Tomato Disease Detection

Introduction:

> *Problem Statement*:
>
> > Few farmers are facing with issue with in the farm. There are lots of problems in the agricultural sector in the perspective of the farmer, but we can help them by integrating the AI Technology. Even after selecting and growing the crop in the field, few crop diseases are not identified by the farmer which results to decrease in the crop yield. This is the main problem in the field so we are going to solve this issue by developing a model which can recognize the disease that is caused by the input of an image of the diseased plant. By tackling this, we can increase the crop yield and maintain the crop production.

> *Overview of the project*:
>
> > This project involves building and loading the data, **Plant Village Dataset**, Exploratory Data Analysis, Model Building and Training.
>
> *Goal of this project*:
>
> > The goal of this project is to build model for tomato crop and to observe the performance metrics of the model
>
> *Result*:
>
> > With this we can hence use the model for any web application for tomato crop managment systems or Tomato plant Disease detection system.

```
%%bash
#install kaggle
pip install -q kaggle

#create a Kaggle folder andcopy kaggle.json to copied folder
echo '{"username":"disha1503","key":"3d1810121b6c88f023679868aa91845b"}' > ~/.kaggle/kaggle.json

#permission for json to act
chmod 600 ~/.kaggle/kaggle.json

#downloading the dataset
kaggle datasets download -d shylesh101/tomato-leaf-disease

# unziping the dataset
unzip tomato-leaf-disease.zip

# installing the tensorflow library
pip install tensorflow

```

Show hidden output

Importing all the required libraries

```
import pandas as pd
import numpy as np
import tensorflow as tf
import seaborn as sns
from tensorflow.python.client import device_lib
device_lib.list_local_devices()
import os
from tensorflow.keras.utils import image_dataset_from_directory
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
import math
from tensorflow import keras
# import tensorflow_addons as tfa
from tensorflow.keras import layers
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
from PIL import Image, ImageEnhance
import random
import cv2
from sklearn.preprocessing import MultiLabelBinarizer
from tqdm import tqdm
from tensorflow.keras.utils import plot_model
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import TensorBoard
import tensorflow_hub as hub
from sklearn.metrics import classification_report, confusion_matrix

from tensorflow.keras.optimizers import Adam
from tensorflow.keras import Model
from tensorflow.keras.models import load_model
import warnings
warnings.filterwarnings('ignore')
```

```
bash: line 5: /root/.kaggle/kaggle.json: No such file or directory
chmod: cannot access '/root/.kaggle/kaggle.json': No such file or directory
100%|██████████| 370M/370M [00:12<00:00, 31.8MB/s]
```

1. Exploratory Data Analysis

Defining a function to get the path for folder paths

```
train_data_dir = '/content/tomato_dataset/train'
test_data_dir = '/content/tomato_dataset/test'
val_data_dir = '/content/tomato_dataset/valid'
```

```
def get_path(plant_dir:str, dir_test:str):
    if dir_test == 'Test':
        return test_data_dir
    elif dir_test == 'Train':
        return train_data_dir
    elif dir_test == 'Valid':
        return val_data_dir
plant_path = '/content/tomato_dataset'
plant_dirs = os.listdir("/content/tomato_dataset")
plant_dirs
```

```
['train', 'valid', 'test']
```

Printing the information about the Training set, the directories and the images

```
img_dim = (256,256)
batch_size = 32
num_channels = 3
input_size = (batch_size, img_dim[0], img_dim[1], num_channels)
train_dataset = {}

print("-_-_-_-_-_-_-_-_-_-_Images & Classes for Training-_-_-_-_-_-_-_-_-_-_")
for plant in plant_dirs:
    print(f'>>> No of Images & Classes in "{plant}" directory')
    train_dataset[plant] = image_dataset_from_directory(get_path(plant, "Train"),
                                                         shuffle=True,
                                                         labels = 'inferred',
                                                         label_mode = 'int',
                                                         image_size = img_dim,
                                                         batch_size = batch_size)
```

```
-_-_-_-_-_-_-_-_-_-_Images & Classes for Training-_-_-_-_-_-_-_-_-_-_
>>> No of Images & Classes in "train" directory
Found 18345 files belonging to 10 classes.
>>> No of Images & Classes in "valid" directory
Found 18345 files belonging to 10 classes.
>>> No of Images & Classes in "test" directory
Found 18345 files belonging to 10 classes.
```

Printing the disease names of each plant

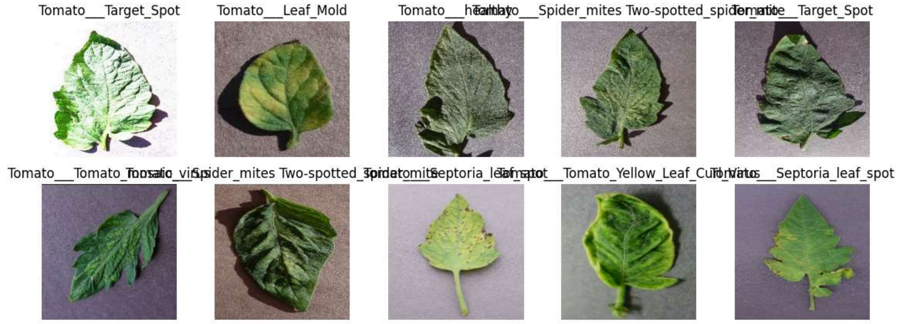
```
classes  ={}
for plant in plant_dirs:
    print(f">>> Classes in "{plant}" dataset :-")
    classes[plant] = []
    for num, cat in enumerate(train_dataset[plant].class_names, start=1):
        classes[plant].append(cat)
        print(num, cat)
    print("\n")
```

```
>>> Classes in train dataset :-
1 Tomato___Bacterial_spot
2 Tomato___Early_blight
3 Tomato___Late_blight
4 Tomato___Leaf_Mold
5 Tomato___Septoria_leaf_spot
6 Tomato___Spider_mites Two-spotted_spider_mite
7 Tomato___Target_Spot
8 Tomato___Tomato_Yellow_Leaf_Curl_Virus
9 Tomato___Tomato_mosaic_virus
10 Tomato___healthy


>>> Classes in valid dataset :-
1 Tomato___Bacterial_spot
2 Tomato___Early_blight
3 Tomato___Late_blight
4 Tomato___Leaf_Mold
5 Tomato___Septoria_leaf_spot
6 Tomato___Spider_mites Two-spotted_spider_mite
7 Tomato___Target_Spot
8 Tomato___Tomato_Yellow_Leaf_Curl_Virus
9 Tomato___Tomato_mosaic_virus
10 Tomato___healthy


>>> Classes in test dataset :-
1 Tomato___Bacterial_spot
2 Tomato___Early_blight
3 Tomato___Late_blight
4 Tomato___Leaf_Mold
5 Tomato___Septoria_leaf_spot
6 Tomato___Spider_mites Two-spotted_spider_mite
7 Tomato___Target_Spot
8 Tomato___Tomato_Yellow_Leaf_Curl_Virus
9 Tomato___Tomato_mosaic_virus
10 Tomato___healthy
```

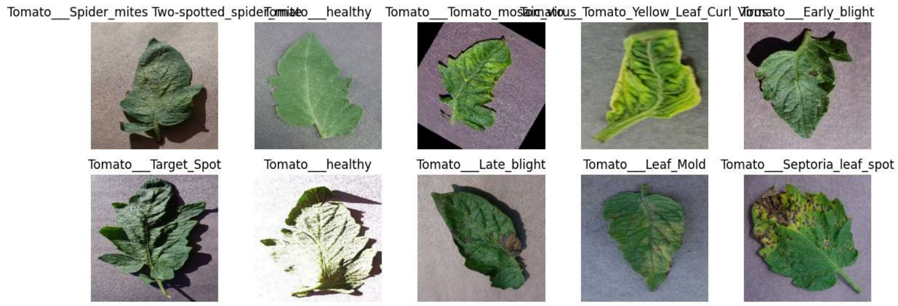
Plotting few random samples from each plant directory

```python
for plant in plant_dirs:
    print(f'>>>> Sample Images of "{plant}" dataset')
    plt.figure(figsize=(14,5))
    for image_batch, image_label in train_dataset[plant].take(1):
        for i in range(10):
            plt.subplot(2,5,i+1)
            plt.imshow(image_batch[i].numpy().astype('uint8'))
            plt.title(classes[plant][image_label[i]])
            plt.axis('off')
        plt.show()
    print("\n\n")
```

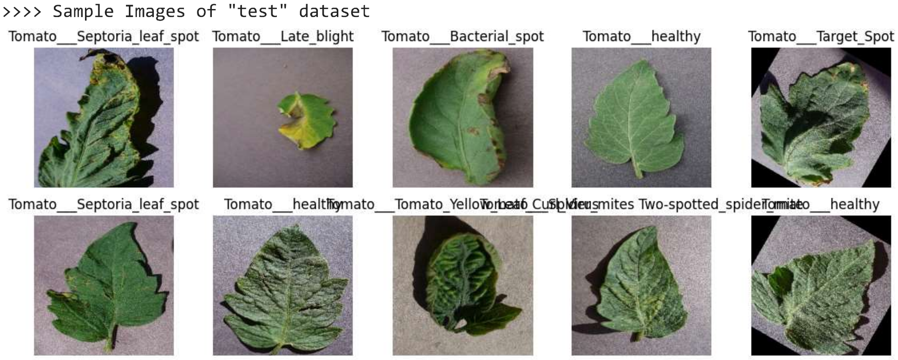
```
>>>> Sample Images of "train" dataset
```




```
>>>> Sample Images of "valid" dataset
```




```
>>>> Sample Images of "test" dataset
```



```
# getting values of training dataset
train_dataset.values()
```

```
dict_values([<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>, <_PrefetchDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>, <_PrefetchDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>])
```

Plotting the standardized images for random plant leaf images

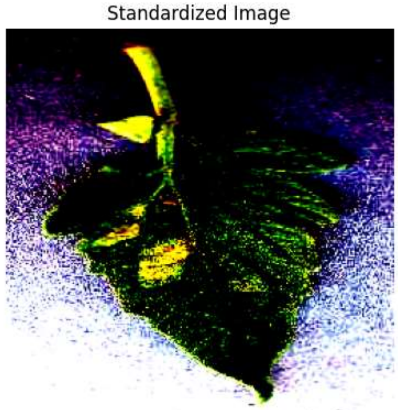
```
# Creating a function for standardizing images
def std_img(img):
    img_flat = img.reshape(-1,3)
    scaler = StandardScaler()
    img_std = scaler.fit_transform(img_flat)
    img_std = img_std.reshape(256,256,3)
    return img_std

# getting the standardized images with labels
tomato_img = []
tomato_label = []
for img,label in train_dataset[plant].take(1):
    for i in range(5):
        tomato_img.append(img[i])
        tomato_label.append(classes["test"][label[i]])

for i in range(5):
    # typcasting
    nik = np.array(tomato_img[i]).astype('uint8')
    img_std = std_img(nik)


    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.imshow(nik)
    plt.title("Tomato "+tomato_label[i])
    plt.axis('off')
    plt.subplot(1, 2, 2)
    plt.imshow(img_std)
    plt.title('Standardized Image')
    plt.axis('off')
plt.show()
```

Tomato Tomato___Spider_mites Two-spotted_spider_mite

Standardized Image

Tomato Tomato___Leaf_Mold

Standardized Image



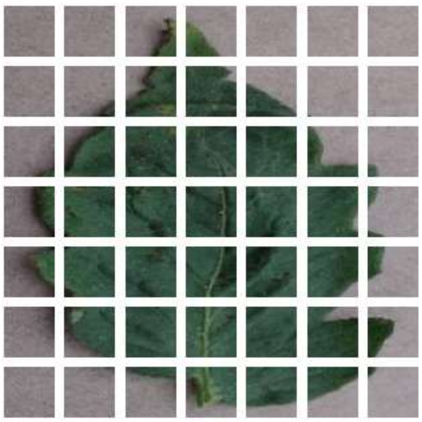
Tomato Tomato___Early_blight

Standardized Image

Plotting the 32X32 patch format of a image

```
image_size = 224
img_height, img_width = 512, 512
patch_size = 32
num_patches = (image_size // patch_size) ** 2
class Patches(layers.Layer):

    def __init__(self, patch_size):
        super(Patches, self).__init__()
        super(Patches, self).__init__()
        self.patch_size = patch_size
    def call(self, images):
        batch_size = tf.shape(images)[0]
        patches = tf.image.extract_patches(
            images=images,
            sizes=[1, self.patch_size, self.patch_size, 1],
            strides=[1, self.patch_size, self.patch_size, 1],
            rates=[1, 1, 1, 1],
            padding="VALID",
        )
        patch_dims = patches.shape[-1]
        patches = tf.reshape(patches, [batch_size, -1, patch_dims])
        return patches


import matplotlib.pyplot as plt
import matplotlib.image as mpimg
plt.figure(figsize=(4, 4))

target = "/content/tomato_dataset/train/Tomato___Bacterial_spot"
random_num = random.choice(os.listdir(target))
image = mpimg.imread("/content/tomato_dataset/train/Tomato___Bacterial_spot/" + random_num)
plt.imshow(image.astype("uint8"))
plt.axis("off")
resized_image = tf.image.resize(
    tf.convert_to_tensor([image]), size=(image_size, image_size)
)
patches = Patches(patch_size)(resized_image)
print(f"Image size: {image_size} X {image_size}")
print(f"Patch size: {patch_size} X {patch_size}")
print(f"Patches per image: {patches.shape[1]}")
print(f"Elements per patch: {patches.shape[-1]}")
n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize=(4, 4))
for i, patch in enumerate(patches[0]):
    ax = plt.subplot(n, n, i + 1)
    patch_img = tf.reshape(patch, (patch_size, patch_size, 3))
    plt.imshow(patch_img.numpy().astype("uint8"))
    plt.axis("off")
```

```
Image size: 224 X 224
Patch size: 32 X 32
Patches per image: 49
Elements per patch: 3072
```



Model Development

Enter the plant name for which you want to develop the model, as the variable

```
plant = "Tomato"
```

Declaring the paths for the training, testing, validation path, labels for the given plant diseases and the output length

```
train_path = f"{plant_path}/train"
val_path = f"{plant_path}/valid"
test_path = f"{plant_path}/test"
out_labels = os.listdir(f"{plant_path}/train/")
out_len = len(out_labels)
```

```
out_len
```

```
10
```

Declaring the batch size of 64 and the image size of 224X224 pixels

```
batch_size = 64
img_height = 224
```

Declare the ImageDataGenerator for the train_datagen and test_datagen, val_datagen. For train_datagen the images are augumented and for all the three datagenerators the pixels are scaled

```
train_datagen = ImageDataGenerator(rescale = 1./255.,rotation_range=20,shear_range=0.15,horizontal_flip=True,)
val_datagen = ImageDataGenerator(rescale = 1./255)
test_datagen = ImageDataGenerator(rescale = 1./255)
```

Declaring the train, test and valid sets for the input to the model, making every image to be of the size 224X224 pixels

```
train_set = train_datagen.flow_from_directory(train_path,target_size = (224,224),batch_size = 64,shuffle = True,class_mode = 'categorical
val_set = val_datagen.flow_from_directory(val_path,target_size = (224, 224),batch_size = 64,shuffle = False,class_mode = 'categorical')
test_set = val_datagen.flow_from_directory(test_path,target_size = (224, 224),batch_size = 64,shuffle = False,class_mode = 'categorical')
```

```
Found 18345 images belonging to 10 classes.
Found 4585 images belonging to 10 classes.
Found 50 images belonging to 10 classes.
```

Loading the pretrained VIT model with RESNET50 as backbone with 32 patch size and pretrained on ImageNet-21k dataset. Building a classifier head over the pretrained VIT Model with out_len as the output shape which is equal to the number of disease of plant

```
fe_L2 = hub.KerasLayer("https://tfhub.dev/sayakpaul/vit_r50_l32_fe/1",input_shape = (224,224,3),trainable = False,name = "Pre_Trained_")
VIT = tf.keras.Sequential([
    fe_L2,
    layers.Dense(128,activation = "relu"),
    layers.Dropout(0.5),
    layers.Dense(out_len, activation = "softmax", name = "output_layer")
])

VIT.compile(loss = "categorical_crossentropy",optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0001),metrics = ["accuracy"])
```

Trianing the model for 10 epochs

```
epochs = 10
r=VIT.fit(train_set,epochs = epochs,validation_data = val_set,steps_per_epoch=len(train_set),validation_steps = len(val_set))
```

```
Epoch 1/10
287/287 [==============================] - 518s 2s/step - loss: 1.9442 - accuracy: 0.4606 - val_loss: 0.7074 - val_accuracy: 0.7895
Epoch 2/10
287/287 [==============================] - 385s 1s/step - loss: 0.8067 - accuracy: 0.7290 - val_loss: 0.4303 - val_accuracy: 0.8713
Epoch 3/10
287/287 [==============================] - 391s 1s/step - loss: 0.5602 - accuracy: 0.8132 - val_loss: 0.2970 - val_accuracy: 0.9093
Epoch 4/10
287/287 [==============================] - 415s 1s/step - loss: 0.4359 - accuracy: 0.8545 - val_loss: 0.2397 - val_accuracy: 0.9243
Epoch 5/10
287/287 [==============================] - 396s 1s/step - loss: 0.3495 - accuracy: 0.8827 - val_loss: 0.2119 - val_accuracy: 0.9328
Epoch 6/10
287/287 [==============================] - 387s 1s/step - loss: 0.3039 - accuracy: 0.9011 - val_loss: 0.1793 - val_accuracy: 0.9400
Epoch 7/10
287/287 [==============================] - 388s 1s/step - loss: 0.2636 - accuracy: 0.9137 - val_loss: 0.1715 - val_accuracy: 0.9453
Epoch 8/10
287/287 [==============================] - 411s 1s/step - loss: 0.2286 - accuracy: 0.9250 - val_loss: 0.1443 - val_accuracy: 0.9514
Epoch 9/10
287/287 [==============================] - 412s 1s/step - loss: 0.1972 - accuracy: 0.9340 - val_loss: 0.1273 - val_accuracy: 0.9586
Epoch 10/10
287/287 [==============================] - 391s 1s/step - loss: 0.1893 - accuracy: 0.9373 - val_loss: 0.1197 - val_accuracy: 0.9605
```

Saving the model with plant name

```
model_name = "tomato"+"_model.h5"
VIT.save(model_name)
```

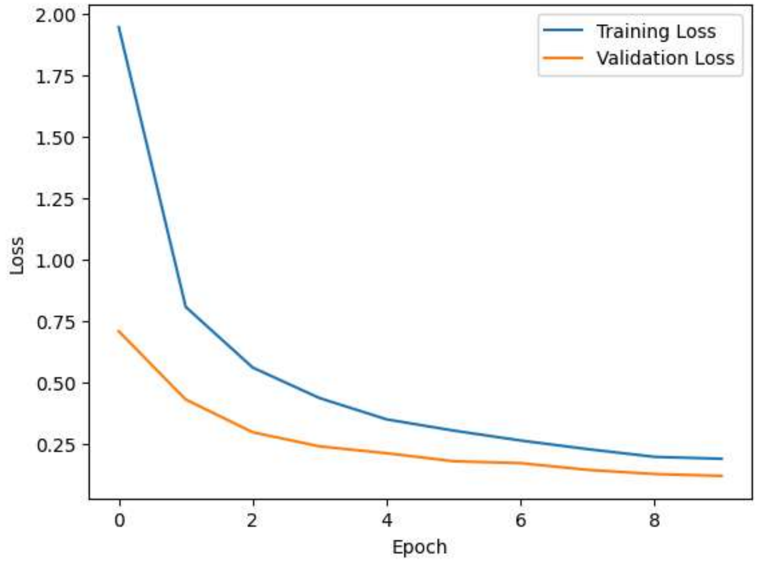
To make the model file to be availabel for download, run the following code

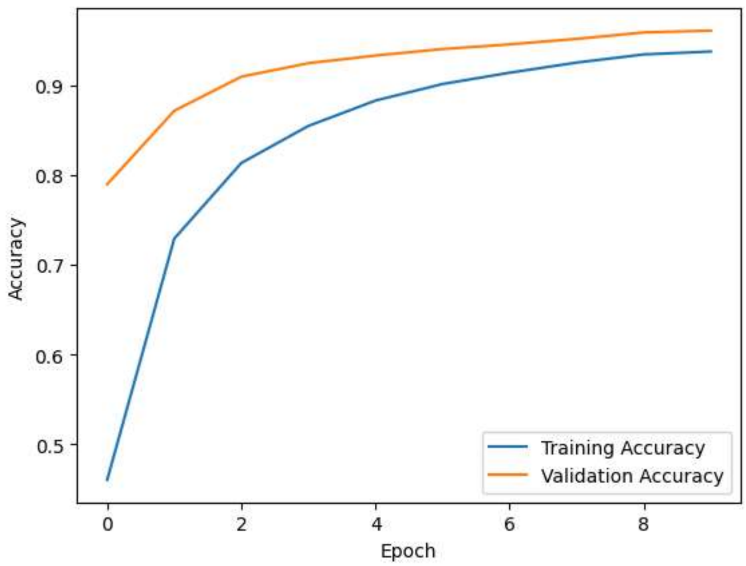
```
!zip model_file.zip /content/
```

```
updating: content/df/ (stored 0%)
```

Plotting Accuracy Curve

```
# import matplotlib.pyplot as plt
# history_with_dropout = r
# # Plot training and validation loss
# plt.plot(r.history['loss'], label='Training Loss')
# plt.plot(r.history['val_loss'], label='Validation Loss')
# plt.xlabel('Epoch')
# plt.ylabel('Loss')
# plt.legend()
# plt.show()

# # Plot training and validation accuracy
# plt.plot(r.history['accuracy'], label='Training Accuracy')
# plt.plot(r.history['val_accuracy'], label='Validation Accuracy')
# plt.xlabel('Epoch')
# plt.ylabel('Accuracy')
# plt.legend()
# plt.show()

# # Evaluate the model on the test set
# test_loss, test_accuracy = VIT.evaluate(test_set)
# print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')

```






```
1/1 [==============================] - 1s 789ms/step - loss: 0.1120 - accuracy: 0.9600
Test Loss: 0.11198386549949646, Test Accuracy: 0.9599999785423279
```

Learning rate graph

```
r.history.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
# import matplotlib.pyplot as plt
# import numpy as np
# import seaborn as sns
# # Plot learning rate over epochs
# plt.figure(figsize=(5, 5))
# plt.plot(VIT.history['accuracy'], label='Learning Rate')
# plt.title('Learning Rate Over Epochs')
# plt.xlabel('Epochs')
# plt.ylabel('Learning Rate')
# plt.legend()
# plt.show()

```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-48-ab4421230a9f> in <cell line: 6>()
      4 # Plot learning rate over epochs
      5 plt.figure(figsize=(5, 5))
----> 6 plt.plot(VIT.history['accuracy'], label='Learning Rate')
      7 plt.title('Learning Rate Over Epochs')
      8 plt.xlabel('Epochs')

TypeError: 'History' object is not subscriptable

<Figure size 500x500 with 0 Axes>
```

Predicting the test_set for the model

```
Y_pred = VIT.predict(test_set, steps = len(test_set) )
y_pred = np.argmax(Y_pred, axis=1)
```

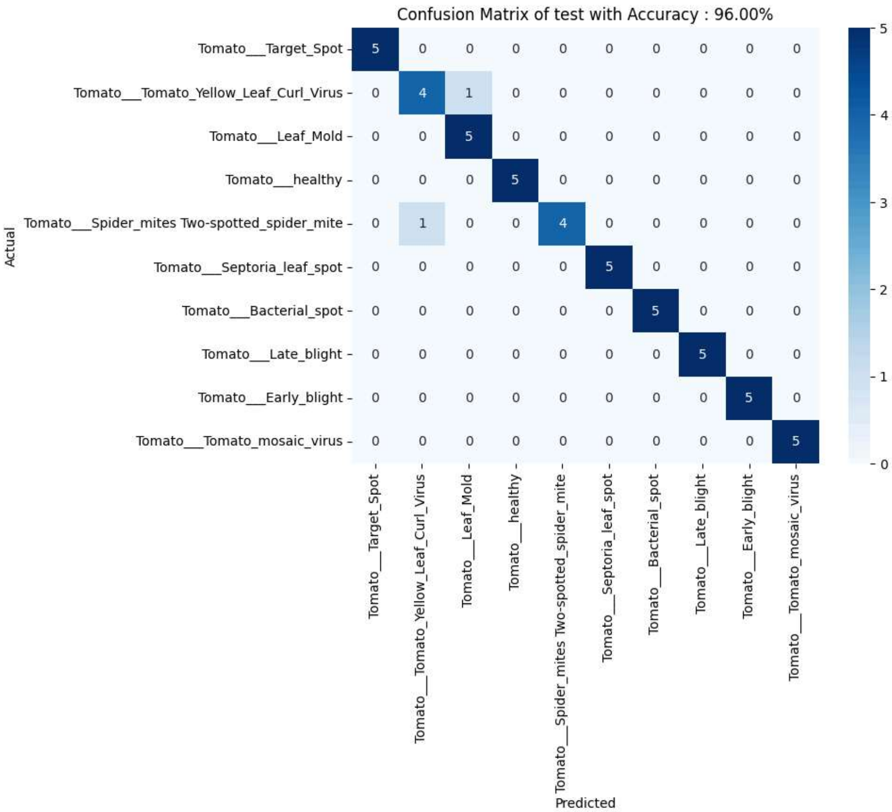
```
1/1 [==============================] - 32s 32s/step
```

```
y_pred
```

```
array([0, 0, 0, 0, 0, 1, 2, 1, 1, 1, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 1, 4,
       4, 4, 4, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 7, 7, 7, 7, 7, 8, 8, 8, 8,
       8, 9, 9, 9, 9, 9])
```

Plotting the confusion matrix for given y_pred and y_true

```
cf = confusion_matrix(test_set.classes, y_pred)
list = os.listdir(f"{plant_path}/train")
plt.figure(figsize=(8, 6))
sns.heatmap(cf, annot=True, fmt='d', cmap='Blues',xticklabels=out_labels,yticklabels=out_labels)
plt.title(f'Confusion Matrix of {plant} with Accuracy : {accuracy_score(test_set.classes, y_pred) * 100:.2f}%')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt_name = plant+"_CF.png"
plt.savefig(plt_name)
plt.show()
```



Printing the classification report

```
1 print('-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_->>>>Classification Report<<<<-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_')
2 print(classification_report(test_set.classes, y_pred, target_names=out_labels))
```

```
-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_->>>>Classification Report<<<<-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_-_
                                               precision    recall  f1-score   support

                         Tomato___Target_Spot       1.00      1.00      1.00         5
       Tomato___Tomato_Yellow_Leaf_Curl_Virus       0.80      0.80      0.80         5
                           Tomato___Leaf_Mold       0.83      1.00      0.91         5
                             Tomato___healthy       1.00      1.00      1.00         5
Tomato___Spider_mites Two-spotted_spider_mite       1.00      0.80      0.89         5
                  Tomato___Septoria_leaf_spot       1.00      1.00      1.00         5
                      Tomato___Bacterial_spot       1.00      1.00      1.00         5
                         Tomato___Late_blight       1.00      1.00      1.00         5
                        Tomato___Early_blight       1.00      1.00      1.00         5
                 Tomato___Tomato_mosaic_virus       1.00      1.00      1.00         5

                                     accuracy                           0.96        50
                                    macro avg       0.96      0.96      0.96        50
                                 weighted avg       0.96      0.96      0.96        50
```

Plotting the model Accuracy and Loss Graphs