In [1]:
```
import os
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```
from pathlib import Path
```

In [3]:
```
import tensorflow as tf
from tensorflow import keras
```

In [4]:
```
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
```

In [5]:
```
datapath = "/kaggle/input/tomato-leaf-disease/dataset"
DATA_DIR = Path(datapath)

EPOCHS = 20
BATCHES = 32
IMAGE_SIZE = 256
CHANNEL = 3
```

In [6]:
```
data = keras.utils.image_dataset_from_directory(DATA_DIR)
```

```
Found 16011 files belonging to 10 classes.
```

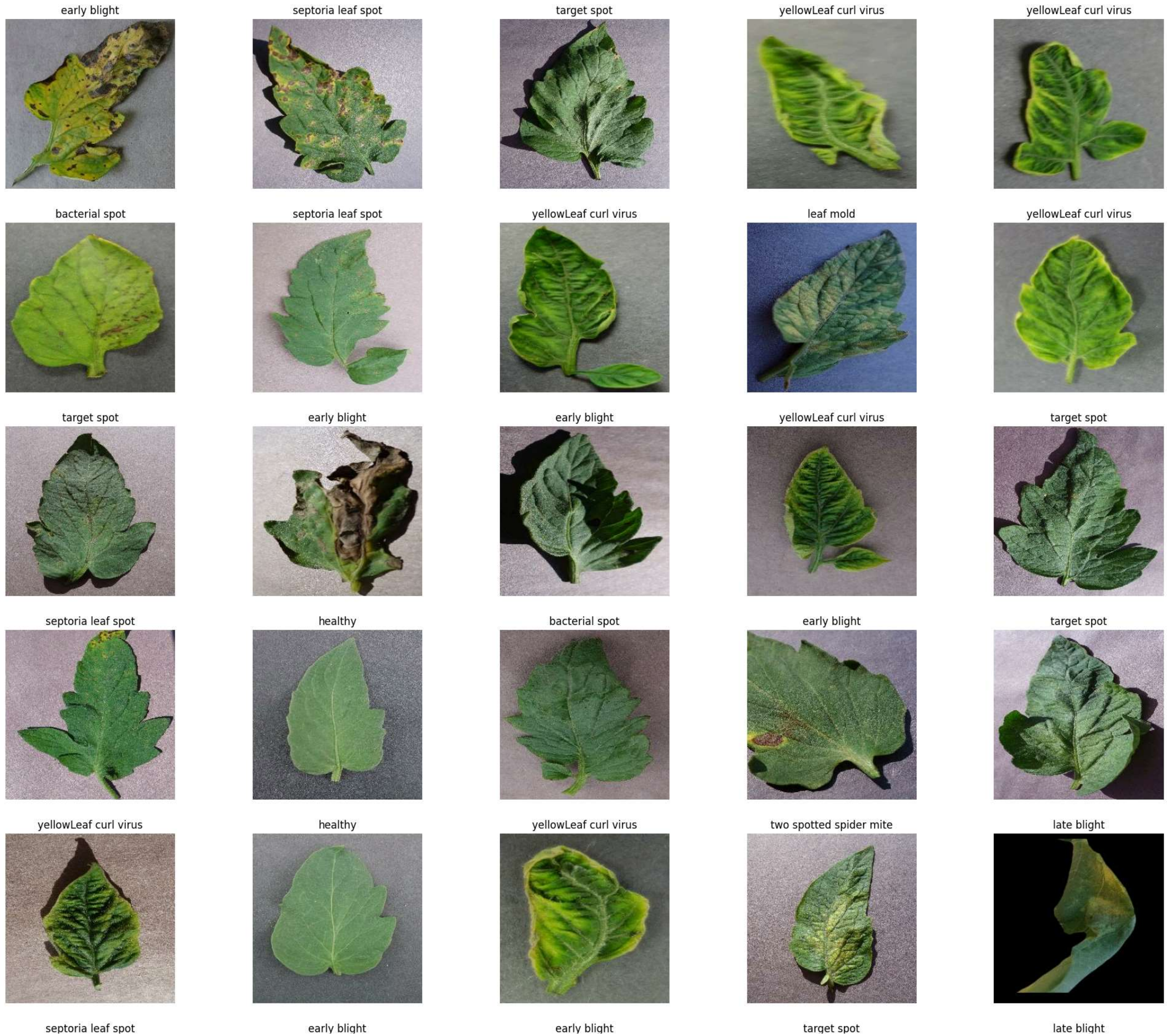
In [7]:
```
class_names = data.class_names
class_names
```

Out[7]:
```
['bacterial spot',
 'early blight',
 'healthy',
 'late blight',
 'leaf mold',
 'mosaic virus',
 'septoria leaf spot',
 'target spot',
 'two spotted spider mite',
 'yellowLeaf curl virus']
```

In [8]:
```
no_of_classes = len(class_names)
no_of_classes
```

Out[8]:
```
10
```

In [9]:
```
plt.figure(figsize=(25, 25))

for images, classes in data.take(1):
    for i in range(30):
        plt.subplot(6, 5, i + 1)
        plt.imshow(images[i].numpy().astype(int))
        plt.axis("off")
        plt.title(class_names[classes[i]])
```


early blight
septoria leaf spot
target spot
yellowLeaf curl virus
yellowLeaf curl virus
bacterial spot
septoria leaf spot
yellowLeaf curl virus
leaf mold
yellowLeaf curl virus
target spot
early blight
early blight
yellowLeaf curl virus
target spot
septoria leaf spot
healthy
bacterial spot
early blight
target spot
yellowLeaf curl virus
healthy
yellowLeaf curl virus
two spotted spider mite
late blight
septoria leaf spot
early blight
early blight
target spot
late blight





In [10]:
```
def train_test_val_split(dataset, test_split=0.2, val_split=0.1, shuffle=True, shuffle_size=1000):
    ds_size = len(dataset)

    if shuffle:
        dataset = dataset.shuffle(shuffle_size, seed=45)

    test_size = int(ds_size * test_split)
    val_size = int(ds_size * val_split)

    ds_test = dataset.take(test_size)
    ds_val = dataset.skip(test_size).take(val_size)
    ds_train = dataset.skip(test_size).skip(val_size)

    return ds_train, ds_test, ds_val
```

In [11]:
```
ds_train, ds_test, ds_val = train_test_val_split(data)
```

In [12]:
```
# data resizing

resize_and_rescale = keras.models.Sequential()

resize_and_rescale.add(keras.layers.Resizing(IMAGE_SIZE, IMAGE_SIZE))
resize_and_rescale.add(keras.layers.Rescaling(scale = 1./255))
```

In [13]:
```
# creating augmented data for training

aug_data = keras.models.Sequential()

aug_data.add(keras.layers.RandomFlip())
aug_data.add(keras.layers.RandomRotation(0.2))
```

In [14]:
```
ds_aug = ds_train.map(lambda x, y: (aug_data(x, training=True), y))
```

In [15]:
```
ds_train = ds_train.concatenate(ds_aug)
```

In [16]:
```
#model building

model = keras.models.Sequential()

model.add(resize_and_rescale)
model.add(keras.layers.Conv2D(64, 3, 1, activation="relu"))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.Conv2D(32, 3, 1, activation="relu"))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.Conv2D(32, 3, 1, activation="relu"))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.Conv2D(16, 3, 1, activation="relu"))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(64, activation="relu"))
model.add(keras.layers.Dense(no_of_classes, activation="softmax"))
```

In [17]:
```
INPUT_SHAPE = (BATCHES, IMAGE_SIZE, IMAGE_SIZE, CHANNEL)
model.build(input_shape = INPUT_SHAPE)
```

In [18]:
```
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 64)	1,792
max_pooling2d (MaxPooling2D)	(32, 127, 127, 64)	0
conv2d_1 (Conv2D)	(32, 125, 125, 32)	18,464
max_pooling2d_1 (MaxPooling2D)	(32, 62, 62, 32)	0
conv2d_2 (Conv2D)	(32, 60, 60, 32)	9,248
max_pooling2d_2 (MaxPooling2D)	(32, 30, 30, 32)	0
conv2d_3 (Conv2D)	(32, 28, 28, 16)	4,624
max_pooling2d_3 (MaxPooling2D)	(32, 14, 14, 16)	0
flatten (Flatten)	(32, 3136)	0
dense (Dense)	(32, 64)	200,768
dense_1 (Dense)	(32, 10)	650

Total params: 235,546 (920.10 KB)

Trainable params: 235,546 (920.10 KB)

Non-trainable params: 0 (0.00 B)

In [19]:
```
model.compile(optimizer='adam', loss=keras.losses.SparseCategoricalCrossentropy(), metrics=['accuracy'])
```

In [20]:
```
history = model.fit(ds_train, batch_size=BATCHES, validation_data=ds_val, epochs=EPOCHS)
```

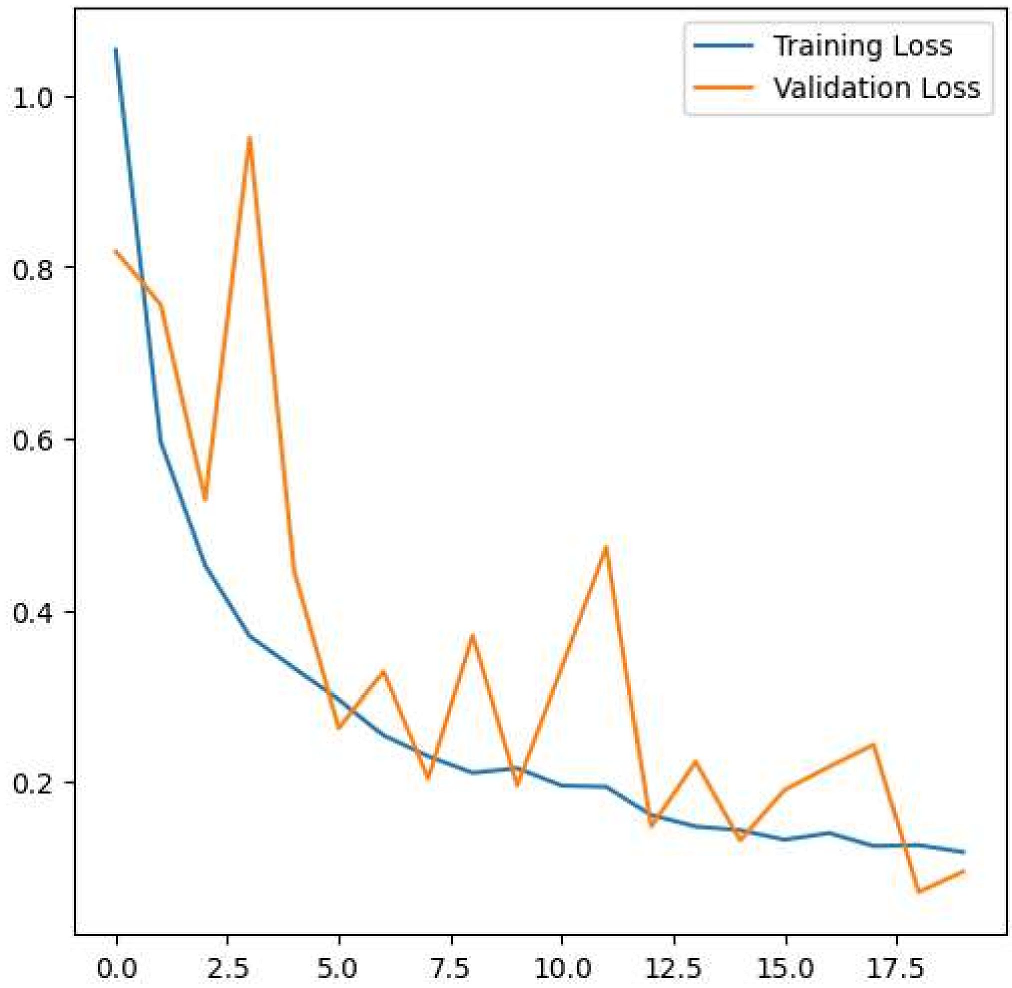
```
Epoch 1/20

WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1731684539.593454      73 service.cc:145] XLA service 0x7cc68c0060d0 initialized for platform CU
DA (this does not guarantee that XLA will be used). Devices:
I0000 00:00:1731684539.593504      73 service.cc:153]   StreamExecutor device (0): Tesla T4, Compute Capabil
ity 7.5
I0000 00:00:1731684539.593508      73 service.cc:153]   StreamExecutor device (1): Tesla T4, Compute Capabil
ity 7.5

  3/702 ━━━━━━━━━━━━━━━━━━━━ 37s 54ms/step - accuracy: 0.1146 - loss: 2.2869

I0000 00:00:1731684547.063188      73 device_compiler.h:188] Compiled cluster using XLA!  This line is logge
d at most once for the lifetime of the process.
```

```
702/702 ━━━━━━━━━━━━━━━━━━━━ 178s 203ms/step - accuracy: 0.5186 - loss: 1.3716 - val_accuracy: 0.7144 - val_
loss: 0.8179
Epoch 2/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 144s 196ms/step - accuracy: 0.7932 - loss: 0.5930 - val_accuracy: 0.7481 - val_
loss: 0.7564
Epoch 3/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 200ms/step - accuracy: 0.8411 - loss: 0.4492 - val_accuracy: 0.8037 - val_
loss: 0.5292
Epoch 4/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 144s 197ms/step - accuracy: 0.8794 - loss: 0.3422 - val_accuracy: 0.7144 - val_
loss: 0.9512
Epoch 5/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 199ms/step - accuracy: 0.8900 - loss: 0.3130 - val_accuracy: 0.8419 - val_
loss: 0.4457
Epoch 6/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 199ms/step - accuracy: 0.9060 - loss: 0.2681 - val_accuracy: 0.9038 - val_
loss: 0.2629
Epoch 7/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 145s 199ms/step - accuracy: 0.9223 - loss: 0.2188 - val_accuracy: 0.8981 - val_
loss: 0.3285
Epoch 8/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 199ms/step - accuracy: 0.9327 - loss: 0.1921 - val_accuracy: 0.9269 - val_
loss: 0.2041
Epoch 9/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 147s 200ms/step - accuracy: 0.9393 - loss: 0.1700 - val_accuracy: 0.8694 - val_
loss: 0.3706
Epoch 10/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 148s 202ms/step - accuracy: 0.9367 - loss: 0.1793 - val_accuracy: 0.9344 - val_
loss: 0.1959
Epoch 11/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 143s 195ms/step - accuracy: 0.9518 - loss: 0.1402 - val_accuracy: 0.8769 - val_
loss: 0.3331
Epoch 12/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 144s 196ms/step - accuracy: 0.9476 - loss: 0.1499 - val_accuracy: 0.8481 - val_
loss: 0.4738
Epoch 13/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 199ms/step - accuracy: 0.9583 - loss: 0.1199 - val_accuracy: 0.9494 - val_
loss: 0.1479
Epoch 14/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 147s 201ms/step - accuracy: 0.9652 - loss: 0.1028 - val_accuracy: 0.9250 - val_
loss: 0.2236
Epoch 15/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 198ms/step - accuracy: 0.9626 - loss: 0.1056 - val_accuracy: 0.9481 - val_
```

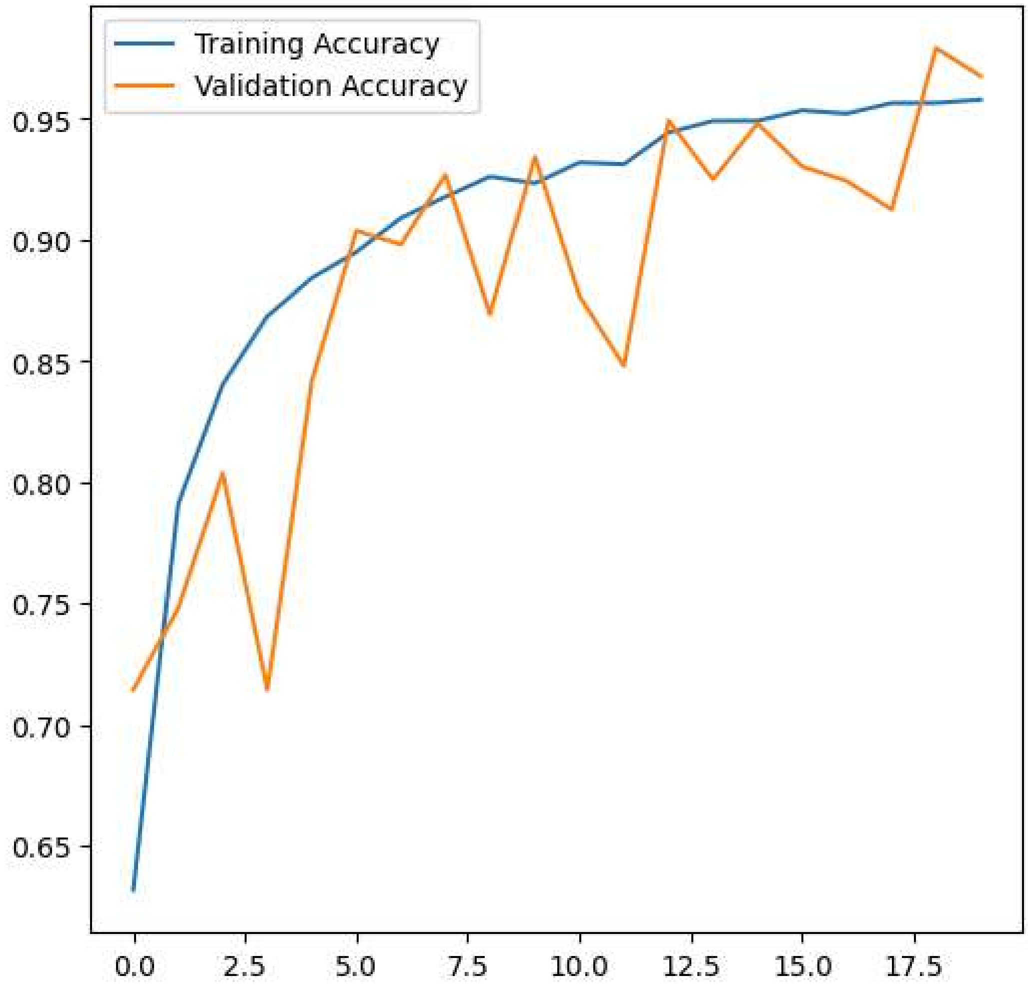
```
loss: 0.1317
Epoch 16/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 199ms/step - accuracy: 0.9690 - loss: 0.0880 - val_accuracy: 0.9303 - val_
loss: 0.1909
Epoch 17/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 145s 198ms/step - accuracy: 0.9703 - loss: 0.0894 - val_accuracy: 0.9244 - val_
loss: 0.2178
Epoch 18/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 201s 195ms/step - accuracy: 0.9721 - loss: 0.0810 - val_accuracy: 0.9125 - val_
loss: 0.2436
Epoch 19/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 144s 197ms/step - accuracy: 0.9748 - loss: 0.0743 - val_accuracy: 0.9791 - val_
loss: 0.0714
Epoch 20/20
702/702 ━━━━━━━━━━━━━━━━━━━━ 146s 200ms/step - accuracy: 0.9738 - loss: 0.0734 - val_accuracy: 0.9675 - val_
loss: 0.0952
```

In [21]:

```
plt.figure(figsize=(6, 6))
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label ="Validation Loss")
plt.legend(loc="best")
plt.show()
```



In [22]:
```
plt.figure(figsize=(6, 6))
plt.plot(history.history["accuracy"], label="Training Accuracy")
plt.plot(history.history["val_accuracy"], label ="Validation Accuracy")
plt.legend(loc="best")
plt.show()
```



In [23]:
```
plt.figure(figsize=(20, 20))
for image, label in ds_test.take(1):
    for i in range(16):
        plt.subplot(4, 4, i + 1)
        plt.imshow(image[i].numpy().astype(int))
        img_arr = np.expand_dims(image[i], axis=0)
        probabilities = model.predict(img_arr)
        prediction = class_names[np.argmax(probabilities[0])]
        confidence = round((100 * np.max(probabilities[0])), 2)
        actual = class_names[label[i]]
        plt.title(f"Actual: {actual}, \n Predicted: {prediction}, \n Confidence: {confidence}")
        plt.axis("off")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 730ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
```


Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 100.0
Actual: target spot,
Predicted: target spot,
Confidence: 99.97
Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 99.99
Actual: septoria leaf spot,
Predicted: septoria leaf spot,
Confidence: 92.46
Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 100.0
Actual: early blight,
Predicted: early blight,
Confidence: 99.9
Actual: two spotted spider mite,
Predicted: two spotted spider mite,
Confidence: 96.87
Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 100.0
Actual: target spot,
Predicted: target spot,
Confidence: 100.0
Actual: bacterial spot,
Predicted: bacterial spot,
Confidence: 92.07
Actual: target spot,
Predicted: target spot,
Confidence: 99.71
Actual: mosaic virus,
Predicted: mosaic virus,
Confidence: 100.0
Actual: late blight,
Predicted: late blight,
Confidence: 67.19
Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 100.0
Actual: septoria leaf spot,
Predicted: septoria leaf spot,
Confidence: 99.99
Actual: yellowLeaf curl virus,
Predicted: yellowLeaf curl virus,
Confidence: 100.0