

▼ Recognize ingredients using Transfer Learning

```

1 from __future__ import absolute_import, division, print_function, unicode_literals
2 # from google_images_download import google_images_download
3
4 try:
5     # The %tensorflow_version magic only works in colab.
6     %tensorflow_version 2.x
7 except Exception:
8     pass
9 import tensorflow as tf
10
11 import os
12 import numpy as np
13 import matplotlib.pyplot as plt
14 import matplotlib.image as mpimg

```

```
1 tf.__version__
```

```
↳ '2.1.0'
```

```

1 import os
2 from tqdm import tqdm
3 from tensorflow.keras import models, layers
4 from tensorflow.keras.models import Model
5 from tensorflow.keras.layers import BatchNormalization, Activation, Flatten
6 from tensorflow.keras.optimizers import Adam
7 from tensorflow.keras.preprocessing.image import ImageDataGenerator
8 from tensorflow.keras.regularizers import l2
9 from tensorflow.keras.layers import Dense, AveragePooling2D, BatchNormalization, Conv2D
10 from keras.preprocessing.image import ImageDataGenerator
11 from time import time
12 from datetime import datetime
13 from tensorflow.python.keras.callbacks import TensorBoard

```

```
↳ Using TensorFlow backend.
```

▼ Setup Input Pipeline

```

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

```

```
↳ Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client\_id=...
```

```

Enter your authorization code:
.....
Mounted at /content/drive

```

```
1 !pwd
```

```
📁 /content
```

```
1 path = 'drive/My Drive/Project ideas/Recipe_Finder/'
2
```

```
1 os.chdir(path)
```

```
1 base_dir = os.path.join('/content/drive/My Drive/Project ideas/Recipe_Finder/',
```

```
1 base_dir
```

```
📁 '/content/drive/My Drive/Project ideas/Recipe_Finder/downloads'
```

```
1 os.chdir(base_dir)
2 !ls
```

```
📁  almonds      cucumber      lemon          prawn
   asparagus    dates         lettuce        pumpkin
   bananas      egg           mango          raisins
   'bay leaf'    eggplant      mint           'raw banana'
   'bell pepper' 'fenugreek leaves' 'mint leaf'    'raw mango'
   broccoli     'fenugreek seed' mushrooms      'raw masoor dal'
   carrot       fish          mussels       'raw moong dal'
   'cashew nut' 'fruit apple' okra           rice
   cauliflower  garlic        onion          rosemary
   'cayenne pepper' ginger        orange         spinach
   cherry       gourd        paneer         strawberries
   chicken     'granny smith' papaya         tamarind
   chickpeas    grape        peanut         tomato
   chilli       guava        pear           turnip
   cinnamon    hazelnut     peas           vanilla
   coconut     jackfruit    pineapple      'vegetable drumstick'
   'coriander leaf' 'kidney bean' pistachio      watermelon
   corn        kiwis        pomegranate   yam
   cranberries labels.txt    potatoes
```

```
1
```

```
1
```

```
1
```

▼ Method-1

▼ Train and test Image set preparation

Use `ImageDataGenerator` to rescale the images.

Create the train generator and specify where the train dataset directory, image size, batch size.

Create the validation generator with similar approach as the train generator with the `flow_from_directory`

```

1 IMAGE_SIZE = 224
2 BATCH_SIZE = 64
3
4 datagen = tf.keras.preprocessing.image.ImageDataGenerator(
5     rescale=1./255,
6     validation_split=0.2)
7
8 # rotation_range=40,
9 #     width_shift_range=0.2,
10 #     height_shift_range=0.2,
11 #     shear_range=0.2,
12 #     zoom_range=0.2,
13 #     horizontal_flip=True,
14 #     fill_mode='nearest',
15
16
17 train_generator = datagen.flow_from_directory(
18     base_dir,
19     target_size=(IMAGE_SIZE, IMAGE_SIZE),
20     batch_size=BATCH_SIZE,
21     subset='training')
22
23 val_generator = datagen.flow_from_directory(
24     base_dir,
25     target_size=(IMAGE_SIZE, IMAGE_SIZE),
26     batch_size=BATCH_SIZE,
27     subset='validation')
```

Found 3202 images belonging to 74 classes.
Found 769 images belonging to 74 classes.

```
1 datagen
```

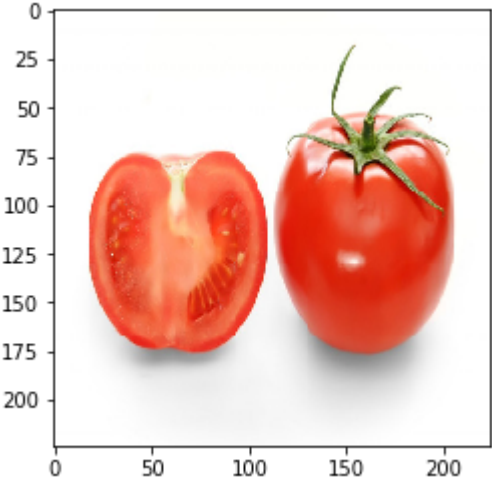
<tensorflow.python.keras.preprocessing.image.ImageDataGenerator at 0x7fc4887ae'

```
1 # len_len()
```

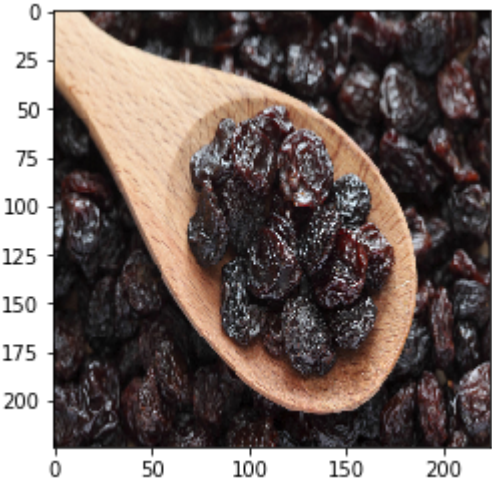
```

1 x,y = train_generator.next()
2 for i in range(0,3):
3     image = x[i]
4     label = y[i]
5     print (label)
6     plt.imshow(image)
7     plt.show()
8
```

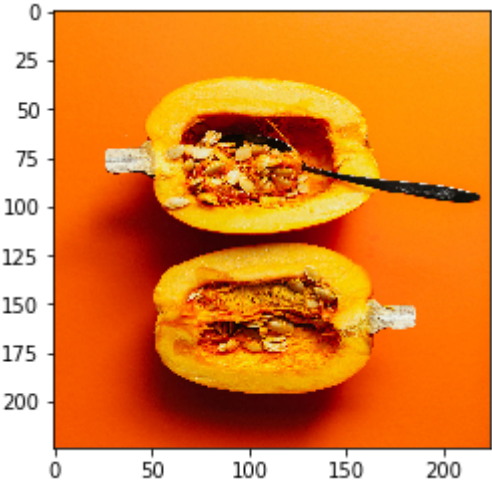
```
[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  1.  0.  0.  0.
  0.  0.]
```



```
[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  1.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.]
```



```
[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  1.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.]
```



1 sbase_dir

```
↳ '/content/drive/My Drive/Project ideas/Recipe_Finder/downloads'
```

```
1 for image_batch, label_batch in train_generator:
2     break
3 image_batch.shape, label_batch.shape
```

```
↳ /usr/local/lib/python3.6/dist-packages/PIL/Image.py:989: UserWarning: Palette :
    "Palette images with Transparency expressed in bytes should be "
    ((64, 224, 224, 3), (64, 74))
```

Save the labels in a file which will be downloaded later.

```
1 print (train_generator.class_indices)
2
3 labels = '\n'.join(sorted(train_generator.class_indices.keys()))
4
5 with open('labels.txt', 'w') as f:
6     f.write(labels)
```

```
↳ {'almonds': 0, 'asparagus': 1, 'bananas': 2, 'bay leaf': 3, 'bell pepper': 4,
```

```
1 print(len(train_generator.class_indices))
```

```
↳ 74
```

```
1 !cat labels.txt
```

```
↳
```

almonds
asparagus
bananas
bay leaf
bell pepper
broccoli
carrot
cashew nut
cauliflower
cayenne pepper
cherry
chicken
chickpeas
chilli
cinnamon
coconut
coriander leaf
corn
cranberries
cucumber
dates
egg
eggplant
fenugreek leaves
fenugreek seed
fish
fruit apple
garlic
ginger
gourd
granny smith
grape
guava
hazelnut
jackfruit
kidney bean
kiwis
lemon
lettuce
mango
mint
mint leaf
mushrooms
mussels
okra
onion
orange
paneer
papaya
peanut
pear
peas
pineapple
pistachio
pomegranate
potatoes
prawn
pumpkin
raisins
raw banana
raw mango

```

raw masoor dal
raw moong dal
rice
rosemary
spinach
strawberries
tamarind
tomato
turnip
vanilla
vegetable drumstick
watermelon
yam

```

```

1 input_shape_img = (image_batch.shape[1],image_batch.shape[2],image_batch.shape[3]
2 print(input_shape_img)

```

```

↳ (224, 224, 3)

```

▼ Create the base model from the pre-trained convnets

Create the base model from the **MobileNet V2** model developed at Google, and pre-trained on the I images and 1000 classes of web images.

First, pick which intermediate layer of MobileNet V2 will be used for feature extraction. A common layer before the flatten operation, the so-called "bottleneck layer". The reasoning here is that the fo specialized to the task the network was trained on, and thus the features learned by these layers w bottleneck features, however, retain much generality.

Let's instantiate an MobileNet V2 model pre-loaded with weights trained on ImageNet. By specifyir load a network that doesn't include the classification layers at the top, which is ideal for feature ext

```

1 IMG_SHAPE = (IMAGE_SIZE, IMAGE_SIZE, 3)
2
3
4 # Create the base model from the pre-trained model MobileNet V2
5 base_model = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
6                                                 include_top=False,
7                                                 weights='imagenet')

1 base_model.trainable = True
2
3 # Let's take a look to see how many layers are in the base model
4 print("Number of layers in the base model: ", len(base_model.layers))
5
6 # Fine tune from this layer onwards
7 fine_tune_at = 100 #20 # 100 thila
8
9 # Freeze all the layers before the `fine_tune_at` layer
10 for layer in base_model.layers[:fine_tune_at]:
11     layer.trainable = False

```

```

1 from keras.models import Sequential
2 from keras.layers import Conv2D,MaxPooling2D
3 from keras.layers import Activation, Dense, Flatten, Dropout
4 from keras.preprocessing.image import ImageDataGenerator
5 from keras.callbacks import ModelCheckpoint
6 from keras import backend as K
7

1

1 from keras.regularizers import l2,l1

1 base_model.trainable = False
2
3
4 model = tf.keras.Sequential([
5     base_model,
6     tf.keras.layers.Conv2D(filters = 128, kernel_size = (3,3), activation= 'relu')
7     tf.keras.layers.Dropout(0.5),
8     tf.keras.layers.Conv2D(filters = 256, kernel_size = (3,3), activation= 'relu')
9     # tf.keras.layers.Dropout(0.5),
10    # tf.keras.layers.Conv2D(filters = 512, kernel_size = (3,3), activation= 'relu'
11    tf.keras.layers.Dropout(0.5),
12    tf.keras.layers.Dense(150, activation= 'relu'),
13    tf.keras.layers.Dropout(0.5),
14    tf.keras.layers.GlobalAveragePooling2D(),
15    tf.keras.layers.Dense(len(train_generator.class_indices), activation='softmax'
16 ])
17
18

1 model.summary()

1
2 # sgd = tf.keras.optimizers.SGD(lr = 0.1,momentum = 0.7, nesterov = True)
3 rmsprop = tf.keras.optimizers.RMSprop(learning_rate=0.001, rho=0.9)
4 adam = tf.keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, a
5 adam_0 = tf.keras.optimizers.Adam(1e-5)
6
7 model.compile(loss='categorical_crossentropy',
8               optimizer=rmsprop, #adam_0,#adam #rmsprop
9               metrics=[ 'accuracy' ])
10 # print('Compiled!')

1 # model.summary()
2
3 # Call Backs
4 filepath = "weights.{epoch:02d}-{val_loss:.2f}.hdf5"
5 history = tf.keras.callbacks.History()
6 tensorboard = TensorBoard(log_dir="logs/{}".format(time()))
7 filepath = "weights.{epoch:02d}-{val_accuracy:.2f}.hdf5"
8 path = os.path.abspath('__model_save/')

```



```

9
10 filepath = os.path.join(path, filepath)
11 learning_rate_reduction = tf.keras.callbacks.ReduceLROnPlateau(monitor='val_accu
12 checkpoint_save = tf.keras.callbacks.ModelCheckpoint(filepath, monitor='val_accu
13 early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_accuracy', patien
14 callbacks_list = [checkpoint_save, history, tensorboard, learning_rate_reduction, ea
15

1 filepath

1 os.getcwd()

1 epochs = 300
2
3 model.load_weights(os.path.join(path, 'weights.28-0.65.hdf5')) # weights.52-1.54
4
5 history = model.fit_generator(train_generator, epochs=epochs, callbacks = callba
6

1 #Loss plot
2 acc = history.history['accuracy']
3 val_acc = history.history['val_accuracy']
4
5 loss = history.history['loss']
6 val_loss = history.history['val_loss']
7
8 plt.figure(figsize=(8, 8))
9 plt.subplot(2, 1, 1)
10 plt.plot(acc, label='Training Accuracy')
11 plt.plot(val_acc, label='Validation Accuracy')
12 plt.legend(loc='lower right')
13 plt.ylabel('Accuracy')
14 plt.ylim([min(plt.ylim()), 1.2])
15 plt.title('Training and Validation Accuracy')
16
17 plt.subplot(2, 1, 2)
18 plt.plot(loss, label='Training Loss')
19 plt.plot(val_loss, label='Validation Loss')
20 plt.legend(loc='upper right')
21 plt.ylabel('Cross Entropy')
22 plt.ylim([0, 3.0])
23 plt.title('Training and Validation Loss')
24 plt.xlabel('epoch')
25 plt.show()

1

```

► Convert to TFLite

↳ 10 cells hidden

► CNN 4 layer Own Model

↳ 6 cells hidden

► Inception Model

↳ 6 cells hidden

▼ VGG16 Model

```
1 IMG_SHAPE = (IMAGE_SIZE, IMAGE_SIZE, 3)
2
3 vgg16_base_model = tf.keras.applications.VGG16(input_shape=IMG_SHAPE,
4                                                  include_top=False,
5                                                  weights='imagenet')
6
```

↳ Downloading data from <https://github.com/fchollet/deep-learning-models/releases/tag/v0.8>: 58892288/58889256 [=====] - 1s 0us/step

```
1
2 for layer in vgg16_base_model.layers[:]: # add [:50] for next time
3     layer.trainable = False
```

```
1
2
3 vgg16_model = tf.keras.Sequential([
4     vgg16_base_model,
5     tf.keras.layers.Conv2D(filters = 128, kernel_size = 2, activation= 'relu'),
6     tf.keras.layers.Dropout(0.5),
7     tf.keras.layers.Conv2D(filters = 256, kernel_size = 2, activation= 'relu'),
8     # tf.keras.layers.Dropout(0.5),
9     # tf.keras.layers.Conv2D(filters = 512, kernel_size = (3,3), activation= 'relu'),
10    tf.keras.layers.Dropout(0.5),
11    tf.keras.layers.Dense(150, activation= 'relu'),
12    tf.keras.layers.Dropout(0.5),
13    tf.keras.layers.GlobalAveragePooling2D(),
14    tf.keras.layers.Dense(len(train_generator.class_indices), activation='softmax')
15 ])
16
17
18 vgg16_model.summary()
```

↳

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 7, 7, 512)	14714688
conv2d (Conv2D)	(None, 6, 6, 128)	262272
dropout (Dropout)	(None, 6, 6, 128)	0
conv2d_1 (Conv2D)	(None, 5, 5, 256)	131328
dropout_1 (Dropout)	(None, 5, 5, 256)	0
dense (Dense)	(None, 5, 5, 150)	38550
dropout_2 (Dropout)	(None, 5, 5, 150)	0
global_average_pooling2d (Gl	(None, 150)	0
dense_1 (Dense)	(None, 74)	11174
Total params: 15,158,012		
Trainable params: 443,324		
Non-trainable params: 14,714,688		

```

1
2 # filepath = "weights.{epoch:02d}-{val_loss:.2f}.hdf5"
3 history = tf.keras.callbacks.History()
4 tensorboard = TensorBoard(log_dir="logs/{}".format(time()))
5 filepath = "vgg_weights-epoch:{epoch:02d}-train_acc:_{accuracy:.2f}-test_acc:_{v
6 path = os.path.abspath('__model_save/')
7 filepath = os.path.join(path, filepath)
8 learning_rate_reduction = tf.keras.callbacks.ReduceLROnPlateau(monitor='val_accu
9 checkpoint_save = tf.keras.callbacks.ModelCheckpoint(filepath, monitor='val_accu
10 early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_accuracy', patienc
11 callbacks_list = [checkpoint_save, history, tensorboard, learning_rate_reduction, ea
12

```

```

1 rmsprop = tf.keras.optimizers.RMSprop(learning_rate=0.001, rho=0.9)
2 adam = tf.keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, a
3 adam_0 = tf.keras.optimizers.Adam(1e-5)
4
5 vgg16_model.compile(loss='categorical_crossentropy',
6                     optimizer=adam,
7                     metrics=['accuracy'])
8 print('Compiled!')

```

☞ Compiled!

```

1                                     #vgg_weights-epoch_31-train_acc__0.9
2 vgg16_model.load_weights(os.path.join(path, 'vgg_weights-epoch_31-train_acc__0.9
3
4 history = vgg16_model.fit_generator(train_generator, epochs=100, callbacks = cal

```



```

WARNING:tensorflow:From <ipython-input-28-b5ab640f1648>:3: Model.fit_generator
Instructions for updating:
Please use Model.fit, which supports generators.
WARNING:tensorflow:sample_weight modes were coerced from
...
to
['...']
WARNING:tensorflow:sample_weight modes were coerced from
...
to
['...']
Train for 51 steps, validate for 13 steps
Epoch 1/100
1/51 [.....] - ETA: 23:47 - loss: 0.0456 - accuracy:
"Palette images with Transparency expressed in bytes should be "
15/51 [=====>.....] - ETA: 11:16 - loss: 0.2105 - accuracy:
warnings.warn(str(msg))
30/51 [=====>.....] - ETA: 6:33 - loss: 0.2107 - accuracy:
warnings.warn(str(msg))
50/51 [=====>.] - ETA: 18s - loss: 0.1928 - accuracy: 0
Epoch 00001: val_accuracy improved from -inf to 0.72172, saving model to /cont
51/51 [=====] - 1158s 23s/step - loss: 0.1928 - accuracy:
Epoch 2/100
50/51 [=====>.] - ETA: 1s - loss: 0.1031 - accuracy: 0.
Epoch 00002: val_accuracy improved from 0.72172 to 0.72432, saving model to /co
51/51 [=====] - 107s 2s/step - loss: 0.1049 - accuracy:
Epoch 3/100
50/51 [=====>.] - ETA: 1s - loss: 0.1204 - accuracy: 0.
Epoch 00003: val_accuracy did not improve from 0.72432
51/51 [=====] - 106s 2s/step - loss: 0.1211 - accuracy:
Epoch 4/100
50/51 [=====>.] - ETA: 1s - loss: 0.1248 - accuracy: 0.
Epoch 00004: val_accuracy did not improve from 0.72432
51/51 [=====] - 107s 2s/step - loss: 0.1258 - accuracy:
Epoch 5/100
50/51 [=====>.] - ETA: 1s - loss: 0.1262 - accuracy: 0.
Epoch 00005: val_accuracy did not improve from 0.72432
51/51 [=====] - 108s 2s/step - loss: 0.1283 - accuracy:
Epoch 6/100
50/51 [=====>.] - ETA: 1s - loss: 0.1188 - accuracy: 0.
Epoch 00006: val_accuracy did not improve from 0.72432
51/51 [=====] - 108s 2s/step - loss: 0.1201 - accuracy:
Epoch 7/100
50/51 [=====>.] - ETA: 1s - loss: 0.1675 - accuracy: 0.
Epoch 00007: val_accuracy did not improve from 0.72432

Epoch 00007: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257
51/51 [=====] - 108s 2s/step - loss: 0.1660 - accuracy:
Epoch 8/100
50/51 [=====>.] - ETA: 1s - loss: 0.0721 - accuracy: 0.
Epoch 00008: val_accuracy improved from 0.72432 to 0.75423, saving model to /co
51/51 [=====] - 108s 2s/step - loss: 0.0713 - accuracy:
Epoch 9/100
50/51 [=====>.] - ETA: 1s - loss: 0.0398 - accuracy: 0.
Epoch 00009: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0393 - accuracy:
Epoch 10/100
50/51 [=====>.] - ETA: 1s - loss: 0.0395 - accuracy: 0.
Epoch 00010: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0397 - accuracy:
Epoch 11/100

```

```
50/51 [=====>.] - ETA: 1s - loss: 0.0366 - accuracy: 0.9
Epoch 00011: val_accuracy did not improve from 0.75423
51/51 [=====] - 108s 2s/step - loss: 0.0363 - accuracy: 0.9
Epoch 12/100
50/51 [=====>.] - ETA: 1s - loss: 0.0374 - accuracy: 0.9
Epoch 00012: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0374 - accuracy: 0.9
Epoch 13/100
50/51 [=====>.] - ETA: 1s - loss: 0.0431 - accuracy: 0.9
Epoch 00013: val_accuracy did not improve from 0.75423

Epoch 00013: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628
51/51 [=====] - 109s 2s/step - loss: 0.0426 - accuracy: 0.9
Epoch 14/100
50/51 [=====>.] - ETA: 1s - loss: 0.0261 - accuracy: 0.9
Epoch 00014: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0260 - accuracy: 0.9
Epoch 15/100
50/51 [=====>.] - ETA: 1s - loss: 0.0224 - accuracy: 0.9
Epoch 00015: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0230 - accuracy: 0.9
Epoch 16/100
50/51 [=====>.] - ETA: 1s - loss: 0.0251 - accuracy: 0.9
Epoch 00016: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0248 - accuracy: 0.9
Epoch 17/100
50/51 [=====>.] - ETA: 1s - loss: 0.0236 - accuracy: 0.9
Epoch 00017: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0234 - accuracy: 0.9
Epoch 18/100
50/51 [=====>.] - ETA: 1s - loss: 0.0179 - accuracy: 0.9
Epoch 00018: val_accuracy did not improve from 0.75423

Epoch 00018: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814
51/51 [=====] - 108s 2s/step - loss: 0.0179 - accuracy: 0.9
Epoch 19/100
49/51 [=====>..] - ETA: 3s - loss: 0.0170 - accuracy: 0.9
Epoch 00019: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0166 - accuracy: 0.9
Epoch 20/100
50/51 [=====>.] - ETA: 1s - loss: 0.0149 - accuracy: 0.9
Epoch 00020: val_accuracy did not improve from 0.75423
51/51 [=====] - 108s 2s/step - loss: 0.0166 - accuracy: 0.9
Epoch 21/100
50/51 [=====>.] - ETA: 1s - loss: 0.0151 - accuracy: 0.9
Epoch 00021: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0150 - accuracy: 0.9
Epoch 22/100
49/51 [=====>..] - ETA: 3s - loss: 0.0154 - accuracy: 0.9
Epoch 00022: val_accuracy did not improve from 0.75423
51/51 [=====] - 111s 2s/step - loss: 0.0150 - accuracy: 0.9
Epoch 23/100
50/51 [=====>.] - ETA: 1s - loss: 0.0128 - accuracy: 0.9
Epoch 00023: val_accuracy did not improve from 0.75423

Epoch 00023: ReduceLROnPlateau reducing learning rate to 6.25000029685907e-05.
51/51 [=====] - 111s 2s/step - loss: 0.0127 - accuracy: 0.9
Epoch 24/100
50/51 [=====>.] - ETA: 1s - loss: 0.0110 - accuracy: 0.9
Epoch 00024: val_accuracy did not improve from 0.75423
51/51 [=====] - 110s 2s/step - loss: 0.0112 - accuracy: 0.9
Epoch 25/100
```

```

50/51 [=====>.] - ETA: 1s - loss: 0.0124 - accuracy: 0.75423
Epoch 00025: val_accuracy did not improve from 0.75423
51/51 [=====] - 110s 2s/step - loss: 0.0129 - accuracy: 0.75423
Epoch 26/100
50/51 [=====>.] - ETA: 1s - loss: 0.0121 - accuracy: 0.75423
Epoch 00026: val_accuracy did not improve from 0.75423
51/51 [=====] - 109s 2s/step - loss: 0.0120 - accuracy: 0.75423
Epoch 27/100
50/51 [=====>.] - ETA: 1s - loss: 0.0140 - accuracy: 0.75423
Epoch 00027: val_accuracy did not improve from 0.75423
51/51 [=====] - 108s 2s/step - loss: 0.0138 - accuracy: 0.75423
Epoch 28/100
50/51 [=====>.] - ETA: 1s - loss: 0.0111 - accuracy: 0.75423
Epoch 00028: val_accuracy did not improve from 0.75423

Epoch 00028: ReduceLROnPlateau reducing learning rate to 3.125000148429535e-05
51/51 [=====] - 108s 2s/step - loss: 0.0111 - accuracy: 0.75423
Epoch 29/100
50/51 [=====>.] - ETA: 1s - loss: 0.0120 - accuracy: 0.75423
Epoch 00029: val_accuracy did not improve from 0.75423
51/51 [=====] - 107s 2s/step - loss: 0.0121 - accuracy: 0.75423
Epoch 30/100
50/51 [=====>.] - ETA: 1s - loss: 0.0108 - accuracy: 0.75423
Epoch 00030: val_accuracy did not improve from 0.75423
51/51 [=====] - 107s 2s/step - loss: 0.0106 - accuracy: 0.75423
Epoch 31/100
50/51 [=====>.] - ETA: 1s - loss: 0.0122 - accuracy: 0.75423
Epoch 00031: val_accuracy did not improve from 0.75423
51/51 [=====] - 106s 2s/step - loss: 0.0120 - accuracy: 0.75423
Epoch 32/100
50/51 [=====>.] - ETA: 1s - loss: 0.0110 - accuracy: 0.75423
Epoch 00032: val_accuracy did not improve from 0.75423
51/51 [=====] - 107s 2s/step - loss: 0.0108 - accuracy: 0.75423
Epoch 33/100
50/51 [=====>.] - ETA: 1s - loss: 0.0110 - accuracy: 0.75423
Epoch 00033: val_accuracy did not improve from 0.75423

Epoch 00033: ReduceLROnPlateau reducing learning rate to 1.5625000742147677e-05
51/51 [=====] - 108s 2s/step - loss: 0.0109 - accuracy: 0.75423

```

```

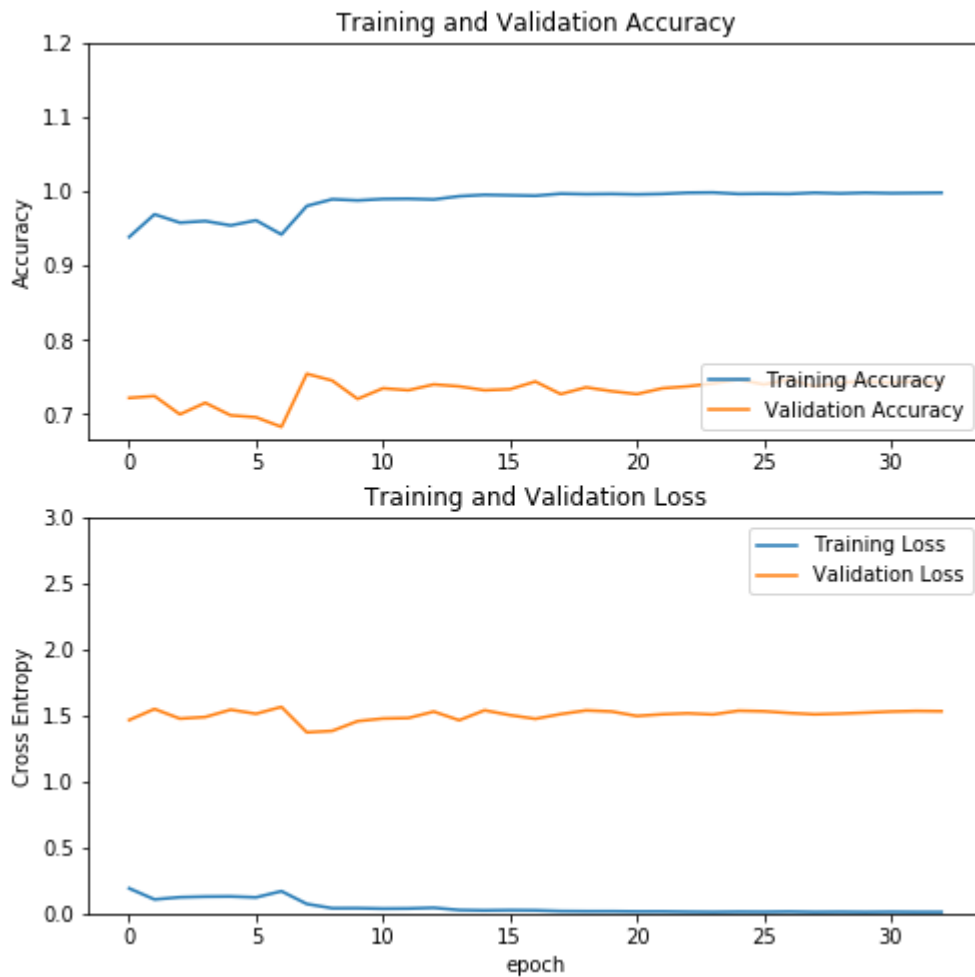
1  #Loss plot
2  acc = history.history['accuracy']
3  val_acc = history.history['val_accuracy']
4
5  loss = history.history['loss']
6  val_loss = history.history['val_loss']
7
8  plt.figure(figsize=(8, 8))
9  plt.subplot(2, 1, 1)
10 plt.plot(acc, label='Training Accuracy')
11 plt.plot(val_acc, label='Validation Accuracy')
12 plt.legend(loc='lower right')
13 plt.ylabel('Accuracy')
14 plt.ylim([min(plt.ylim()),1.2])
15 plt.title('Training and Validation Accuracy')
16
17 plt.subplot(2, 1, 2)

```

```

18 plt.plot(loss, label='Training Loss')
19 plt.plot(val_loss, label='Validation Loss')
20 plt.legend(loc='upper right')
21 plt.ylabel('Cross Entropy')
22 plt.ylim([0,3.0])
23 plt.title('Training and Validation Loss')
24 plt.xlabel('epoch')
25 plt.show()

```



▼ Saving to tflite

1

```

1 saved_model_dir = 'save/fine_tuning'
2 tf.saved_model.save(vgg16_model, saved_model_dir)
3
4 converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)
5 tflite_model = converter.convert()
6
7 with open('model_75.tflite', 'wb') as f:
8     f.write(tflite_model)

```




```
WARNING:tensorflow:From /tensorflow-2.1.0/python3.6/tensorflow_core/python/ops.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: save/fine_tuning/assets
```

```
1 from google.colab import files
2
3 files.download('model_75.tflite')
4 files.download('labels.txt')
```

▼ Observation

- Make model with 4 different Transfer learning based models those are Inceptionv3, VGG16, MobileNet, and Own Model.
- From all this I found out that for this specific problem set with these images VGG16 worked best.

```
1 from prettytable import PrettyTable
2
3
4
5 x = PrettyTable()
6
7 x.field_names = ["Model Name", "Hidden Layer", "Accuracy"]
8
9 x.add_row(["Inceptionv3", 3, 60.5])
10 x.add_row(["VGG16", 2, 75.6])
11 x.add_row(["Mobilenet", 2, 55.2])
12 x.add_row(["Own Model", 4, 51.0])
13
14 print(x)
```

```
➡ +-----+-----+-----+
| Model Name | Hidden Layer | Accuracy |
+-----+-----+-----+
| Inceptionv3 | 3 | 60.5 |
| VGG16 | 2 | 75.6 |
| Mobilenet | 2 | 55.2 |
| Own Model | 4 | 51.0 |
+-----+-----+-----+
```

1

1

