POTATO LEAF DISEASE DETECTION USING TENSORFLOW.ipynb

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```
[ ] import tensorflow as tf
    from tensorflow.keras import models, layers
    import matplotlib.pyplot as plt                # USED FOR DATA VISUALIZATION USING PYPLOTS. GRAPHS
```

```
[ ] from google.colab import drive
```

```
[ ] drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[ ] IMAGE_SIZE = 256
    BATCH_SIZE = 32
    EPOCHS = 55
    CHANNELS = 3            # RGB
```

```
[ ] dataset = tf.keras.preprocessing.image_dataset_from_directory(
        "/content/drive/MyDrive/MINORPROJECT/PlantVillage",
        shuffle = True,
        image_size = (IMAGE_SIZE, IMAGE_SIZE),
        batch_size = BATCH_SIZE
    )
```

```
Found 2968 files belonging to 3 classes.
```

Found 2968 files belonging to 3 classes.

```
[ ] class_names = dataset.class_names
    class_names
```

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

```
[ ] len(dataset)            # This implies that the number of batching done i.e. len(dataset) * batch_size  =  total no of datasets
```

```
93
```

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

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

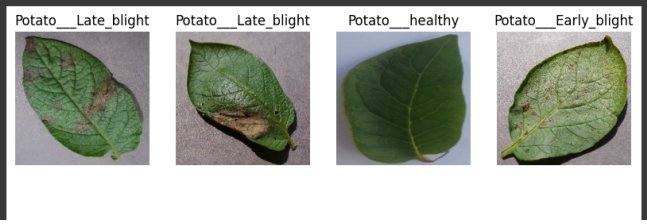
```
[ ] for image_batch, label_batch in dataset.take(1):
        print(image_batch[0].numpy())
```

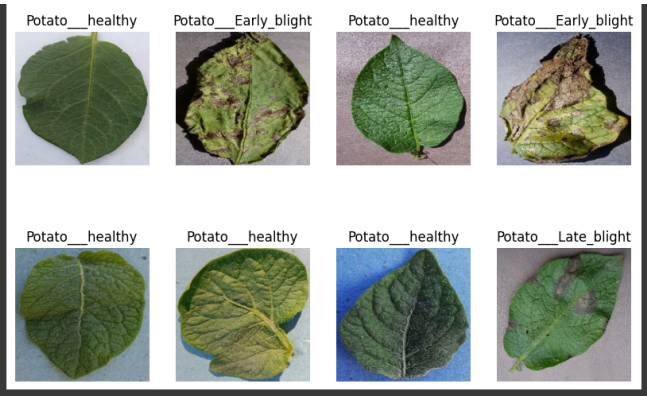
```
[[[106. 102. 116.]
  [151. 147. 161.]
  [ 97.  93. 107.]
  ...
  [178. 180. 193.]
  [178. 180. 193.]
  [173. 175. 188.]]

 [[127. 123. 137.]
  [107. 103. 117.]
  [127. 123. 137.]
  ...
  [153. 155. 168.]
  [153. 155. 168.]
  [150. 152. 165.]]

 [[126. 122. 136.]
  [ 87.  83.  97.]
  [134. 130. 144.]
  ...
  [160. 162. 175.]
  [160. 162. 175.]
  [155. 157. 170.]]

 ...

 [[137. 135. 148.]
  [154. 152. 165.]
  [136. 134. 147.]
  ...
  [180. 182. 194.]
  [184. 186. 198.]
  [174. 176. 188.]]

 [[133. 131. 144.]
  [146. 144. 157.]
  [120. 118. 131.]
  ...
  [197. 199. 211.]
  [185. 187. 199.]
  [194. 196. 208.]]

 [[138. 136. 149.]
  [132. 130. 143.]
  [131. 129. 142.]
  ...
  [194. 196. 208.]
  [167. 169. 181.]
  [189. 191. 203.]]]
```

```
[ ] for image_batch, label_batch in dataset.take(1):
        print(image_batch[0].shape)
```

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

```
[ ] 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.axis("off")
            plt.title(class_names[label_batch[i]])
```






```
[ ] len(dataset)          # Total number of batches
```

```
93
```

80% is our Training Data Set

20% is our again splitted into 2

10% is now Validation Set

10% is nor Testing Set

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

```
74.4
```

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

```
54
```

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

```
39
```

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

```
9.3
```

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

```
6
```

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

```
33
```

```
[ ] def get_datset_partitions_tf(ds, train_split= 0.8, val_split = 0.1, test_split = 0.1, shuffle=True, shuffle_size = 10000):
        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_datset_partitions_tf(dataset)
```

```
[ ] len(train_ds)
```

```
74
```

```
[ ] len(test_ds)
```

```
10
```

```
[ ] len(val_ds)
```

```
9
```

```
[ ] 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)
```

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

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

```
[ ] 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.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)
```

```
[ ] 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 (MaxPooling2  (32, 127, 127, 32)        0
 D)

 conv2d_1 (Conv2D)           (32, 125, 125, 64)        18496

 max_pooling2d_1 (MaxPoolin  (32, 62, 62, 64)          0
 g2D)

 conv2d_2 (Conv2D)           (32, 60, 60, 64)          36928

 max_pooling2d_2 (MaxPoolin  (32, 30, 30, 64)          0
 g2D)

 conv2d_3 (Conv2D)           (32, 28, 28, 64)          36928

 max_pooling2d_3 (MaxPoolin  (32, 14, 14, 64)          0
 g2D)

 conv2d_4 (Conv2D)           (32, 12, 12, 64)          36928

 max_pooling2d_4 (MaxPoolin  (32, 6, 6, 64)            0
 g2D)

 conv2d_5 (Conv2D)           (32, 4, 4, 64)            36928

 max_pooling2d_5 (MaxPoolin  (32, 2, 2, 64)            0
 g2D)

 flatten (Flatten)           (32, 256)                 0

 dense (Dense)               (32, 64)                  16448

 dense_1 (Dense)             (32, 3)                   195

=================================================================
Total params: 183747 (717.76 KB)
Trainable params: 183747 (717.76 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

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

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

```
Epoch 27/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0116 - accuracy: 0.9975 - val_loss: 0.0108 - val_accuracy: 0.9965
Epoch 28/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0134 - accuracy: 0.9958 - val_loss: 0.0562 - val_accuracy: 0.9722
Epoch 29/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0120 - accuracy: 0.9966 - val_loss: 0.0342 - val_accuracy: 0.9861
Epoch 30/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0411 - accuracy: 0.9864 - val_loss: 0.0283 - val_accuracy: 0.9896
Epoch 31/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0518 - accuracy: 0.9809 - val_loss: 0.0388 - val_accuracy: 0.9931
Epoch 32/55
74/74 [==============================] - 5s 62ms/step - loss: 0.0168 - accuracy: 0.9936 - val_loss: 0.0261 - val_accuracy: 0.9931
Epoch 33/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0124 - accuracy: 0.9953 - val_loss: 0.0229 - val_accuracy: 0.9896
Epoch 34/55
74/74 [==============================] - 5s 64ms/step - loss: 0.0556 - accuracy: 0.9843 - val_loss: 0.2027 - val_accuracy: 0.9236
Epoch 35/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0530 - accuracy: 0.9826 - val_loss: 0.0247 - val_accuracy: 0.9896
Epoch 36/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0254 - accuracy: 0.9907 - val_loss: 0.0320 - val_accuracy: 0.9896
Epoch 37/55
74/74 [==============================] - 5s 62ms/step - loss: 0.0446 - accuracy: 0.9843 - val_loss: 0.3526 - val_accuracy: 0.8715
Epoch 38/55
74/74 [==============================] - 5s 61ms/step - loss: 0.0528 - accuracy: 0.9809 - val_loss: 0.0514 - val_accuracy: 0.9757
Epoch 39/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0153 - accuracy: 0.9962 - val_loss: 0.0208 - val_accuracy: 0.9931
Epoch 40/55
74/74 [==============================] - 5s 64ms/step - loss: 0.0114 - accuracy: 0.9962 - val_loss: 0.0107 - val_accuracy: 0.9931
Epoch 41/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0264 - accuracy: 0.9911 - val_loss: 0.0329 - val_accuracy: 0.9896
Epoch 42/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0224 - accuracy: 0.9928 - val_loss: 0.0376 - val_accuracy: 0.9861
Epoch 43/55
74/74 [==============================] - 5s 64ms/step - loss: 0.0029 - accuracy: 0.9996 - val_loss: 0.0471 - val_accuracy: 0.9861
Epoch 44/55
74/74 [==============================] - 4s 60ms/step - loss: 0.0029 - accuracy: 0.9996 - val_loss: 0.0068 - val_accuracy: 0.9965
Epoch 45/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0211 - accuracy: 0.9945 - val_loss: 0.0196 - val_accuracy: 0.9931
Epoch 46/55
74/74 [==============================] - 5s 66ms/step - loss: 0.0100 - accuracy: 0.9953 - val_loss: 0.0650 - val_accuracy: 0.9861
Epoch 47/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0213 - accuracy: 0.9932 - val_loss: 0.0701 - val_accuracy: 0.9722
Epoch 48/55
74/74 [==============================] - 5s 61ms/step - loss: 0.0395 - accuracy: 0.9860 - val_loss: 0.0126 - val_accuracy: 0.9931
Epoch 49/55
74/74 [==============================] - 5s 64ms/step - loss: 0.0235 - accuracy: 0.9924 - val_loss: 0.0317 - val_accuracy: 0.9896
Epoch 50/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0079 - accuracy: 0.9979 - val_loss: 0.0156 - val_accuracy: 0.9931
Epoch 51/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0256 - accuracy: 0.9890 - val_loss: 0.0071 - val_accuracy: 0.9965
Epoch 52/55
74/74 [==============================] - 5s 63ms/step - loss: 0.0195 - accuracy: 0.9915 - val_loss: 0.0202 - val_accuracy: 0.9896
Epoch 53/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0197 - accuracy: 0.9932 - val_loss: 0.0135 - val_accuracy: 0.9931
Epoch 54/55
74/74 [==============================] - 4s 61ms/step - loss: 0.0154 - accuracy: 0.9936 - val_loss: 0.0105 - val_accuracy: 1.0000
```

```
Epoch 55/55
74/74 [==============================] - 5s 64ms/step - loss: 0.0052 - accuracy: 0.9987 - val_loss: 0.0077 - val_accuracy: 0.9965
```

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

```
10/10 [==============================] - 4s 28ms/step - loss: 0.0370 - accuracy: 0.9937
```

```
[ ] scores
```

```
[0.0370352640748024, 0.9937499761581421]
```

```
[ ] history
```

```
<keras.src.callbacks.History at 0x7d82fc679000>
```

```
[ ] history.params
```

```
{'verbose': 1, 'epochs': 55, 'steps': 74}
```

```
[ ] history.history.keys()
```

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

```
[ ] history.history['accuracy']
```

```
[0.6190677881240845,
 0.8105932474136353,
 0.9110169410705566,
 0.9080508351325989,
 0.9605932235717773,
 0.9576271176338196,
 0.9707627296447754,
 0.9711864590644836,
 0.9817796349525452,
 0.9834745526313782,
 0.9788135886192322,
 0.9762712121009827,
 0.98220338432534,
 0.9877118468284607,
 0.9906779527664185,
 0.9885593056678772,
 0.9809321761131287,
 0.9838982820510864,
 0.9847457408905029,
 0.993220329284668,
 0.9957627058029175,
 0.9923728704452515,
 0.9919491410255432,
 0.9877118468284607,
 0.9957627058029175,
 0.993220329284668,
 0.9974576234817505,
 0.9957627058029175,
 0.99661016464232,
 0.9864406585693359,
 0.9809321761131287,
 0.9936440587043762,
 0.9953389763832092,
 0.9843220114707947,
 0.9826270937919617,
 0.9906779527664185,
 0.9843220114707947,
 0.9809321761131287,
 0.9961864352226257,
 0.9961864352226257,
 0.9911016821861267,
 0.9927965998649597,
 0.9995762705802917,
 0.9995762705802917,
 0.9944915175437927,
 0.9953389763832092,
 0.993220329284668,
 0.9860169291496277,
 0.9923728704452515,
 0.9978813529014587,
 0.9889830350875854,
 0.991525411605835,
 0.993220329284668,
 0.9936440587043762,
 0.9987288117408752]
```

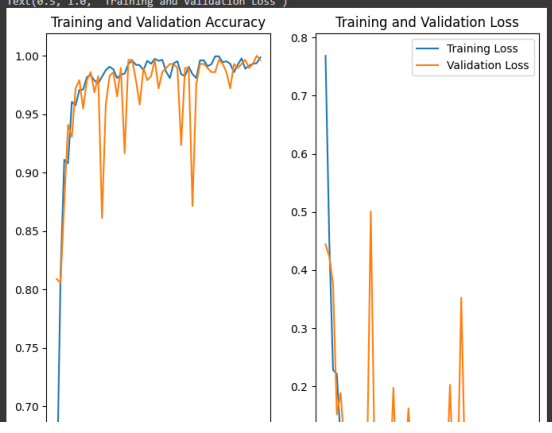
```
[ ] len(history.history['accuracy'])
```

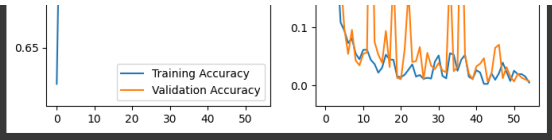
```
55
```

```
[ ] 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(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.subplot(1,2,2)
    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")
```

```
Text(0.5, 1.0, 'Training and Validation Loss')
```





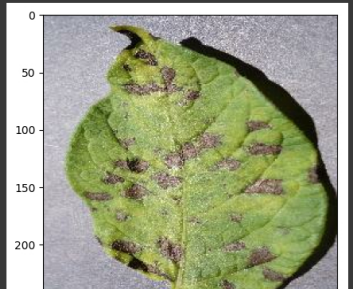

```
[ ] for images_batch, labels_batch in test_ds.take(1):
        print(images_batch[0].numpy())
```

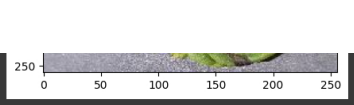
```
[[[194. 188. 192.]
  [185. 179. 183.]
  [179. 173. 177.]
  ...
  [152. 143. 148.]
  [144. 135. 140.]
  [136. 127. 132.]]

 [[196. 190. 194.]
  [187. 181. 185.]
  [181. 175. 179.]
  ...
  [155. 146. 151.]
  [149. 140. 145.]
  [154. 145. 150.]]

 [[192. 186. 190.]
  [184. 178. 182.]
  [178. 172. 176.]
  ...
  [152. 141. 145.]
  [156. 145. 149.]
  [125. 114. 118.]]

 ...

 [[157. 151. 153.]
  [159. 153. 155.]
  [162. 156. 158.]
  ...
  [119. 110. 113.]
  [123. 114. 117.]
  [123. 114. 117.]]

 [[164. 158. 160.]
  [165. 159. 161.]
  [165. 159. 161.]
  ...
  [121. 112. 115.]
  [121. 112. 115.]
  [115. 106. 109.]]

 [[167. 161. 163.]
  [165. 159. 161.]
  [162. 156. 158.]
  ...
  [122. 113. 116.]
  [114. 105. 108.]
  [117. 108. 111.]]]
```

```
[ ] for images_batch, labels_batch in test_ds.take(1):
        print(images_batch[0].numpy().astype('uint8'))
```

```
[[[194 188 192]
  [185 179 183]
  [179 173 177]
  ...
  [152 143 148]
  [144 135 140]
  [136 127 132]]

 [[196 190 194]
  [187 181 185]
  [181 175 179]
  ...
  [155 146 151]
  [149 140 145]
  [154 145 150]]

 [[192 186 190]
  [184 178 182]
  [178 172 176]
  ...
  [152 141 145]
  [156 145 149]
  [125 114 118]]

 ...

 [[157 151 153]
  [159 153 155]
  [162 156 158]
  ...
  [119 110 113]
  [123 114 117]
  [123 114 117]]

 [[164 158 160]
  [165 159 161]
  [165 159 161]
  ...
  [121 112 115]
  [121 112 115]
  [115 106 109]]

 [[167 161 163]
  [165 159 161]
  [162 156 158]
  ...
  [122 113 116]
  [114 105 108]
  [117 108 111]]]
```

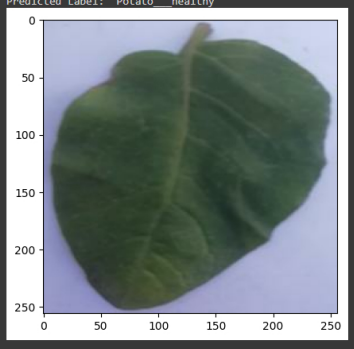
```
for images_batch, labels_batch in test_ds.take(1):
    plt.imshow(images_batch[0].numpy().astype('uint8'))
```






```
[ ]  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]

         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])])
```

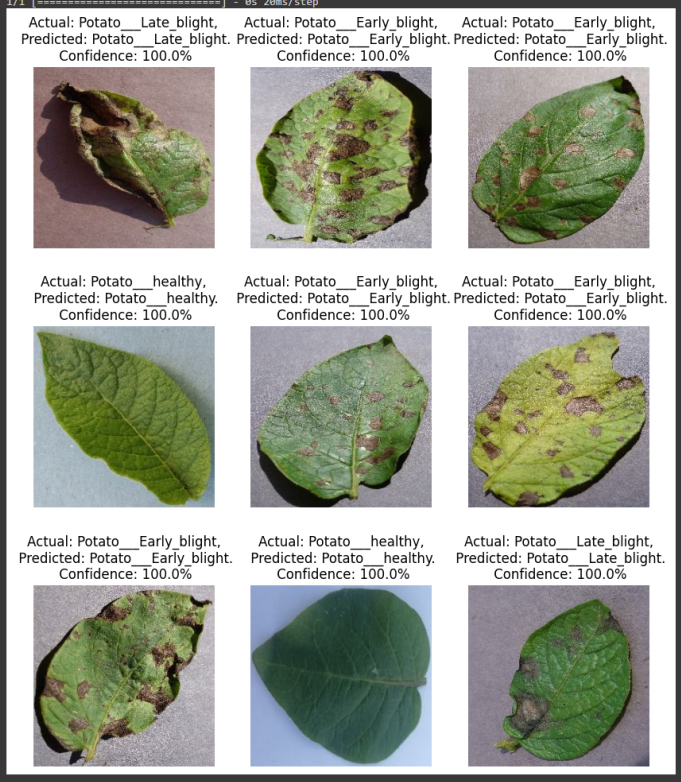
```
First image to predict
Actual label:  Potato___healthy
1/1 [==============================] - 0s 148ms/step
Predicted Label:  Potato___healthy
```



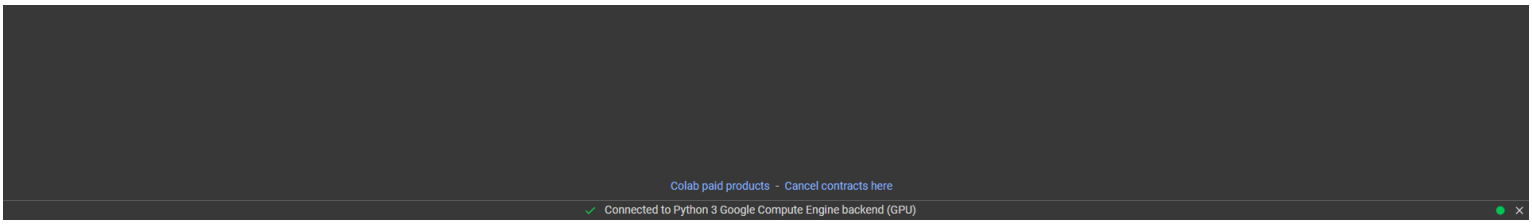

```
[ ]  def predict(model, img):
         img_array = tf.keras.preprocessing.image.img_to_array(images[i].numpy())
         img_array = tf.expand_dims(img_array, 0)    #Create a Batch

         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=(10,12))

     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 17ms/step
1/1 [==============================] - 0s 20ms/step
```




```
[ ]
```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