Module Name: SE4050 - Deep Learning Assignment

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

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Import all the Dependencies

```
import tensorflow as tf
from tensorflow.keras import models, layers
import matplotlib.pyplot as plt
```

Set all the Constants

```
BATCH_SIZE = 32
IMAGE_SIZE = 256
CHANNELS=3
EPOCHS=50
```

Import data into tensorflow dataset object

```
import os
import tensorflow as tf

# Step 1: Unzip the file from Google Drive to a local directory
zip_path = '/content/drive/MyDrive/DL_Project/PlantVillage'


dataset = tf.keras.preprocessing.image_dataset_from_directory(
    zip_path,
    seed=123,
    shuffle=True,
    image_size=(IMAGE_SIZE, IMAGE_SIZE),
    batch_size=BATCH_SIZE
)
```

```
Found 2152 files belonging to 3 classes.
```

```
class_names = dataset.class_names
class_names
```

```
['Potato___Early_blight', 'Potato___Late_blight', 'Potato___healthy']
```

```
len(dataset)
```

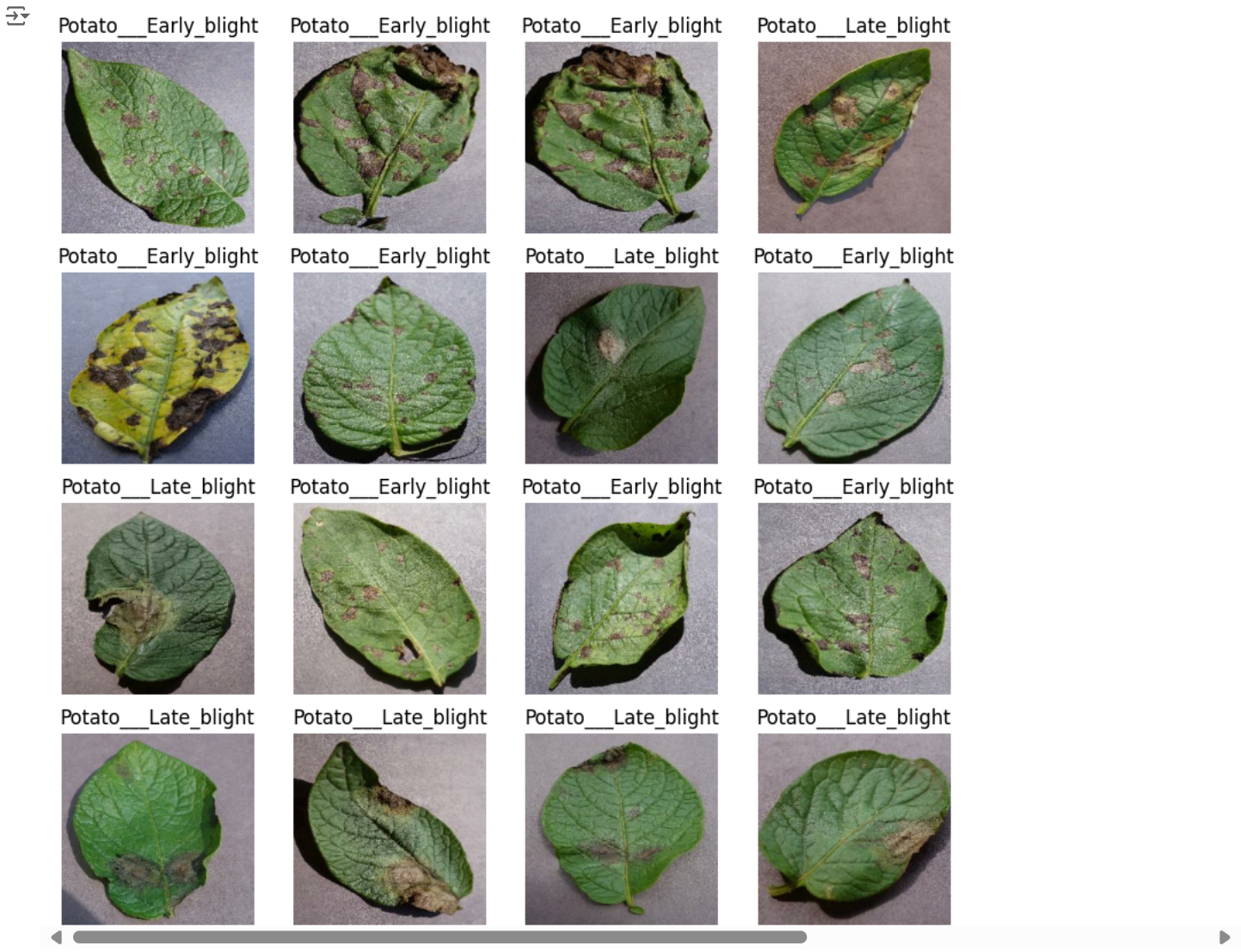
```
68
```

```
for image_batch, labels_batch in dataset.take(1):
    print(image_batch.shape)
    print(labels_batch.numpy())
```

```
(32, 256, 256, 3)
[1 1 1 0 0 0 0 0 1 1 1 1 0 1 0 1 1 1 0 1 0 1 0 0 1 0 0 1 1 2 0 0]
```

Visualize some of the images from our dataset

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for image_batch, labels_batch in dataset.take(1):
    for i in range(16):
        ax = plt.subplot(4, 4, i + 1) # Changed the grid to 4x4 to accommodate 16 images
        plt.imshow(image_batch[i].numpy().astype("uint8"))
        plt.title(class_names[labels_batch[i]])
        plt.axis("off")
```



Function to Split Dataset Dataset should be bifurcated into 3 subsets, namely: **bold text**

Training: Dataset to be used while training Validation: Dataset to be tested against while training Test: Dataset to be tested against after we trained a model

```
len(dataset)
```

```
68
```

```
train_size = 0.8
len(dataset)*train_size
```

```
54.400000000000006
```

```
train_ds = dataset.take(54)
len(train_ds)
```

```
54
```

```
test_ds = dataset.skip(54)
len(test_ds)
```

```
14
```

```
val_size=0.1
len(dataset)*val_size
```

```
6.800000000000001
```

```
val_ds = test_ds.take(6)
len(val_ds)
```

```
6
```

```
test_ds = test_ds.skip(6)
len(test_ds)
```

```
8
```

```
def get_dataset_partitions_tf(ds, train_split=0.8, val_split=0.1, test_split=0.1, shuffle=True, shuffle_size=10000):
    assert (train_split + test_split + val_split) == 1

    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
```

```
train_ds, val_ds, test_ds = get_dataset_partitions_tf(dataset)
```

```
len(train_ds)
```

```
54
```

```
len(val_ds)
```

```
6
```

```
len(test_ds)
```

```
8
```

Cache, Shuffle, and Prefetch the Dataset

```
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)
```

IT21302862 - Building the Model

Creating a Layer for Resizing and Normalization

Before feed our images to network, we should be resizing it to the desired size. Moreover, to improve model performance, we should normalize the image pixel value (keeping them in range 0 and 1 by dividing by 256). This should happen while training as well as inference. Hence we can

add that as a layer in our Sequential Model.

```
resize_and_rescale = tf.keras.Sequential([
  tf.keras.layers.Resizing(IMAGE_SIZE, IMAGE_SIZE),
  tf.keras.layers.Rescaling(1./255),
])
```

Data Augmentation

This boosts the accuracy of our model by augmenting the data.

```
import tensorflow as tf

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

Applying Data Augmentation to Train Dataset

```
train_ds = train_ds.map(
    lambda x, y: (data_augmentation(x, training=True), y)
).prefetch(buffer_size=tf.data.AUTOTUNE)
```

IT21302862 - Model Architecture

We use a CNN coupled with a Softmax activation in the output layer. We also add the initial layers for resizing, normalization and Data Augmentation.

```
input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes = 3

model = models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32, kernel_size = (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.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)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpu
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (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

IT21302862 - Compiling the Model

We use adam Optimizer, SparseCategoricalCrossentropy for losses, accuracy as a metric

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


history = model.fit(
    train_ds,
    batch_size=BATCH_SIZE,
    validation_data=val_ds,
    verbose=1,
    epochs=20,
)
```

```
Epoch 1/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 470s 6s/step - accuracy: 0.4312 - loss: 0.9595 - val_accuracy: 0.6354 - val_loss: 0.8600
Epoch 2/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 309s 6s/step - accuracy: 0.6871 - loss: 0.7637 - val_accuracy: 0.7656 - val_loss: 0.5883
Epoch 3/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 302s 6s/step - accuracy: 0.8042 - loss: 0.4430 - val_accuracy: 0.8854 - val_loss: 0.3083
Epoch 4/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 297s 6s/step - accuracy: 0.9038 - loss: 0.2448 - val_accuracy: 0.9062 - val_loss: 0.2241
Epoch 5/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 304s 6s/step - accuracy: 0.9382 - loss: 0.1706 - val_accuracy: 0.9010 - val_loss: 0.2900
Epoch 6/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 302s 6s/step - accuracy: 0.9483 - loss: 0.1519 - val_accuracy: 0.9323 - val_loss: 0.1513
Epoch 7/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 315s 6s/step - accuracy: 0.9482 - loss: 0.1259 - val_accuracy: 0.9323 - val_loss: 0.1549
Epoch 8/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 299s 6s/step - accuracy: 0.9452 - loss: 0.1401 - val_accuracy: 0.8385 - val_loss: 0.4454
Epoch 9/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 307s 6s/step - accuracy: 0.9712 - loss: 0.0873 - val_accuracy: 0.9010 - val_loss: 0.3574
Epoch 10/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 306s 6s/step - accuracy: 0.9669 - loss: 0.0723 - val_accuracy: 0.9219 - val_loss: 0.1956
Epoch 11/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 299s 6s/step - accuracy: 0.9673 - loss: 0.1062 - val_accuracy: 0.9219 - val_loss: 0.1877
Epoch 12/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 299s 6s/step - accuracy: 0.9841 - loss: 0.0385 - val_accuracy: 0.9271 - val_loss: 0.1953
```

```
Epoch 13/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 313s 6s/step - accuracy: 0.9847 - loss: 0.0444 - val_accuracy: 0.9323 - val_loss: 0.1756
Epoch 14/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 300s 6s/step - accuracy: 0.9607 - loss: 0.1096 - val_accuracy: 0.8906 - val_loss: 0.3854
Epoch 15/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 300s 6s/step - accuracy: 0.9772 - loss: 0.0757 - val_accuracy: 0.9688 - val_loss: 0.0927
Epoch 16/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 304s 6s/step - accuracy: 0.9738 - loss: 0.0698 - val_accuracy: 0.9167 - val_loss: 0.3765
Epoch 17/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 320s 6s/step - accuracy: 0.9765 - loss: 0.0731 - val_accuracy: 0.9375 - val_loss: 0.2430
Epoch 18/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 301s 6s/step - accuracy: 0.9910 - loss: 0.0304 - val_accuracy: 1.0000 - val_loss: 0.0150
Epoch 19/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 299s 6s/step - accuracy: 0.9764 - loss: 0.0760 - val_accuracy: 0.9844 - val_loss: 0.0460
Epoch 20/20
54/54 ━━━━━━━━━━━━━━━━━━━━ 297s 6s/step - accuracy: 0.9890 - loss: 0.0371 - val_accuracy: 0.9844 - val_loss: 0.0563
```

```
scores = model.evaluate(test_ds)
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 22s 2s/step - accuracy: 0.9745 - loss: 0.0788
```

```
scores
```

```
[0.09146903455257416, 0.96484375]
```

Plotting the Accuracy and Loss Curves

```
history
```

```
<keras.src.callbacks.history.History at 0x7ef188654040>
```

```
history.params
```

```
{'verbose': 1, 'epochs': 20, 'steps': 54}
```

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

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

```
type(history.history['loss'])
```

```
list
```

```
len(history.history['loss'])
```

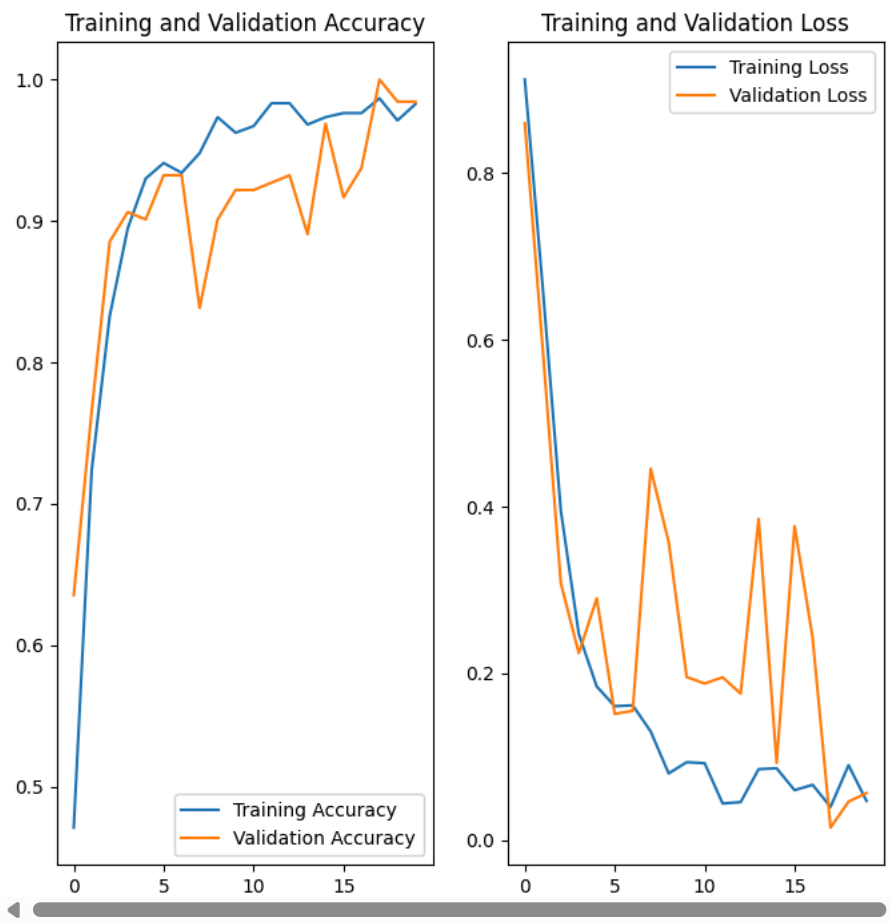
```
20
```

```
history.history['loss'][:5]
```

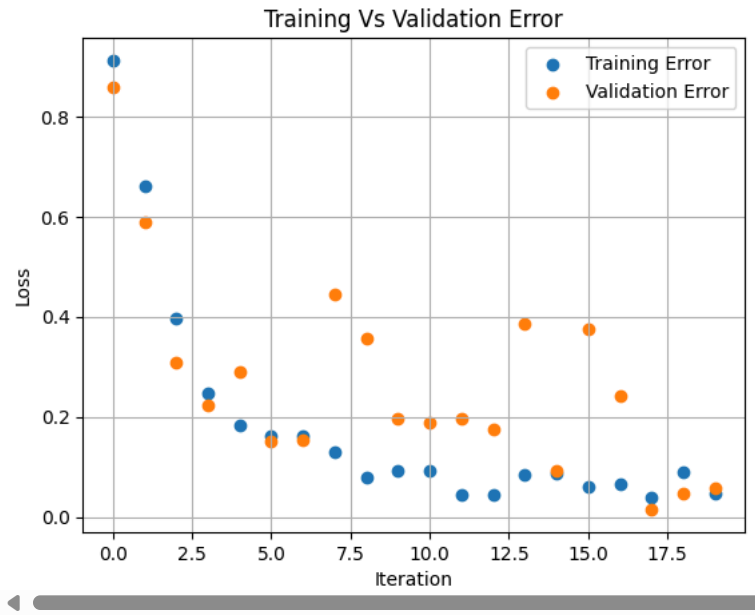
```
[0.9123921394348145,
 0.661983847618103,
 0.395614892244339,
 0.24741561710834503,
 0.1841520071029663]
```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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


plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(range(len(acc)), acc, label='Training Accuracy')
plt.plot(range(len(val_acc)), val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(range(len(loss)), loss, label='Training Loss')
plt.plot(range(len(val_loss)), val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
```

```
plt.title('Training and Validation Loss')
plt.show()
```



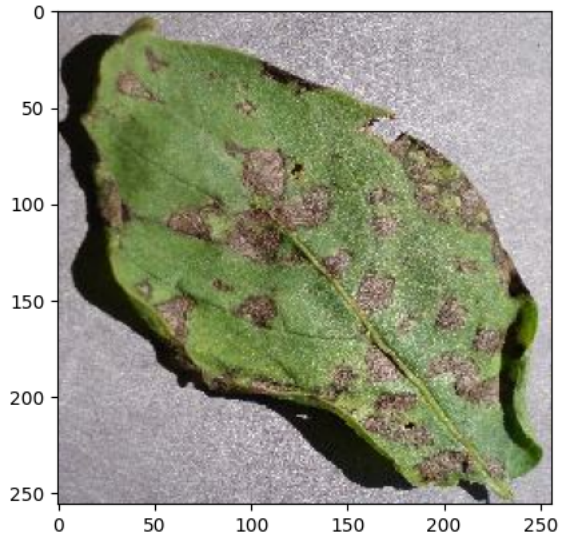

```
plt.scatter(x=history.epoch,y=history.history['loss'],label='Training Error')
plt.scatter(x=history.epoch,y=history.history['val_loss'],label='Validation Error')
plt.grid(True)
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Training Vs Validation Error')
plt.legend()
plt.show()
```



Run prediction on a sample image

```
import numpy as np
for images_batch, labels_batch in test_ds.take(1):

    first_image = images_batch[0].numpy().astype('uint8')
    first_label = labels_batch[0].numpy()

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

    batch_prediction = model.predict(images_batch)
    print("predicted label:",class_names[np.argmax(batch_prediction[0])])
```

```
first image to predict
actual label: Potato___Early_blight
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
predicted label: Potato___Early_blight
```



Write a function for inference

```
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


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 Confidence: {confidence}%")

        plt.axis("off")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 200ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
```

Actual: Potato___Early_blight,
Predicted: Potato___Early_blight.
Confidence: 99.98%

Actual: Potato___Late_blight,
Predicted: Potato___Late_blight.
Confidence: 99.97%

Actual: Potato___healthy,
Predicted: Potato___healthy.
Confidence: 84.53%

Actual: Potato___Late_blight,
Predicted: Potato___Late_blight.
Confidence: 100.0%

Actual: Potato___Early_blight,
Predicted: Potato___Early_blight.
Confidence: 100.0%

Actual: Potato___Late_blight,
Predicted: Potato___Late_blight.
Confidence: 98.57%

Actual: Potato___Early_blight,
Predicted: Potato___Early_blight.
Confidence: 100.0%

Actual: Potato___Early_blight,
Predicted: Potato___Early_blight.
Confidence: 99.99%

Actual: Potato___Early_blight,
Predicted: Potato___Early_blight.
Confidence: 100.0%

Saving the Model

We append the model to the list of models as a new version

```
import os

# Create the directory if it doesn't exist
if not os.path.exists("../models"):
    os.makedirs("../models")

# Extract file names without extensions and convert them to integers
model_files = [f for f in os.listdir("../models") if f.endswith(".keras")]
model_versions = [int(f.split('.')[0]) for f in model_files]

# Get the maximum model version, or default to 0 if no models exist
model_version = max(model_versions + [0]) + 1

# Save the new model with the next version number
model.save(f"../models/{model_version}.keras")
```

```
model.save("../potatoes.keras")
```

```
import os

model_path = os.path.abspath(f"../models/{model_version}.keras")
print(f"Model saved at: {model_path}")
```

```
Model saved at: /models/1.keras
```

```
import os
print(os.getcwd())

print(os.path.exists("../models"))
!ls /models
```

```
/content
True
1.keras
```

```
import tensorflow as tf
from tensorflow.keras import metrics

model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=[
        'accuracy',
        metrics.Precision(name='precision'),
        metrics.Recall(name='recall')
    ]
)
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Step 1: Generate predictions on the test dataset
y_true = []
y_pred = []

for images, labels in test_ds:
    predictions = model.predict(images)
    predicted_classes = np.argmax(predictions, axis=1)

    y_true.extend(labels.numpy())
    y_pred.extend(predicted_classes)

# Step 2: Calculate the confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Step 3: Plot the confusion matrix
plt.figure(figsize=(10, 8))
```

```
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
```