Import necessary libraries

```
import tensorflow as tf
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

Load Training Data

```
training_set = tf.keras.utils.image_dataset_from_directory(
    'train',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=32,
    image_size=(128, 128),
    shuffle=True,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)
```

```
Found 70295 files belonging to 38 classes.
```

Load Validation Data

```
validation_set = tf.keras.utils.image_dataset_from_directory(
    'valid',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=32,
    image_size=(128, 128),
    shuffle=True,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)
```

```
Found 17572 files belonging to 38 classes.
```

Initialize the Sequential model

```
cnn = tf.keras.models.Sequential()
```

Add convolutional and pooling layers to the model

```
cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,padding='same',activation='relu',input_shape=[128,128,3]))
cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,padding='same',activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=128,kernel_size=3,padding='same',activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=128,kernel_size=3,activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=256,kernel_size=3,padding='same',activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=256,kernel_size=3,activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=512,kernel_size=3,padding='same',activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=512,kernel_size=3,activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))
```

Add Dropout layer to reduce overfitting

```
cnn.add(tf.keras.layers.Dropout(0.25))
```

Flatten the input

```
cnn.add(tf.keras.layers.Flatten())
```

Add Dense layer with 1500 units and ReLU activation

```
cnn.add(tf.keras.layers.Dense(units=1500,activation='relu'))
```

Add Dropout layer to reduce overfitting

```
cnn.add(tf.keras.layers.Dropout(0.4))
```

Add output Dense layer with 38 units and softmax activation

```

cnn.add(tf.keras.layers.Dense(units=38,activation='softmax'))
```

Compile the model with Adam optimizer, categorical crossentropy loss, and accuracy metric

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

Print the model summary

```
cnn.summary()
```

```
Model: "sequential_1"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                     ┃ Output Shape            ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ conv2d_2 (Conv2D)                │ (None, 128, 128, 32)    │
896 │
├──────────────────────────────────┼─────────────────────────┼──────────
─────┤
│ conv2d_3 (Conv2D)                │ (None, 126, 126, 32)    │
9,248 │
├──────────────────────────────────┼─────────────────────────┼──────────
─────┤
│ max_pooling2d_1 (MaxPooling2D)   │ (None, 63, 63, 32)      │
0 │
├──────────────────────────────────┼─────────────────────────┼──────────
─────┤
│ conv2d_4 (Conv2D)                │ (None, 63, 63, 64)      │
18,496 │
├──────────────────────────────────┼─────────────────────────┼──────────
─────┤
│ conv2d_5 (Conv2D)                │ (None, 61, 61, 64)      │
36,928 │
├──────────────────────────────────┼─────────────────────────┼──────────
─────┤
│ max_pooling2d_2 (MaxPooling2D)   │ (None, 30, 30, 64)      │
0 │
```

```
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_6 (Conv2D)               │ (None, 30, 30, 128)    │
73,856 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_7 (Conv2D)               │ (None, 28, 28, 128)    │
147,584 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ max_pooling2d_3 (MaxPooling2D)  │ (None, 14, 14, 128)    │
0 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_8 (Conv2D)               │ (None, 14, 14, 256)    │
295,168 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_9 (Conv2D)               │ (None, 12, 12, 256)    │
590,080 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ max_pooling2d_4 (MaxPooling2D)  │ (None, 6, 6, 256)      │
0 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_10 (Conv2D)              │ (None, 6, 6, 512)      │
1,180,160 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ conv2d_11 (Conv2D)              │ (None, 4, 4, 512)      │
2,359,808 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ max_pooling2d_5 (MaxPooling2D)  │ (None, 2, 2, 512)      │
0 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ dropout (Dropout)               │ (None, 2, 2, 512)      │
0 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ flatten (Flatten)               │ (None, 2048)           │
0 │
├─────────────────────────────────┼────────────────────────┼─────────
───────┤
│ dense (Dense)                   │ (None, 1500)           │
3,073,500 │
├─────────────────────────────────┼────────────────────────┼─────────
```

```
───────┤
│ dropout_1 (Dropout)                │ (None, 1500)              │
0 │
├──────────────────────────────────┼─────────────────────────┼────────
───────┤
│ dense_1 (Dense)                    │ (None, 38)                │
57,038 │
└──────────────────────────────────┴─────────────────────────┴────────
───────┘

 Total params: 7,842,762 (29.92 MB)

 Trainable params: 7,842,762 (29.92 MB)

 Non-trainable params: 0 (0.00 B)
```

Train the model with the training set and validate with the validation set for 10 epochs

```
training_history =
cnn.fit(x=training_set,validation_data=validation_set,epochs=10)

Epoch 1/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1790s 813ms/step - accuracy: 0.3815 -
loss: 2.1848 - val_accuracy: 0.8297 - val_loss: 0.5510
Epoch 2/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1721s 783ms/step - accuracy: 0.8337 -
loss: 0.5256 - val_accuracy: 0.8910 - val_loss: 0.3283
Epoch 3/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1718s 782ms/step - accuracy: 0.9066 -
loss: 0.2950 - val_accuracy: 0.9081 - val_loss: 0.2818
Epoch 4/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1714s 780ms/step - accuracy: 0.9330 -
loss: 0.2066 - val_accuracy: 0.9158 - val_loss: 0.2571
Epoch 5/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1706s 776ms/step - accuracy: 0.9523 -
loss: 0.1462 - val_accuracy: 0.9481 - val_loss: 0.1617
Epoch 6/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1709s 778ms/step - accuracy: 0.9614 -
loss: 0.1186 - val_accuracy: 0.9544 - val_loss: 0.1408
Epoch 7/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1726s 786ms/step - accuracy: 0.9704 -
loss: 0.0927 - val_accuracy: 0.9500 - val_loss: 0.1609
Epoch 8/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1731s 788ms/step - accuracy: 0.9726 -
loss: 0.0827 - val_accuracy: 0.9468 - val_loss: 0.1605
Epoch 9/10
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1727s 786ms/step - accuracy: 0.9780 -
loss: 0.0672 - val_accuracy: 0.9644 - val_loss: 0.1213
Epoch 10/10
```

```
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1737s 790ms/step - accuracy: 0.9804 -
loss: 0.0613 - val_accuracy: 0.9668 - val_loss: 0.1108
```

Training set Accuracy

```python
train_loss, train_acc = cnn.evaluate(training_set)
print('Training accuracy:', train_acc)
```

```
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 448s 204ms/step - accuracy: 0.9891 -
loss: 0.0295
Training accuracy: 0.9904544949531555
```

Validation set Accuracy

```python
val_loss, val_acc = cnn.evaluate(validation_set)
print('Validation accuracy:', val_acc)
```

```
550/550 ━━━━━━━━━━━━━━━━━━━━ 113s 205ms/step - accuracy: 0.9682 -
loss: 0.1085
Validation accuracy: 0.9668222069740295
```

Save the trained model to a file

```python
cnn.save('trained_plant_disease_model.keras')
```

Return dictionary of training history

```python
training_history.history
```

```
{'accuracy': [0.5865281820297241,
  0.8562344312667847,
  0.9146454334259033,
  0.9385020136833191,
  0.9554022550582886,
  0.9635109305381775,
  0.9710505604743958,
  0.9749626517295837,
  0.9788320660591125,
  0.9806387424468994],
 'loss': [1.3972781896591187,
  0.45114046335220337,
  0.26727038621902466,
  0.18771201372146606,
  0.13615547120571136,
  0.1123681366443634,
  0.08959349989891052,
  0.07606132328510284,
  0.06665454059839249,
```

```
  0.05928091554260254],
 'val_accuracy': [0.8296722173690796,
  0.8910198211669922,
  0.9080924391746521,
  0.915831983089447,
  0.9480992555618286,
  0.954359233379364,
  0.9499772191047668,
  0.946790337562561,
  0.9644320607185364,
  0.9668222069740295],
 'val_loss': [0.5510382652282715,
  0.3282625079154968,
  0.2818470895290375,
  0.25710904598236084,
  0.1616627275943756,
  0.1407908797264099,
  0.1609172374010086,
  0.16052775084972382,
  0.12127251923084259,
  0.11083154380321503]}
```

Recording History in json

```python
import json
with open('training_hist.json','w') as f:
  json.dump(training_history.history,f)
```

Print the keys of the training history dictionary

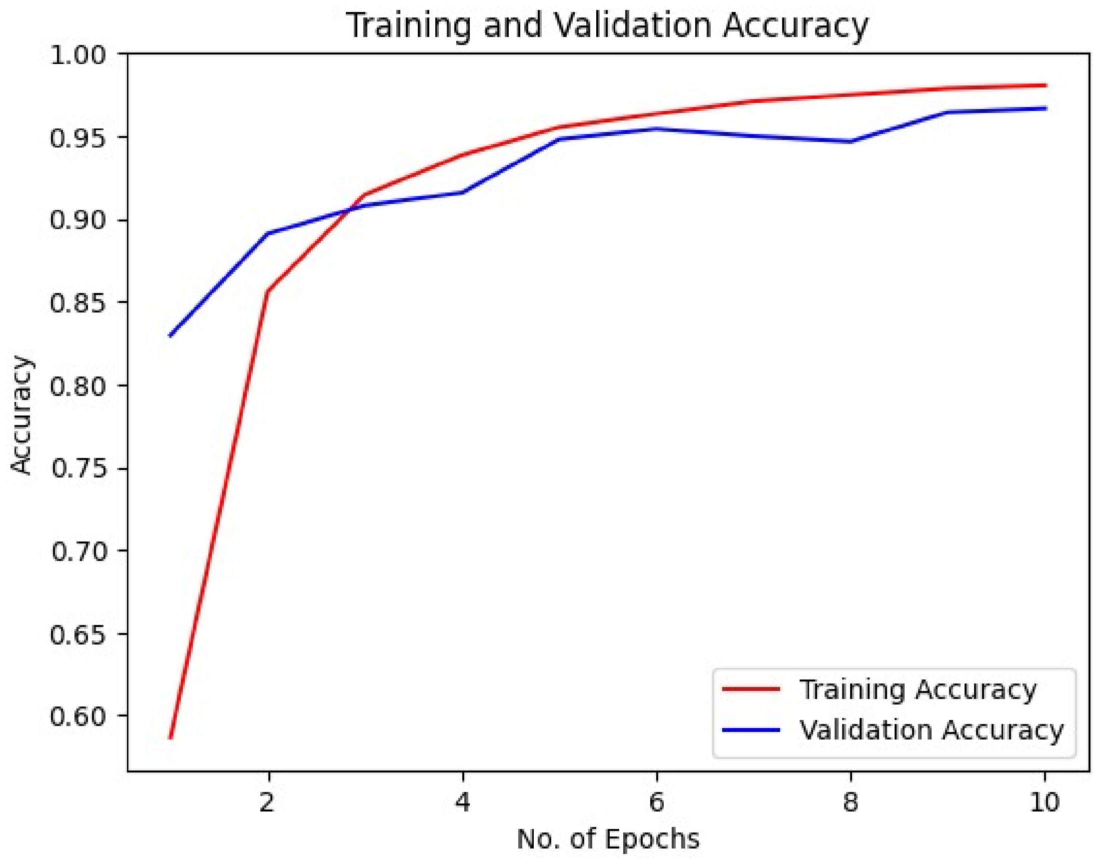
```python
print(training_history.history.keys())
```

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

Plot training and validation accuracy over epochs

```python
num_epochs = len(training_history.history['accuracy'])
epochs = range(1, num_epochs + 1)

# Plot training and validation accuracy
plt.plot(epochs, training_history.history['accuracy'], color='red', 
label='Training Accuracy')
plt.plot(epochs, training_history.history['val_accuracy'], 
color='blue', label='Validation Accuracy')
plt.xlabel('No. of Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.show()
```




```
class_name = validation_set.class_names

test_set = tf.keras.utils.image_dataset_from_directory(
    'valid',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=1,
    image_size=(128, 128),
    shuffle=False,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)

Found 17572 files belonging to 38 classes.

y_pred = cnn.predict(test_set)
predicted_categories = tf.argmax(y_pred, axis=1)
```

```
17572/17572 ━━━━━━━━━━━━━━━━━━━━ 287s 16ms/step

true_categories = tf.concat([y for x, y in test_set], axis=0)
Y_true = tf.argmax(true_categories, axis=1)

Y_true

<tf.Tensor: shape=(17572,), dtype=int64, numpy=array([ 0,  0,  0, ...,
37, 37, 37])>

predicted_categories

<tf.Tensor: shape=(17572,), dtype=int64, numpy=array([ 0,  0,  0, ...,
37, 37, 37])>

from sklearn.metrics import confusion_matrix,classification_report
cm = confusion_matrix(Y_true,predicted_categories)

# Precision Recall Fscore
print(classification_report(Y_true,predicted_categories,target_names=c
lass_name))

                                                    precision
recall  f1-score   support

                                Apple___Apple_scab       0.98
0.97      0.97       504
                                 Apple___Black_rot       0.97
0.99      0.98       497
                          Apple___Cedar_apple_rust       0.97
0.97      0.97       440
                                   Apple___healthy       0.98
0.96      0.97       502
                               Blueberry___healthy       0.93
0.99      0.96       454
          Cherry_(including_sour)___Powdery_mildew       0.99
0.99      0.99       421
                 Cherry_(including_sour)___healthy       0.98
0.99      0.99       456
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot       0.86
0.98      0.92       410
                       Corn_(maize)___Common_rust_       0.99
0.99      0.99       477
               Corn_(maize)___Northern_Leaf_Blight       0.98
0.89      0.93       477
                            Corn_(maize)___healthy       1.00
1.00      1.00       465
                                 Grape___Black_rot       0.96
0.99      0.98       472
                      Grape___Esca_(Black_Measles)       1.00
0.96      0.98       480
```

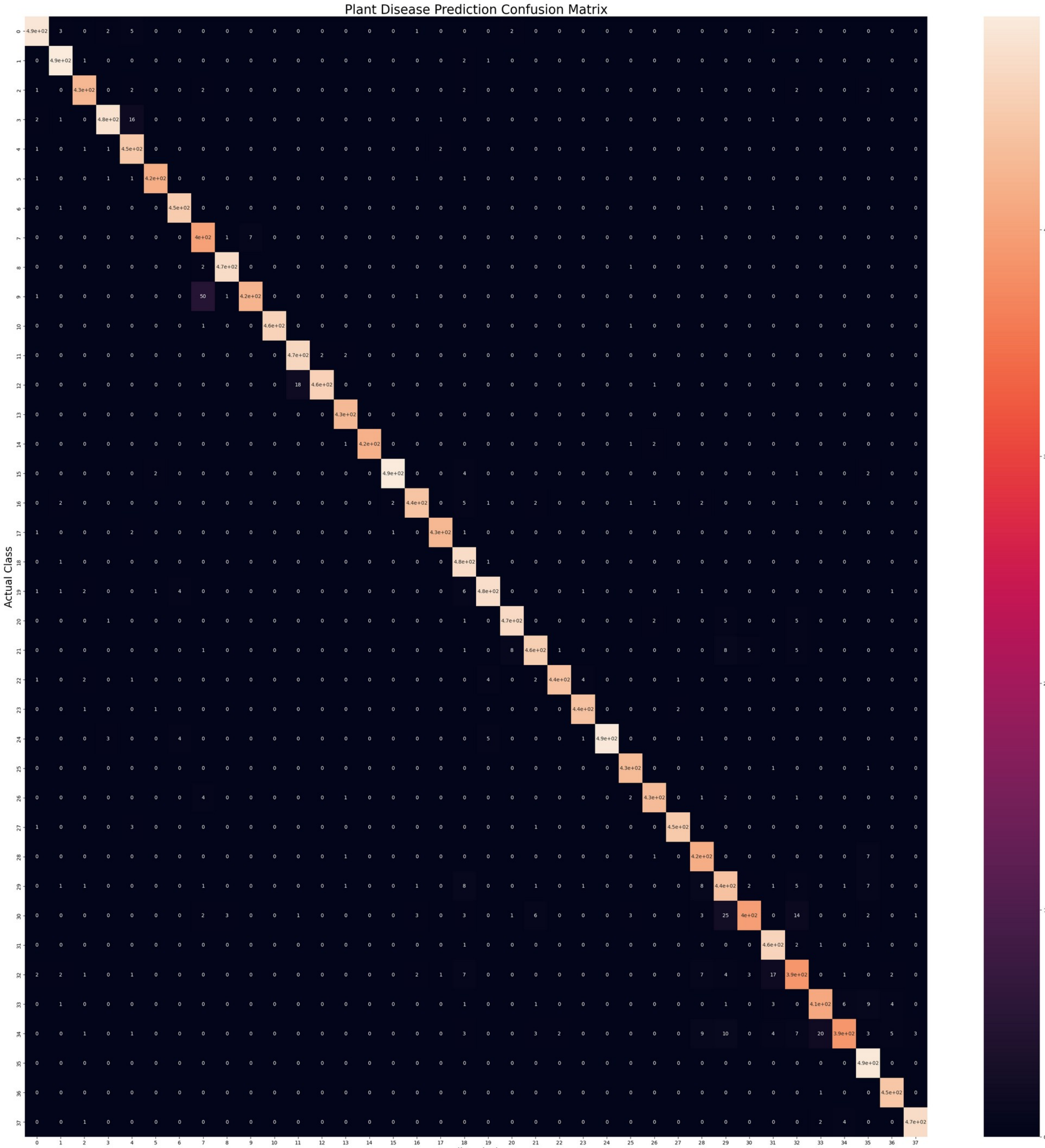
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	0.99	1.00	0.99	430
Grape___healthy	1.00	0.99	1.00	423
Orange___Haunglongbing_(Citrus_greening)	0.99	0.98	0.99	503
Peach___Bacterial_spot	0.98	0.96	0.97	459
Peach___healthy	0.99	0.99	0.99	432
Pepper,_bell___Bacterial_spot	0.91	1.00	0.95	478
Pepper,_bell___healthy	0.98	0.96	0.97	497
Potato___Early_blight	0.98	0.97	0.97	485
Potato___Late_blight	0.97	0.94	0.95	485
Potato___healthy	0.99	0.97	0.98	456
Raspberry___healthy	0.98	0.99	0.99	445
Soybean___healthy	1.00	0.97	0.98	505
Squash___Powdery_mildew	0.98	1.00	0.99	434
Strawberry___Leaf_scorch	0.98	0.98	0.98	444
Strawberry___healthy	0.99	0.99	0.99	456
Tomato___Bacterial_spot	0.92	0.98	0.95	425
Tomato___Early_blight	0.89	0.92	0.90	480
Tomato___Late_blight	0.98	0.86	0.91	463
Tomato___Leaf_Mold	0.94	0.99	0.96	470
Tomato___Septoria_leaf_spot	0.90	0.89	0.89	436
Tomato___Spider_mites Two-spotted_spider_mite	0.94	0.94	0.94	435
Tomato___Target_Spot	0.97	0.84	0.90	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.94	1.00	0.97	490
Tomato___Tomato_mosaic_virus	0.97	1.00	0.99	448
Tomato___healthy	0.99			

```
0.99      0.99       481

                                                accuracy
0.97     17572
                                               macro avg       0.97
0.97      0.97     17572
                                            weighted avg       0.97
0.97      0.97     17572


plt.figure(figsize=(40, 40))
sns.heatmap(cm,annot=True,annot_kws={"size": 10})

plt.xlabel('Predicted Class',fontsize = 20)
plt.ylabel('Actual Class',fontsize = 20)
plt.title('Plant Disease Prediction Confusion Matrix',fontsize = 25)
plt.show()
```


Plant Disease Prediction Confusion Matrix
Actual Class
Predicted Class