## 99-8-acc-alzheimer-detection-and-classification

May 19, 2022

# 1 Alzheimer MRI Preprocessed (detection and classification)

### 2 LIBRARIES

```
[1]: import tensorflow as tf
  import matplotlib.pyplot as plt
  import numpy as np
  import os
  import tensorflow as tf
  from tensorflow import keras
  from keras import layers
  import matplotlib.image as img
  %matplotlib inline
```

### 3 DATA LOAD

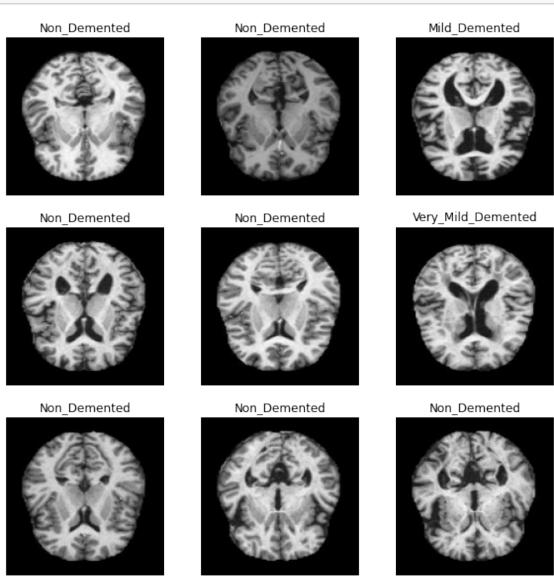
```
[3]: !pip install split-folders
     import splitfolders
     splitfolders.ratio('Dataset', output="output", seed=1345, ratio=(.8, 0.1,0.1))
    WARNING: Ignoring invalid distribution -5py (c:\programdata\anaconda3\lib\site-
    packages)
    WARNING: Ignoring invalid distribution -orchvision
    (c:\programdata\anaconda3\lib\site-packages)
    WARNING: Ignoring invalid distribution -orch (c:\programdata\anaconda3\lib\site-
    packages)
    WARNING: Ignoring invalid distribution - (c:\programdata\anaconda3\lib\site-
    packages)
    WARNING: Ignoring invalid distribution -arkupsafe
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    WARNING: Ignoring invalid distribution -5py (c:\programdata\anaconda3\lib\site-
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packages)
WARNING: Ignoring invalid distribution -orchvision
(c:\programdata\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -orch (c:\programdata\anaconda3\lib\site-
```

```
packages)
    WARNING: Ignoring invalid distribution - (c:\programdata\anaconda3\lib\site-
    packages)
    WARNING: Ignoring invalid distribution -arkupsafe
    (c:\programdata\anaconda3\lib\site-packages)
    WARNING: Ignoring invalid distribution -ackaging
    (c:\programdata\anaconda3\lib\site-packages)
    Requirement already satisfied: split-folders in
    c:\programdata\anaconda3\lib\site-packages (0.5.1)
    Copying files: 6400 files [00:32, 199.11 files/s]
[4]: IMG_HEIGHT = 128
     IMG WIDTH = 128
     train_ds = tf.keras.preprocessing.image_dataset_from_directory(
     "./output/train",
     seed=123,
     image_size=(IMG_HEIGHT, IMG_WIDTH),
     batch_size=64
     test_ds = tf.keras.preprocessing.image_dataset_from_directory(
     "./output/test",
     seed=123,
     image_size=(IMG_HEIGHT, IMG_WIDTH),
     batch size=64
     )
     val_ds = tf.keras.preprocessing.image_dataset_from_directory(
     "./output/val",
     seed=123,
     image_size=(IMG_HEIGHT, IMG_WIDTH),
     batch_size=64
    Found 5119 files belonging to 4 classes.
    Found 642 files belonging to 4 classes.
    Found 639 files belonging to 4 classes.
[5]: class names = train ds.class names
     print(class_names)
     train ds
    ['Mild_Demented', 'Moderate_Demented', 'Non_Demented', 'Very_Mild_Demented']
[5]: <BatchDataset element_spec=(TensorSpec(shape=(None, 128, 128, 3),
     dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32,
    name=None))>
```

### 4 EXAMPLE IMAGE

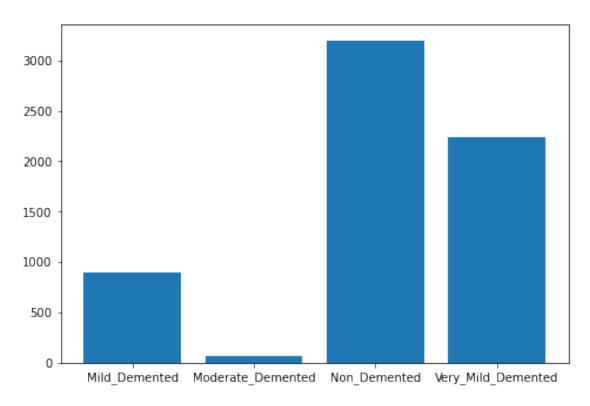
```
[6]: plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```



```
[7]: fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
```

```
size = [896,64,3200,2240]
ax.bar(class_names,size)
plt.show
```

[7]: <function matplotlib.pyplot.show(close=None, block=None)>



### 5 MODEL

### [10]: model.summary()

Model: "sequential"

Layer (type)	• •	Param #
rescaling (Rescaling)		
conv2d (Conv2D)	(None, 128, 128, 16)	448
<pre>max_pooling2d (MaxPooling2D )</pre>	(None, 64, 64, 16)	0
conv2d_1 (Conv2D)	(None, 64, 64, 32)	4640
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 32, 32, 32)	0
dropout (Dropout)	(None, 32, 32, 32)	0
conv2d_2 (Conv2D)	(None, 32, 32, 64)	18496
<pre>max_pooling2d_2 (MaxPooling 2D)</pre>	(None, 16, 16, 64)	0
dropout_1 (Dropout)	(None, 16, 16, 64)	0
flatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 128)	2097280
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 4)	260

Total params: 2,129,380 Trainable params: 2,129,380 Non-trainable params: 0 \_\_\_\_\_ [11]: hist = model.fit(train\_ds,validation\_data=val\_ds,epochs=100, batch\_size=64,\_\_ →verbose=1) Epoch 1/100 80/80 [============ ] - 34s 400ms/step - loss: 1.1069 accuracy: 0.4989 - val\_loss: 0.9679 - val\_accuracy: 0.5837 Epoch 2/100 accuracy: 0.5679 - val\_loss: 0.8599 - val\_accuracy: 0.6103 Epoch 3/100 accuracy: 0.6095 - val\_loss: 0.7424 - val\_accuracy: 0.6886 Epoch 4/100 accuracy: 0.6730 - val\_loss: 0.7297 - val\_accuracy: 0.6823 Epoch 5/100 accuracy: 0.7259 - val\_loss: 0.5482 - val\_accuracy: 0.7966 Epoch 6/100 accuracy: 0.7738 - val\_loss: 0.4868 - val\_accuracy: 0.8075 Epoch 7/100 80/80 [============ ] - 34s 421ms/step - loss: 0.3883 accuracy: 0.8412 - val\_loss: 0.3425 - val\_accuracy: 0.8623 Epoch 8/100 80/80 [============ ] - 32s 394ms/step - loss: 0.3274 accuracy: 0.8711 - val\_loss: 0.2788 - val\_accuracy: 0.9030 Epoch 9/100 80/80 [============ ] - 32s 397ms/step - loss: 0.2486 accuracy: 0.9012 - val\_loss: 0.1804 - val\_accuracy: 0.9437 Epoch 10/100

accuracy: 0.9219 - val\_loss: 0.1765 - val\_accuracy: 0.9374

Epoch 11/100

```
accuracy: 0.9633 - val_loss: 0.0685 - val_accuracy: 0.9812
Epoch 14/100
80/80 [============= ] - 32s 400ms/step - loss: 0.1258 -
accuracy: 0.9537 - val_loss: 0.0872 - val_accuracy: 0.9765
Epoch 15/100
accuracy: 0.9666 - val_loss: 0.0707 - val_accuracy: 0.9765
Epoch 16/100
80/80 [============= ] - 33s 416ms/step - loss: 0.0816 -
accuracy: 0.9709 - val_loss: 0.1023 - val_accuracy: 0.9593
Epoch 17/100
80/80 [============ ] - 32s 400ms/step - loss: 0.0754 -
accuracy: 0.9721 - val_loss: 0.0561 - val_accuracy: 0.9781
Epoch 18/100
accuracy: 0.9801 - val_loss: 0.0326 - val_accuracy: 0.9875
Epoch 19/100
accuracy: 0.9732 - val_loss: 0.0814 - val_accuracy: 0.9703
Epoch 20/100
accuracy: 0.9822 - val_loss: 0.0470 - val_accuracy: 0.9812
Epoch 21/100
80/80 [============ ] - 32s 396ms/step - loss: 0.0706 -
accuracy: 0.9754 - val_loss: 0.0577 - val_accuracy: 0.9844
Epoch 22/100
80/80 [============ ] - 32s 395ms/step - loss: 0.0485 -
accuracy: 0.9834 - val_loss: 0.0350 - val_accuracy: 0.9922
accuracy: 0.9805 - val_loss: 0.0390 - val_accuracy: 0.9875
Epoch 24/100
accuracy: 0.9830 - val_loss: 0.0460 - val_accuracy: 0.9828
Epoch 25/100
accuracy: 0.9857 - val loss: 0.0282 - val accuracy: 0.9906
Epoch 26/100
accuracy: 0.9871 - val_loss: 0.0218 - val_accuracy: 0.9953
Epoch 27/100
80/80 [============ ] - 32s 401ms/step - loss: 0.0334 -
accuracy: 0.9883 - val_loss: 0.0393 - val_accuracy: 0.9875
Epoch 28/100
80/80 [============ ] - 32s 398ms/step - loss: 0.0373 -
accuracy: 0.9867 - val_loss: 0.0366 - val_accuracy: 0.9844
Epoch 29/100
```

```
accuracy: 0.9889 - val_loss: 0.0728 - val_accuracy: 0.9718
Epoch 30/100
80/80 [============ ] - 32s 396ms/step - loss: 0.0334 -
accuracy: 0.9891 - val_loss: 0.0273 - val_accuracy: 0.9906
Epoch 31/100
accuracy: 0.9848 - val_loss: 0.0164 - val_accuracy: 0.9969
Epoch 32/100
80/80 [============ ] - 32s 396ms/step - loss: 0.0245 -
accuracy: 0.9924 - val_loss: 0.0357 - val_accuracy: 0.9906
Epoch 33/100
80/80 [============= ] - 32s 398ms/step - loss: 0.0317 -
accuracy: 0.9891 - val_loss: 0.0171 - val_accuracy: 0.9922
Epoch 34/100
accuracy: 0.9908 - val_loss: 0.0087 - val_accuracy: 0.9984
Epoch 35/100
accuracy: 0.9893 - val_loss: 0.0129 - val_accuracy: 0.9969
Epoch 36/100
accuracy: 0.9898 - val_loss: 0.0133 - val_accuracy: 0.9953
Epoch 37/100
accuracy: 0.9865 - val_loss: 0.0101 - val_accuracy: 0.9984
Epoch 38/100
80/80 [============= ] - 34s 418ms/step - loss: 0.0337 -
accuracy: 0.9896 - val_loss: 0.0145 - val_accuracy: 0.9969
accuracy: 0.9891 - val_loss: 0.0243 - val_accuracy: 0.9890
Epoch 40/100
80/80 [============ ] - 51s 640ms/step - loss: 0.0295 -
accuracy: 0.9893 - val_loss: 0.0165 - val_accuracy: 0.9937
Epoch 41/100
accuracy: 0.9939 - val loss: 0.0104 - val accuracy: 0.9984
Epoch 42/100
accuracy: 0.9941 - val_loss: 0.0053 - val_accuracy: 1.0000
Epoch 43/100
80/80 [============ ] - 51s 638ms/step - loss: 0.0229 -
accuracy: 0.9922 - val_loss: 0.0517 - val_accuracy: 0.9828
Epoch 44/100
80/80 [============ - 51s 637ms/step - loss: 0.0265 -
accuracy: 0.9906 - val_loss: 0.0113 - val_accuracy: 0.9984
Epoch 45/100
```

```
accuracy: 0.9908 - val_loss: 0.0156 - val_accuracy: 0.9953
Epoch 46/100
80/80 [============ ] - 52s 648ms/step - loss: 0.0181 -
accuracy: 0.9937 - val_loss: 0.0179 - val_accuracy: 0.9953
Epoch 47/100
accuracy: 0.9914 - val_loss: 0.0152 - val_accuracy: 0.9937
Epoch 48/100
80/80 [============ ] - 51s 637ms/step - loss: 0.0133 -
accuracy: 0.9947 - val_loss: 0.0073 - val_accuracy: 0.9984
Epoch 49/100
80/80 [============= ] - 52s 642ms/step - loss: 0.0184 -
accuracy: 0.9941 - val_loss: 0.0093 - val_accuracy: 0.9984
Epoch 50/100
80/80 [============= ] - 52s 642ms/step - loss: 0.0195 -
accuracy: 0.9936 - val_loss: 0.0155 - val_accuracy: 0.9953
Epoch 51/100
accuracy: 0.9924 - val_loss: 0.0133 - val_accuracy: 0.9969
Epoch 52/100
accuracy: 0.9922 - val_loss: 0.0172 - val_accuracy: 0.9969
Epoch 53/100
accuracy: 0.9889 - val_loss: 0.0675 - val_accuracy: 0.9797
Epoch 54/100
accuracy: 0.9891 - val_loss: 0.0477 - val_accuracy: 0.9828
Epoch 55/100
accuracy: 0.9920 - val_loss: 0.0362 - val_accuracy: 0.9890
Epoch 56/100
accuracy: 0.9969 - val_loss: 0.0051 - val_accuracy: 1.0000
Epoch 57/100
accuracy: 0.9932 - val loss: 0.0462 - val accuracy: 0.9812
Epoch 58/100
accuracy: 0.9945 - val_loss: 0.0206 - val_accuracy: 0.9937
Epoch 59/100
80/80 [============ ] - 51s 637ms/step - loss: 0.0155 -
accuracy: 0.9937 - val_loss: 0.0116 - val_accuracy: 0.9953
Epoch 60/100
80/80 [============ ] - 51s 639ms/step - loss: 0.0198 -
accuracy: 0.9943 - val_loss: 0.0045 - val_accuracy: 1.0000
Epoch 61/100
```

```
accuracy: 0.9965 - val_loss: 0.0189 - val_accuracy: 0.9937
Epoch 62/100
80/80 [============ ] - 51s 637ms/step - loss: 0.0137 -
accuracy: 0.9949 - val_loss: 0.0154 - val_accuracy: 0.9937
Epoch 63/100
accuracy: 0.9955 - val_loss: 0.0379 - val_accuracy: 0.9922
Epoch 64/100
80/80 [============= ] - 52s 641ms/step - loss: 0.0407 -
accuracy: 0.9867 - val_loss: 0.0397 - val_accuracy: 0.9875
Epoch 65/100
80/80 [============= ] - 52s 641ms/step - loss: 0.0120 -
accuracy: 0.9963 - val_loss: 0.0048 - val_accuracy: 0.9984
Epoch 66/100
80/80 [============= ] - 51s 639ms/step - loss: 0.0053 -
accuracy: 0.9979 - val_loss: 0.0036 - val_accuracy: 1.0000
Epoch 67/100
accuracy: 0.9969 - val_loss: 0.0128 - val_accuracy: 0.9937
Epoch 68/100
accuracy: 0.9893 - val_loss: 0.0170 - val_accuracy: 0.9937
Epoch 69/100
80/80 [============ ] - 51s 638ms/step - loss: 0.0245 -
accuracy: 0.9914 - val_loss: 0.0130 - val_accuracy: 0.9969
Epoch 70/100
80/80 [============ ] - 51s 635ms/step - loss: 0.0248 -
accuracy: 0.9910 - val_loss: 0.0168 - val_accuracy: 0.9906
accuracy: 0.9926 - val_loss: 0.0183 - val_accuracy: 0.9922
Epoch 72/100
accuracy: 0.9953 - val_loss: 0.0421 - val_accuracy: 0.9890
Epoch 73/100
0.9967 - val_loss: 0.0222 - val_accuracy: 0.9906
Epoch 74/100
accuracy: 0.9975 - val_loss: 0.0209 - val_accuracy: 0.9937
Epoch 75/100
80/80 [============ ] - 52s 653ms/step - loss: 0.0102 -
accuracy: 0.9961 - val_loss: 0.0089 - val_accuracy: 0.9969
Epoch 76/100
80/80 [=========== ] - 53s 656ms/step - loss: 0.0180 -
accuracy: 0.9949 - val_loss: 0.0121 - val_accuracy: 0.9969
Epoch 77/100
```

```
accuracy: 0.9973 - val_loss: 0.0103 - val_accuracy: 0.9969
Epoch 78/100
80/80 [============ ] - 53s 658ms/step - loss: 0.0092 -
accuracy: 0.9969 - val_loss: 0.0427 - val_accuracy: 0.9890
Epoch 79/100
accuracy: 0.9939 - val_loss: 0.0215 - val_accuracy: 0.9922
Epoch 80/100
80/80 [============ ] - 52s 643ms/step - loss: 0.0133 -
accuracy: 0.9941 - val_loss: 0.0210 - val_accuracy: 0.9953
Epoch 81/100
80/80 [============= ] - 52s 645ms/step - loss: 0.0122 -
accuracy: 0.9967 - val_loss: 0.0226 - val_accuracy: 0.9953
Epoch 82/100
accuracy: 0.9953 - val_loss: 0.0310 - val_accuracy: 0.9906
Epoch 83/100
accuracy: 0.9924 - val_loss: 0.0110 - val_accuracy: 0.9969
Epoch 84/100
accuracy: 0.9943 - val_loss: 0.0097 - val_accuracy: 0.9953
Epoch 85/100
80/80 [============= ] - 36s 450ms/step - loss: 0.0146 -
accuracy: 0.9949 - val_loss: 0.0083 - val_accuracy: 0.9953
Epoch 86/100
80/80 [============= ] - 36s 452ms/step - loss: 0.0141 -
accuracy: 0.9943 - val_loss: 0.0078 - val_accuracy: 0.9984
accuracy: 0.9939 - val_loss: 0.0062 - val_accuracy: 0.9984
Epoch 88/100
accuracy: 0.9979 - val_loss: 0.0016 - val_accuracy: 1.0000
Epoch 89/100
accuracy: 0.9953 - val loss: 0.0195 - val accuracy: 0.9906
Epoch 90/100
accuracy: 0.9965 - val_loss: 0.0017 - val_accuracy: 1.0000
Epoch 91/100
80/80 [============= ] - 36s 450ms/step - loss: 0.0200 -
accuracy: 0.9920 - val_loss: 0.0114 - val_accuracy: 0.9969
Epoch 92/100
80/80 [============= ] - 37s 456ms/step - loss: 0.0179 -
accuracy: 0.9939 - val_loss: 0.0089 - val_accuracy: 0.9953
Epoch 93/100
```

```
accuracy: 0.9961 - val_loss: 0.0172 - val_accuracy: 0.9953
Epoch 94/100
80/80 [============ ] - 36s 450ms/step - loss: 0.0126 -
accuracy: 0.9957 - val_loss: 0.0043 - val_accuracy: 0.9984
Epoch 95/100
accuracy: 0.9961 - val loss: 0.0383 - val accuracy: 0.9890
Epoch 96/100
80/80 [============ ] - 36s 454ms/step - loss: 0.0110 -
accuracy: 0.9961 - val_loss: 0.0071 - val_accuracy: 0.9969
Epoch 97/100
80/80 [============ ] - 36s 450ms/step - loss: 0.0071 -
accuracy: 0.9973 - val_loss: 0.0122 - val_accuracy: 0.9984
Epoch 98/100
80/80 [============= ] - 36s 452ms/step - loss: 0.0117 -
accuracy: 0.9959 - val_loss: 0.0084 - val_accuracy: 0.9984
Epoch 99/100
80/80 [============ ] - 37s 460ms/step - loss: 0.0057 -
accuracy: 0.9979 - val_loss: 0.0084 - val_accuracy: 0.9969
Epoch 100/100
accuracy: 0.9965 - val_loss: 0.0086 - val_accuracy: 0.9984
```

#### 6 Plot the result

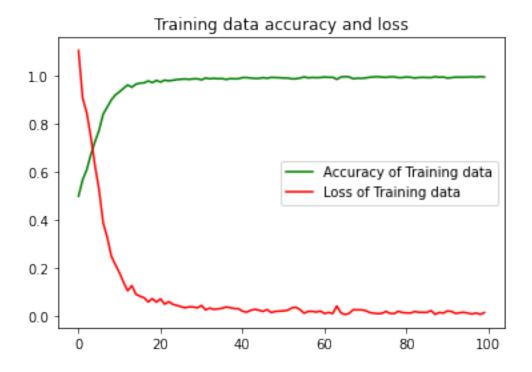
```
[12]: get_ac = hist.history['accuracy']
get_los = hist.history['loss']
val_acc = hist.history['val_accuracy']
val_loss = hist.history['val_loss']
```

```
[13]: epochs = range(len(get_ac))
    plt.plot(epochs, get_ac, 'g', label='Accuracy of Training data')
    plt.plot(epochs, get_los, 'r', label='Loss of Training data')
    plt.title('Training data accuracy and loss')
    plt.legend(loc=0)
    plt.figure()

    plt.plot(epochs, get_ac, 'g', label='Accuracy of Training Data')
    plt.plot(epochs, val_acc, 'r', label='Accuracy of Validation Data')
    plt.title('Training and Validation Accuracy')
    plt.legend(loc=0)
    plt.figure()

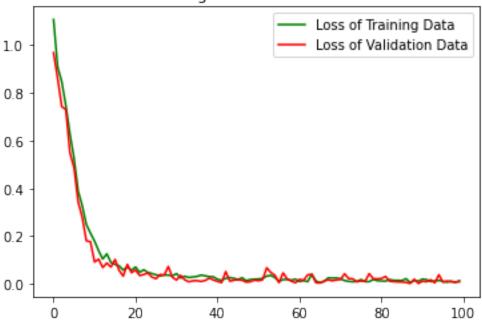
    plt.plot(epochs, get_los, 'g', label='Loss of Training Data')
    plt.plot(epochs, val_loss, 'r', label='Loss of Validation Data')
    plt.title('Training and Validation Loss')
    plt.legend(loc=0)
```

plt.figure()
plt.show()







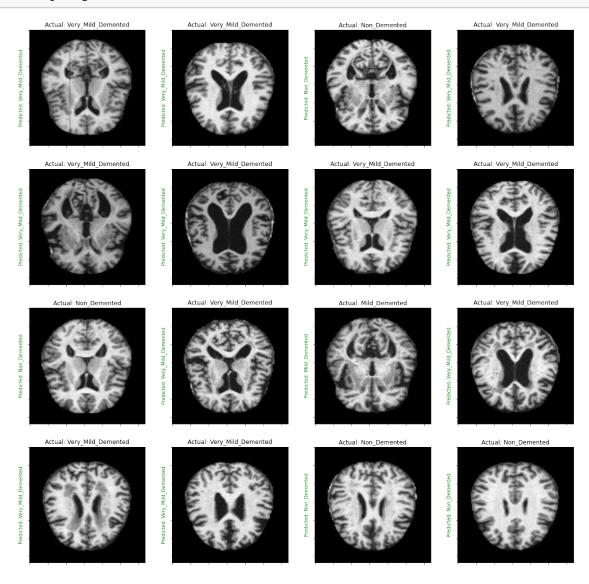


<Figure size 432x288 with 0 Axes>

### 7 Predictions

```
[14]: loss, accuracy = model.evaluate(test_ds)
    0.9938
[15]: plt.figure(figsize=(20, 20))
     for images, labels in test_ds.take(1):
        for i in range(16):
            ax = plt.subplot(4, 4, i + 1)
            plt.imshow(images[i].numpy().astype("uint8"))
            predictions = model.predict(tf.expand_dims(images[i], 0))
            score = tf.nn.softmax(predictions[0])
            if(class_names[labels[i]] == class_names[np.argmax(score)]):
                plt.title("Actual: "+class_names[labels[i]])
                plt.ylabel("Predicted: "+class_names[np.
      →argmax(score)],fontdict={'color':'green'})
            else:
                plt.title("Actual: "+class_names[labels[i]])
                plt.ylabel("Predicted: "+class_names[np.
      →argmax(score)],fontdict={'color':'red'})
```

plt.gca().axes.yaxis.set\_ticklabels([])
plt.gca().axes.xaxis.set\_ticklabels([])



[]: