

```
In [2]: import tensorflow as tf
```

```
In [3]: import numpy as np  
import os
```

```
In [4]: from tensorflow.keras import models, layers
```

```
In [5]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
In [6]: from tensorflow.keras.preprocessing import image
```

```
In [7]: from tensorflow.keras.preprocessing.image import img_to_array
```

```
In [9]: import matplotlib.pyplot as plt
```

```
In [10]: from tensorflow.keras import backend as K
```

```
In [11]: IMAGE_SIZE= 256  
BATCH_SIZE=32  
CHANNELS=3  
EPOCHS=30
```

```
In [12]: dataset=tf.keras.utils.image_dataset_from_directory(  
        "PlantVillage",  
        batch_size=BATCH_SIZE,  
        image_size=(IMAGE_SIZE, IMAGE_SIZE),  
        shuffle=True,  
        )
```

Found 2152 files belonging to 3 classes.

```
In [13]: class_names= dataset.class_names  
class_names
```

```
Out[13]: ['Potato__Early_blight', 'Potato__Late_blight', 'Potato__healthy']
```

```
In [14]: len(dataset)
```

```
Out[14]: 68
```

```
In [15]: plt.figure(figsize=(10, 10))  
for image_batch, label_batch in dataset.take(1):  
    for i in range(12):  
        ax=plt.subplot(3,4,i+1)  
        plt.imshow(image_batch[i].numpy().astype("uint8"))  
        plt.title(class_names[label_batch[0]])  
        plt.axis("off")
```

Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



Potato_Late_blight



```
In [16]: len(dataset)
```

```
Out[16]: 68
```

```
In [18]: train_size=0.8  
train_ds=dataset.take(54)  
len(train_ds)
```

```
Out[18]: 54
```

```
In [19]: test_ds=dataset.skip(54)  
len(test_ds)
```

```
Out[19]: 14
```

```
In [20]: val_size=0.1  
val_ds=test_ds.take(6)  
len(val_ds)
```

Out[20]: 6

```
In [21]: test_ds=test_ds.skip(6)  
len(test_ds)
```

Out[21]: 8

```
In [22]: def get_dataset_patotions_tf(ds, train_split=0.8, val_split=0.1, test_split=0.1, sh  
ds_size=len(ds)  
if shuffle:  
    ds=ds.shuffle(shuffle_size, seed=12)  
    train_size=int(train_split*ds_size)  
    val_size=int(val_split*ds_size)  
    train_ds=ds.take(train_size)  
    val_ds=ds.skip(train_size).take(val_size)  
    test_ds=ds.skip(train_size).skip(val_size)  
return train_ds, val_ds, test_ds
```

```
In [23]: train_ds, val_ds, test_ds= get_dataset_patotions_tf(dataset)
```

```
In [24]: len(train_ds)
```

Out[24]: 54

```
In [25]: len(val_ds)
```

Out[25]: 6

```
In [26]: len(test_ds)
```

Out[26]: 8

```
In [27]: #prefetch and cache concept  
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)  
val_ds = val_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)  
test_ds = test_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
```

```
In [30]: resize_and_rescale = tf.keras.Sequential([  
    layers.Resizing(IMAGE_SIZE, IMAGE_SIZE),  
    layers.Rescaling(1.0/255)  
])
```

```
In [34]: data_augmentation = tf.keras.Sequential([  
    layers.RandomFlip("horizontal_and_vertical"),  
    layers.RandomRotation(0.2),  
])
```

```
In [36]: input_shape=(BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)  
n_classes=3  
model=models.Sequential([  
    resize_and_rescale,  
    data_augmentation,  
    layers.Conv2D(32,(3,3), activation='relu', input_shape=input_shape),
```

```
layers.MaxPooling2D((2,2)),  
  
layers.Conv2D(64,kernel_size=(3,3), activation='relu'),  
layers.MaxPooling2D((2,2)),  
  
layers.Conv2D(64,kernel_size=(3,3), activation='relu'),  
layers.MaxPooling2D((2,2)),  
  
layers.Conv2D(64,(3,3), activation='relu'),  
layers.MaxPooling2D((2,2)),  
  
layers.Conv2D(64,(3,3), activation='relu'),  
layers.MaxPooling2D((2,2)),  
  
layers.Flatten(),  
  
layers.Dense(64, activation='relu'),  
  
layers.Dense(n_classes, activation='softmax')  
])  
  
model.build(input_shape=input_shape)
```

s:\Download\potato-disease\my_env\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:99: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
super().__init__(

In [37]: `model.summary()`

Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36,928
max_pooling2d_3 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36,928
max_pooling2d_4 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36,928
max_pooling2d_5 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16,448
dense_1 (Dense)	(32, 3)	195

Total params: 183,747 (717.76 KB)

Trainable params: 183,747 (717.76 KB)

Non-trainable params: 0 (0.00 B)

In []:

```
In [38]: model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),
    #in each epos what type of matrix?
    metrics=['accuracy']
)
```

```
In [39]: history=model.fit(
    train_ds,
    epochs=EPOCHS,
    batch_size=BATCH_SIZE,
```

```
    verbose=1,  
    validation_data=val_ds  
)
```

Epoch 1/30
54/54 45s 716ms/step - accuracy: 0.4732 - loss: 0.9323 - val_accuracy: 0.6771 - val_loss: 0.6783
Epoch 2/30
54/54 37s 695ms/step - accuracy: 0.6371 - loss: 0.7298 - val_accuracy: 0.7500 - val_loss: 0.5999
Epoch 3/30
54/54 38s 699ms/step - accuracy: 0.7390 - loss: 0.5537 - val_accuracy: 0.8281 - val_loss: 0.3800
Epoch 4/30
54/54 38s 701ms/step - accuracy: 0.8312 - loss: 0.3886 - val_accuracy: 0.8542 - val_loss: 0.3543
Epoch 5/30
54/54 40s 750ms/step - accuracy: 0.8756 - loss: 0.3104 - val_accuracy: 0.8958 - val_loss: 0.2112
Epoch 6/30
54/54 39s 718ms/step - accuracy: 0.9235 - loss: 0.2124 - val_accuracy: 0.9479 - val_loss: 0.1112
Epoch 7/30
54/54 37s 691ms/step - accuracy: 0.9222 - loss: 0.1958 - val_accuracy: 0.9740 - val_loss: 0.0927
Epoch 8/30
54/54 38s 696ms/step - accuracy: 0.9569 - loss: 0.1184 - val_accuracy: 0.8438 - val_loss: 0.3407
Epoch 9/30
54/54 36s 675ms/step - accuracy: 0.9043 - loss: 0.2547 - val_accuracy: 0.9479 - val_loss: 0.1244
Epoch 10/30
54/54 37s 689ms/step - accuracy: 0.9582 - loss: 0.1360 - val_accuracy: 1.0000 - val_loss: 0.0098
Epoch 11/30
54/54 37s 686ms/step - accuracy: 0.9663 - loss: 0.0878 - val_accuracy: 0.9844 - val_loss: 0.0465
Epoch 12/30
54/54 37s 680ms/step - accuracy: 0.9709 - loss: 0.0720 - val_accuracy: 0.9948 - val_loss: 0.0192
Epoch 13/30
54/54 36s 675ms/step - accuracy: 0.9784 - loss: 0.0590 - val_accuracy: 1.0000 - val_loss: 0.0146
Epoch 14/30
54/54 37s 682ms/step - accuracy: 0.9809 - loss: 0.0551 - val_accuracy: 0.9844 - val_loss: 0.0417
Epoch 15/30
54/54 38s 702ms/step - accuracy: 0.9858 - loss: 0.0379 - val_accuracy: 0.9688 - val_loss: 0.0821
Epoch 16/30
54/54 39s 717ms/step - accuracy: 0.9826 - loss: 0.0477 - val_accuracy: 0.9948 - val_loss: 0.0289
Epoch 17/30
54/54 38s 705ms/step - accuracy: 0.9659 - loss: 0.0869 - val_accuracy: 0.9948 - val_loss: 0.0185
Epoch 18/30
54/54 39s 714ms/step - accuracy: 0.9817 - loss: 0.0470 - val_accuracy: 0.9531 - val_loss: 0.1077
Epoch 19/30
54/54 37s 688ms/step - accuracy: 0.9889 - loss: 0.0339 - val_accuracy:

```
accuracy: 0.9792 - val_loss: 0.0424
Epoch 20/30
54/54 37s 684ms/step - accuracy: 0.9886 - loss: 0.0328 - val_ac
curacy: 0.9271 - val_loss: 0.2753
Epoch 21/30
54/54 38s 695ms/step - accuracy: 0.9740 - loss: 0.0727 - val_ac
curacy: 0.9948 - val_loss: 0.0104
Epoch 22/30
54/54 37s 689ms/step - accuracy: 0.9882 - loss: 0.0329 - val_ac
curacy: 0.9844 - val_loss: 0.0309
Epoch 23/30
54/54 37s 685ms/step - accuracy: 0.9915 - loss: 0.0250 - val_ac
curacy: 0.9896 - val_loss: 0.0355
Epoch 24/30
54/54 37s 679ms/step - accuracy: 0.9961 - loss: 0.0158 - val_ac
curacy: 0.9896 - val_loss: 0.0306
Epoch 25/30
54/54 37s 682ms/step - accuracy: 0.9873 - loss: 0.0335 - val_ac
curacy: 1.0000 - val_loss: 0.0018
Epoch 26/30
54/54 36s 672ms/step - accuracy: 0.9731 - loss: 0.0850 - val_ac
curacy: 0.9896 - val_loss: 0.0271
Epoch 27/30
54/54 38s 711ms/step - accuracy: 0.9893 - loss: 0.0295 - val_ac
curacy: 0.9740 - val_loss: 0.0636
Epoch 28/30
54/54 39s 717ms/step - accuracy: 0.9921 - loss: 0.0238 - val_ac
curacy: 0.8594 - val_loss: 0.3788
Epoch 29/30
54/54 38s 697ms/step - accuracy: 0.9532 - loss: 0.1405 - val_ac
curacy: 0.9948 - val_loss: 0.0084
Epoch 30/30
54/54 37s 680ms/step - accuracy: 0.9937 - loss: 0.0182 - val_ac
curacy: 0.9896 - val_loss: 0.0221
```

```
In [40]: scores = model.evaluate(test_ds)
```

```
8/8 2s 183ms/step - accuracy: 0.9864 - loss: 0.0525
```

```
In [41]: scores
#Loss, accuracy
```

```
Out[41]: [0.054242804646492004, 0.984375]
```

```
In [42]: history
```

```
Out[42]: <keras.src.callbacks.history.History at 0x22d1c385350>
```

```
In [43]: history.params
```

```
Out[43]: {'verbose': 1, 'epochs': 30, 'steps': 54}
```

```
In [44]: history.history.keys()
```

```
Out[44]: dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

```
In [45]: history.history['accuracy']
```

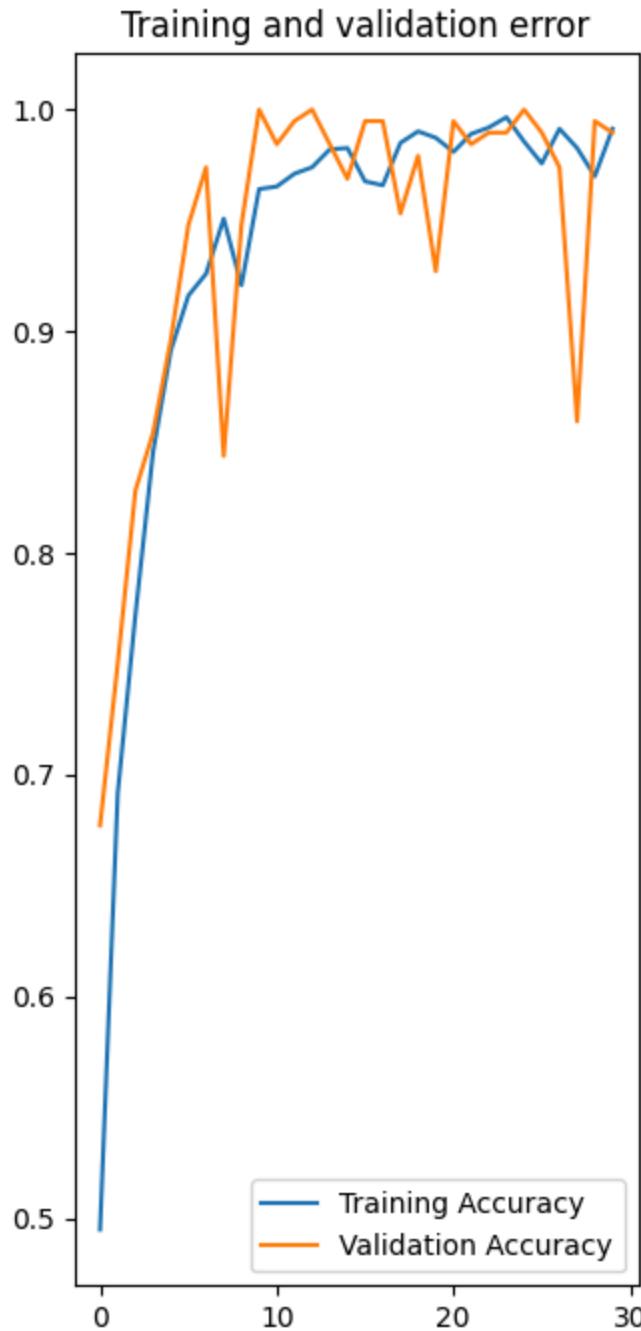
```
Out[45]: [0.4947916567325592,
 0.6915509104728699,
 0.7719907164573669,
 0.8454861044883728,
 0.8912037014961243,
 0.9160879850387573,
 0.9259259104728699,
 0.9508101940155029,
 0.9207175970077515,
 0.9641203880310059,
 0.9652777910232544,
 0.9710648059844971,
 0.9739583134651184,
 0.9820601940155029,
 0.9826388955116272,
 0.9675925970077515,
 0.9658564925193787,
 0.9849537014961243,
 0.9901620149612427,
 0.9872685074806213,
 0.9809027910232544,
 0.9890046119689941,
 0.9918981194496155,
 0.9965277910232544,
 0.9855324029922485,
 0.9756944179534912,
 0.9913194179534912,
 0.9826388955116272,
 0.9699074029922485,
 0.9913194179534912]
```

```
In [46]: acc=history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss=history.history['val_loss']
```

```
In [47]: plt.figure(figsize=(8,8))
plt.subplot(1,2,1)
plt.plot(range(EPOCHS), acc, label='Training Accuracy')
plt.plot(range(EPOCHS), val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and validation error')
```

```
Out[47]: Text(0.5, 1.0, 'Training and validation error')
```

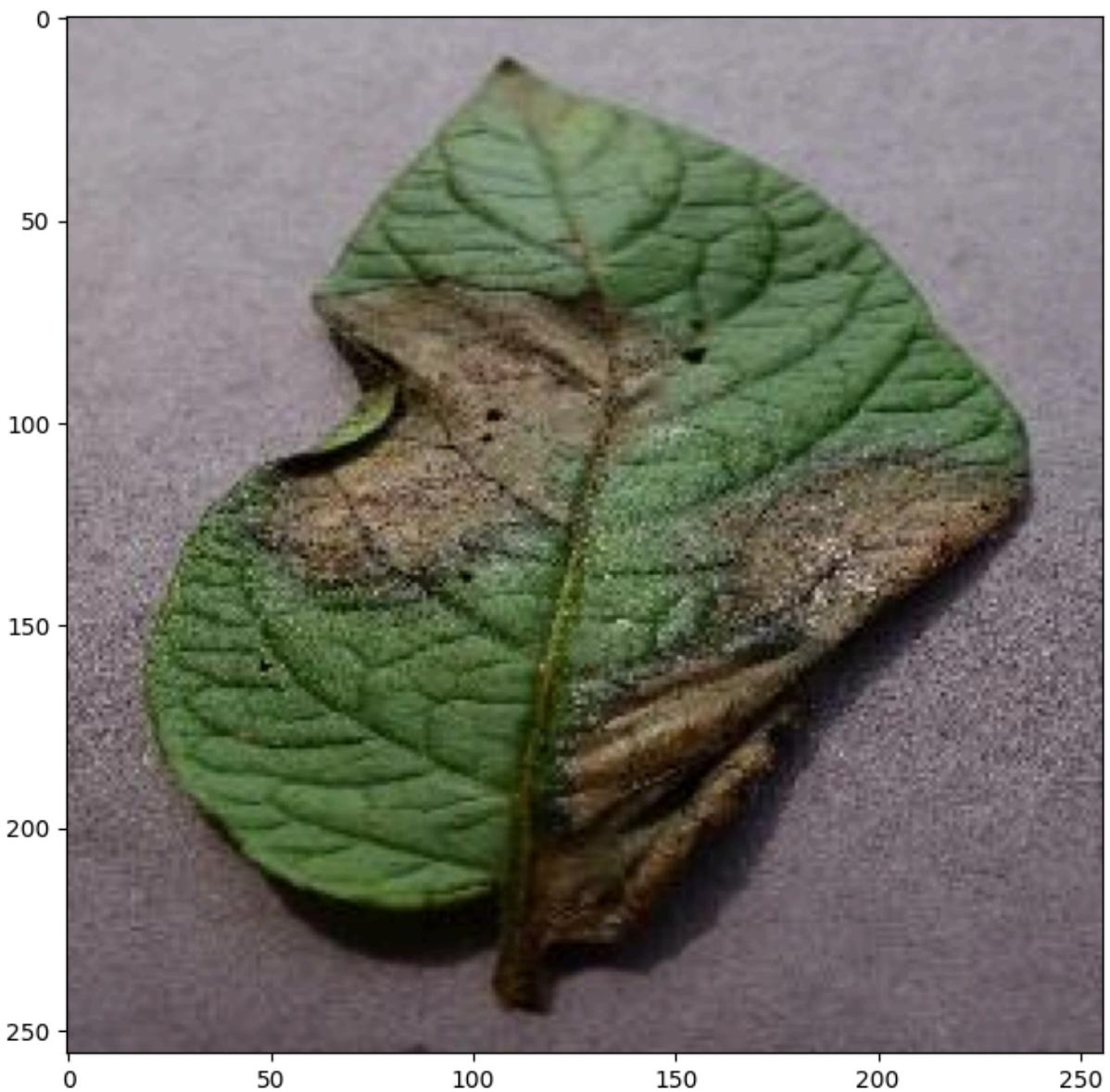


```
In [48]: plt.figure(figsize=(8,8))
import numpy as np
for images_batch, labels_batch in test_ds.take(1):
    first_image=image_batch[0].numpy().astype('uint8')
    first_label=labels_batch[0].numpy()

    print("first image predict")
    plt.imshow(first_image)
    print('actual label:',class_names[first_label])

    batch_prediction=model.predict(image_batch)
    print(class_names[np.argmax(batch_prediction[0])])
```

```
first image predict
actual label: Potato__Late_blight
1/1 ━━━━━━ 1s 520ms/step
Potato__Late_blight
```



```
In [49]: def predict(model, img):
    img_array=tf.keras.preprocessing.image.img_to_array(images[i].numpy())
    img_array=tf.expand_dims(img_array, 0)

    predictions=model.predict(img_array)

    predicted_class = class_names[np.argmax(predictions[0])]
    confidence=round(100 * (np.max(predictions[0])),2)
    return predicted_class, confidence
```

```
In [50]: plt.figure(figsize=(15,15))
for images, labels in test_ds.take(1):
    for i in range(9):
        ax=plt.subplot(3, 3, i+1)
        plt.imshow(images[i].numpy().astype("uint8"))
```

```

predicted_class, confidence = predict(model, images[i].numpy())
actual_class = class_names[labels[i]]

plt.title(f"Actual: {actual_class}, \n Predicted: {predicted_class}, \n Con
plt.axis("off")

```

1/1 ━━━━━━ 0s 249ms/step
 1/1 ━━━━ 0s 60ms/step
 1/1 ━━━━ 0s 54ms/step
 1/1 ━━━━ 0s 53ms/step
 1/1 ━━━━ 0s 59ms/step
 1/1 ━━━━ 0s 61ms/step
 1/1 ━━━━ 0s 58ms/step
 1/1 ━━━━ 0s 59ms/step
 1/1 ━━━━ 0s 60ms/step

Actual: Potato_healthy,
 Predicted: Potato_healthy,
 Confidence: 99.78



Actual: Potato_Early_blight,
 Predicted: Potato_Early_blight,
 Confidence: 100.0

Actual: Potato_Late_blight,
 Predicted: Potato_Late_blight,
 Confidence: 100.0

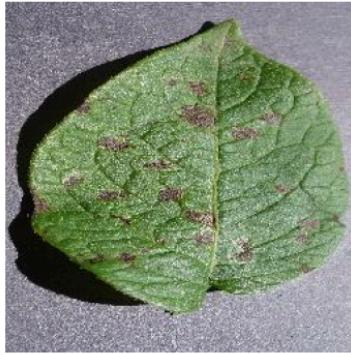


Actual: Potato_Late_blight,
 Predicted: Potato_Late_blight,
 Confidence: 97.71

Actual: Potato_Late_blight,
 Predicted: Potato_Late_blight,
 Confidence: 100.0



Actual: Potato_healthy,
 Predicted: Potato_healthy,
 Confidence: 99.75



Actual: Potato_healthy,
 Predicted: Potato_healthy,
 Confidence: 99.83



Actual: Potato_Early_blight,
 Predicted: Potato_Early_blight,
 Confidence: 100.0



Actual: Potato_Early_blight,
 Predicted: Potato_Early_blight,
 Confidence: 100.0



In []:

In []:	
In []:	