

## Importing required libraries

```
In [31]: import tensorflow as tf
from tensorflow.keras import models, layers
import matplotlib.pyplot as plt
import numpy as np
```

## Setting Batch Size, Image size, Channels, Epochs

```
In [19]: IMAGE_SIZE = 256
BATCH_SIZE = 32
CHANNEL = 3
EPOCHS = 15
```

## Extracting data using api

```
In [4]: dataset = tf.keras.preprocessing.image_dataset_from_directory(
    "PlantVillage",
    shuffle = True,
    image_size = (IMAGE_SIZE, IMAGE_SIZE),
    batch_size = BATCH_SIZE
)
```

Found 2152 files belonging to 3 classes.

```
In [5]: class_names = dataset.class_names
class_names
```

```
Out[5]: ['Potato__Early_blight', 'Potato__Late_blight', 'Potato__healthy']
```

```
In [6]: for image_batch, label_batch in dataset.take(1):
    print(image_batch.shape)
    print(label_batch.numpy())
```

```
(32, 256, 256, 3)
```

```
[2 0 2 1 1 0 1 2 1 0 0 0 0 0 2 1 1 0 0 0 1 1 2 0 1 0 1 0 1 1 0]
```

## Plotting images using numpy functions

```
In [7]: plt.figure(figsize = (10,10))
for image_batch, label_batch in dataset.take(1):
    for i in range(16):
        ax = plt.subplot(4,4,i+1)
        plt.imshow(image_batch[i].numpy().astype("uint8"))
        plt.axis("off")
        plt.title(class_names[label_batch[i]])
```



## Partitioning Dataset (80% Train, 10% Testing, 10% Validation)

```
In [8]: def get_dataset_partitions_tf(ds, train_split = 0.8, val_split = 0.1, test_split =
        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, test_ds, val_ds
```

```
In [9]: train_ds, test_ds, val_ds = get_dataset_partitions_tf(dataset)
```

```
In [10]: len(train_ds)
```

```
Out[10]: 54
```

```
In [11]: len(test_ds)
```

```
Out[11]: 8
```

```
In [12]: len(val_ds)
```

```
Out[12]: 6
```

## Caching and Prefetching

```
In [13]: 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)
```

## Creating Layers and Data Augmentation

```
In [14]: resize_and_rescale = tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE),
    layers.experimental.preprocessing.Rescaling(1.0/255)
])
```

```
In [15]: data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
    layers.experimental.preprocessing.RandomRotation(0.2)
])
```

```
In [16]: input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNEL)
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.Flatten(),
    layers.Dense(64, activation = 'relu'),
    layers.Dense(n_classes, activation = 'softmax')
])
model.build(input_shape = input_shape)
```

```
In [17]: 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
flatten (Flatten)	(32, 516128)	0
dense (Dense)	(32, 64)	33032256
dense_1 (Dense)	(32, 3)	195
=====		
Total params: 33,033,347		
Trainable params: 33,033,347		
Non-trainable params: 0		

## Compiling Model using optimization fucntions

```
In [20]: model.compile(
    optimizer = 'adam',
    loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = False),
    metrics = ['accuracy']
)
```

```
In [21]: history = model.fit(
    train_ds,
    epochs = EPOCHS,
    batch_size = BATCH_SIZE,
    verbose = 1,
    validation_data = val_ds
)
```

```

Epoch 1/15
54/54 [=====] - 43s 745ms/step - loss: 5.2926 - accuracy:
0.6858 - val_loss: 0.7123 - val_accuracy: 0.7083
Epoch 2/15
54/54 [=====] - 39s 731ms/step - loss: 0.4207 - accuracy:
0.8501 - val_loss: 0.6682 - val_accuracy: 0.7240
Epoch 3/15
54/54 [=====] - 40s 733ms/step - loss: 0.3517 - accuracy:
0.8553 - val_loss: 0.2564 - val_accuracy: 0.8958
Epoch 4/15
54/54 [=====] - 40s 738ms/step - loss: 0.2334 - accuracy:
0.9103 - val_loss: 0.1483 - val_accuracy: 0.9531
Epoch 5/15
54/54 [=====] - 40s 738ms/step - loss: 0.1932 - accuracy:
0.9225 - val_loss: 0.2032 - val_accuracy: 0.9062
Epoch 6/15
54/54 [=====] - 40s 739ms/step - loss: 0.2003 - accuracy:
0.9126 - val_loss: 0.1197 - val_accuracy: 0.9531
Epoch 7/15
54/54 [=====] - 41s 751ms/step - loss: 0.1527 - accuracy:
0.9398 - val_loss: 0.1928 - val_accuracy: 0.9271
Epoch 8/15
54/54 [=====] - 39s 719ms/step - loss: 0.1631 - accuracy:
0.9421 - val_loss: 0.0731 - val_accuracy: 0.9688
Epoch 9/15
54/54 [=====] - 39s 717ms/step - loss: 0.1293 - accuracy:
0.9525 - val_loss: 0.4654 - val_accuracy: 0.8594
Epoch 10/15
54/54 [=====] - 39s 723ms/step - loss: 0.1429 - accuracy:
0.9456 - val_loss: 0.1345 - val_accuracy: 0.9427
Epoch 11/15
54/54 [=====] - 39s 716ms/step - loss: 0.1315 - accuracy:
0.9508 - val_loss: 0.1126 - val_accuracy: 0.9531
Epoch 12/15
54/54 [=====] - 38s 714ms/step - loss: 0.1302 - accuracy:
0.9543 - val_loss: 0.0626 - val_accuracy: 0.9688
Epoch 13/15
54/54 [=====] - 39s 719ms/step - loss: 0.1246 - accuracy:
0.9473 - val_loss: 0.0765 - val_accuracy: 0.9688
Epoch 14/15
54/54 [=====] - 39s 718ms/step - loss: 0.1111 - accuracy:
0.9589 - val_loss: 0.0515 - val_accuracy: 0.9896
Epoch 15/15
54/54 [=====] - 39s 721ms/step - loss: 0.0986 - accuracy:
0.9635 - val_loss: 0.0410 - val_accuracy: 0.9844

```

```
In [22]: scores = model.evaluate(test_ds)
```

```

8/8 [=====] - 3s 139ms/step - loss: 0.0618 - accuracy: 0.
9766

```

```
In [23]: scores
```

```
Out[23]: [0.06181748956441879, 0.9765625]
```

## Plotting graphs

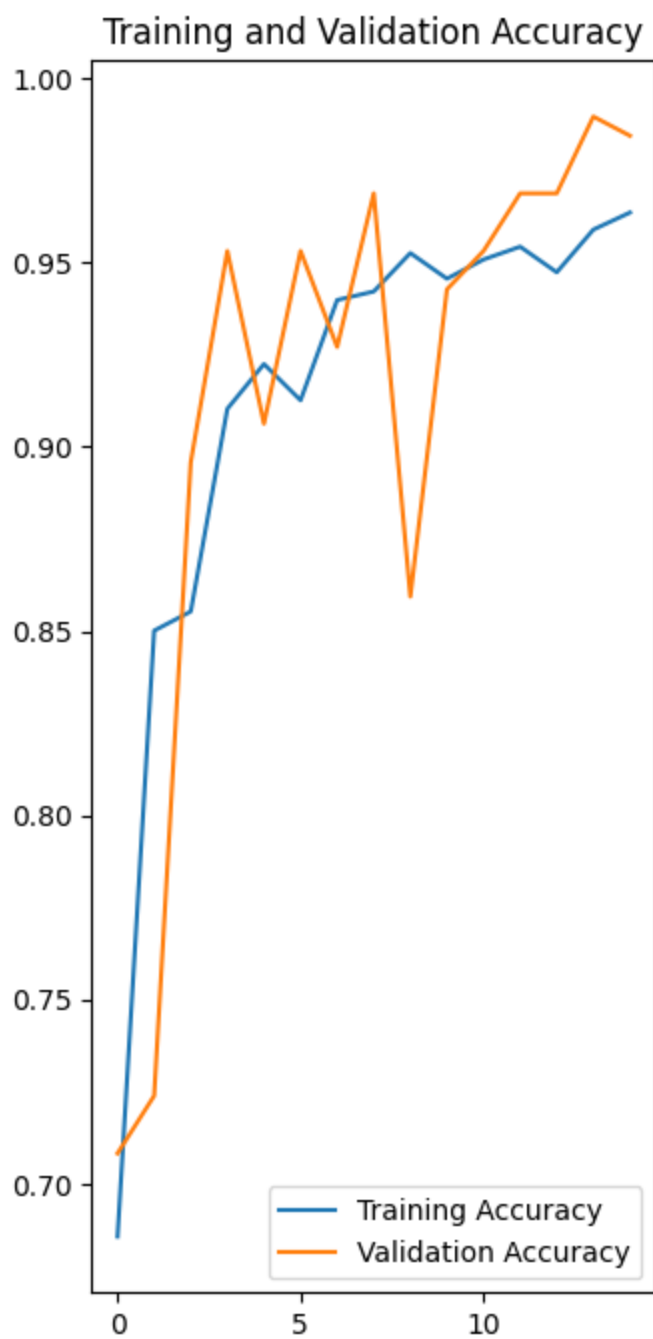
```
In [24]: history.history.keys()
```

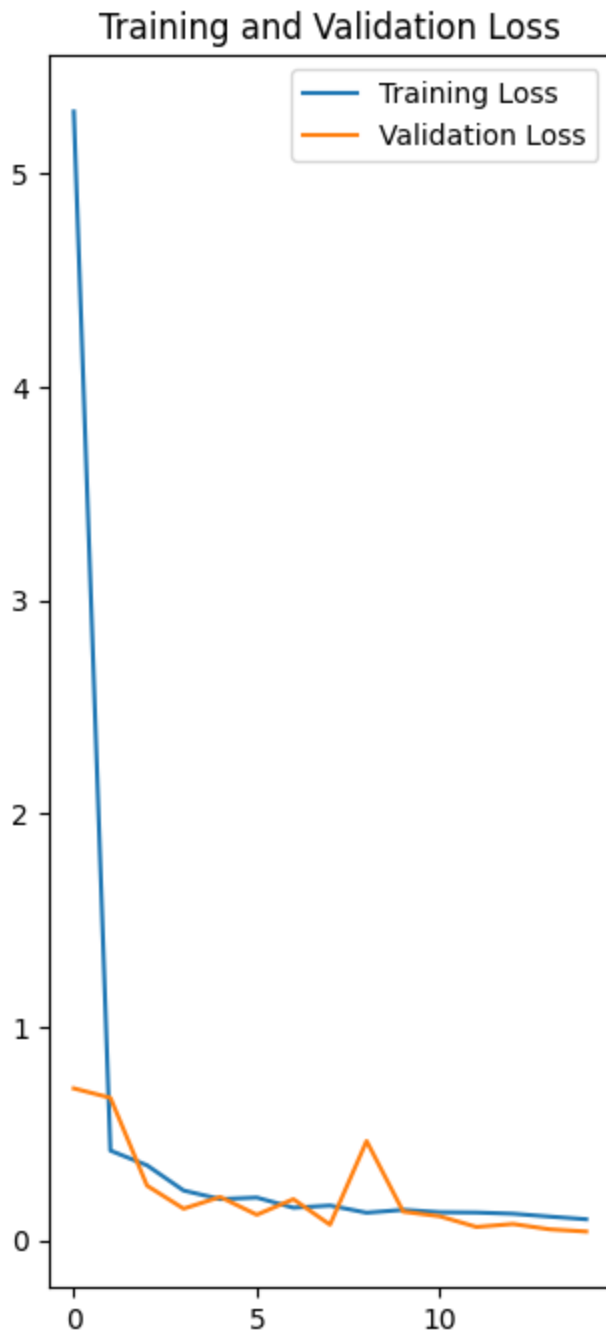
```
Out[24]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
In [25]: acc = history.history['accuracy']  
val_acc = history.history['val_accuracy']  
loss = history.history['loss']  
val_loss = history.history['val_loss']
```

```
In [27]: 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 Accuracy')  
  
plt.figure(figsize=(8,8))  
plt.subplot(1,2,1)  
plt.plot(range(EPOCHS), loss, label = 'Training Loss')  
plt.plot(range(EPOCHS), val_loss, label = 'Validation Loss')  
plt.legend(loc = 'upper right')  
plt.title('Training and Validation Loss')
```

```
Out[27]: Text(0.5, 1.0, 'Training and Validation Loss')
```





## Predictions and Plotting of data

```
In [28]: 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 [37]: 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 Conf
        plt.axis("off")
```

```
1/1 [=====] - 0s 53ms/step
1/1 [=====] - 0s 50ms/step
1/1 [=====] - 0s 50ms/step
1/1 [=====] - 0s 48ms/step
1/1 [=====] - 0s 49ms/step
1/1 [=====] - 0s 47ms/step
1/1 [=====] - 0s 48ms/step
1/1 [=====] - 0s 51ms/step
1/1 [=====] - 0s 52ms/step
```

Actual: Potato\_\_Late\_blight,  
Predicted : Potato\_\_Late\_blight.  
Confidence: 99.51%



Actual: Potato\_\_Early\_blight,  
Predicted : Potato\_\_Early\_blight.  
Confidence: 100.0%



Actual: Potato\_\_Late\_blight,  
Predicted : Potato\_\_Late\_blight.  
Confidence: 96.88%



Actual: Potato\_\_Early\_blight,  
Predicted : Potato\_\_Early\_blight.  
Confidence: 100.0%



Actual: Potato\_\_Early\_blight,  
Predicted : Potato\_\_Early\_blight.  
Confidence: 99.98%



Actual: Potato\_\_Late\_blight,  
Predicted : Potato\_\_Late\_blight.  
Confidence: 99.8%



Actual: Potato\_\_Early\_blight,  
Predicted : Potato\_\_Early\_blight.  
Confidence: 100.0%



Actual: Potato\_\_Early\_blight,  
Predicted : Potato\_\_Early\_blight.  
Confidence: 100.0%



Actual: Potato\_\_Late\_blight,  
Predicted : Potato\_\_Late\_blight.  
Confidence: 99.3%



## Saving models

```
In [41]: import os
model_version = max([int(i) for i in os.listdir("./models")+["0"]])+1
model.save(f"./models/{model_version}")
```

WARNING:absl:Found untraced functions such as \_jit\_compiled\_convolution\_op, \_update\_step\_xla while saving (showing 2 of 2). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: ./models/1/assets

INFO:tensorflow:Assets written to: ./models/1/assets

```
In [ ]:
```