# Project 3

October 6, 2021

## 1 Checking Starting Commandas

```
[0]: import numpy as np
[0]: import pandas as pd
[0]:
    \#\mbox{Import Dog-Bread-Identification}. Zip and extract to train and test data
[0]: #!unzip "drive/My Drive/Kagqle-Dog-Vision/dog-breed-identification.zip" -d_
      → "drive/My Drive/Kaggle-Dog-Vision/"
[0]: 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).
[0]: %ls
    drive/ sample_data/
[0]: %ls drive/'My Drive'
     2020/
                                  'List of Publications'/
    Resumes/
     Applications/
                                  MPhil/
    Tickets/
                                  M.Sc./
     Books/
    Videos/
    'Colab Notebooks'/
                                  Ph.D./
    'Web developer.docx'
     Documents/
                                  Photos/
    'Web developer.gdoc'
     dog-breed-identification/
                                  PPTs/
     Kaggle-Dog-Vision/
                                  Publications/
[0]: %ls -al "drive/My Drive/Kaggle-Dog-Vision"
```

```
total 732613
    -rw----- 1 root root 724495926 May 3 04:26 dog-breed-identification.zip
    drwx---- 2 root root
                               4096 May 5 22:02
    .ipynb_checkpoints/
    -rw----- 1 root root
                             482063 Dec 11 20:54 labels.csv
    drwx---- 2 root root
                               4096 May 5 22:02 logs/
    -rw----- 1 root root 25200295 Dec 11 20:54 sample submission.csv
    drwx----- 2 root root
                              4096 May 3 20:43 test/
    drwx----- 2 root root
                              4096 May 3 20:44 train/
[0]: %ls "drive/My Drive/Kaggle-Dog-Vision/test" | wc -l
    ^C
    1.1 Import TensorFlow
```

```
[0]: import tensorflow as tf

print("Tensorflow Version ", tf.__version__)
```

Tensorflow Version 2.2.0-rc4

```
[0]: import tensorflow_hub as hub
```

```
[0]: # check GPU availablity

print("GPU available, Yes " if tf.config.list_physical_devices("GPU") else "Not⊔

→availabel" )
```

GPU available, Yes

### 1.2 Getting Our Data Ready (Turning into Tensors)

1.2.1 Turning all our data into tensors i.e. into numeric form. Turn all our images into tensors (numeric form)

```
[0]: ### Check The labels
     import pandas as pd
     label_csv=pd.read_csv("drive/My Drive/Kaggle-Dog-Vision/labels.csv")
     print(label csv.describe())
     print(label_csv.head())
                                           id
                                                             breed
    count
                                        10222
                                                             10222
    unique
                                        10222
                                                               120
    top
            6d2fe8f0bb9bbc3232567cd6d930a1e4
                                               scottish_deerhound
                                            1
                                                               126
    freq
                                                      breed
                                      id
    0 000bec180eb18c7604dcecc8fe0dba07
                                               boston_bull
    1 001513dfcb2ffafc82cccf4d8bbaba97
                                                      dingo
```

2 001cdf01b096e06d78e9e5112d419397 pekinese 3 00214f311d5d2247d5dfe4fe24b2303d bluetick 4 0021f9ceb3235effd7fcde7f7538ed62 golden\_retriever

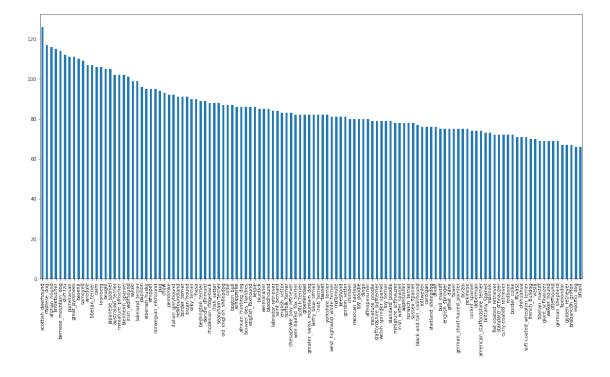
## [0]: label\_csv.breed.value\_counts()

[0]: scottish\_deerhound 126 maltese\_dog 117 afghan\_hound 116 entlebucher 115 bernese\_mountain\_dog 114 komondor 67 67 golden\_retriever brabancon\_griffon 67 66 eskimo\_dog briard 66

Name: breed, Length: 120, dtype: int64

[0]: label\_csv.breed.value\_counts().plot(kind="bar", figsize=(20,10))

[0]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f23c10c4f98>



[0]: label\_csv.breed.value\_counts().median()

[0]: 82.0

[0]: from IPython.display import Image, display
Image("drive/My Drive/Kaggle-Dog-Vision/train/001cdf01b096e06d78e9e5112d419397.

→jpg")

[0]:



- 1.3 Different Files in Our Data
- 1.3.1 train.zip the training set, you are provided the breed for these dogs
- 1.3.2 test.zip the test set, you must predict the probability of each breed for each image
- 1.3.3 sample\_submission.csv a sample submission file in the correct format
- 1.3.4 labels.csv the breeds for the images in the train set

```
[0]: ## save files in a file

filenames=[fname for fname in label_csv["id"]]
filenames[:10]
```

```
[0]: ['000bec180eb18c7604dcecc8fe0dba07',
      '001513dfcb2ffafc82cccf4d8bbaba97',
      '001cdf01b096e06d78e9e5112d419397',
      '00214f311d5d2247d5dfe4fe24b2303d',
      '0021f9ceb3235effd7fcde7f7538ed62',
      '002211c81b498ef88e1b40b9abf84e1d',
      '00290d3e1fdd27226ba27a8ce248ce85',
      '002a283a315af96eaea0e28e7163b21b',
      '003df8b8a8b05244b1d920bb6cf451f9',
      '0042188c895a2f14ef64a918ed9c7b64']
[0]: ## create pathnames for files in train images
     filenames=["drive/My Drive/Kaggle-Dog-Vision/train/" + fname + ".jpg" for fname_u
      →in label_csv["id"]]
     filenames[:10]
[0]: ['drive/My Drive/Kaggle-Dog-Vision/train/000bec180eb18c7604dcecc8fe0dba07.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/001513dfcb2ffafc82cccf4d8bbaba97.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/001cdf01b096e06d78e9e5112d419397.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/00214f311d5d2247d5dfe4fe24b2303d.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/0021f9ceb3235effd7fcde7f7538ed62.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/002211c81b498ef88e1b40b9abf84e1d.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/00290d3e1fdd27226ba27a8ce248ce85.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/002a283a315af96eaea0e28e7163b21b.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/003df8b8a8b05244b1d920bb6cf451f9.jpg',
      'drive/My Drive/Kaggle-Dog-Vision/train/0042188c895a2f14ef64a918ed9c7b64.jpg']
[0]: print(len(filenames))
    10222
[0]: import os
     if len(filenames) == len(os.listdir("drive/My Drive/Kaggle-Dog-Vision/train/")):
       print ("The length in both files are same")
     else:
       print ("Length is not same")
    The length in both files are same
[0]: Image(filenames[9000])
[0]:
```



```
[0]: len(labels)
[0]: 10222
[0]: if len(labels) == len(filenames):
      print("Length is same")
    else:
      print("Lenght different")
    Length is same
[0]: unique_breeds=np.unique(labels)
[0]: len(unique_breeds)
[0]: 120
[0]: unique_breeds[0]
[0]: 'affenpinscher'
[0]: labels[0] == unique_breeds
[0]: array([False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False,
           False, True, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False, False,
           False, False, False, False, False, False, False, False,
           False, False, False])
[0]: boolean_labels=[unique_breeds==label for label in labels]
[0]: len(boolean_labels)
[0]: 10222
[0]: | ## We have converted our labels into boolean types to use in the numeric format
    boolean_labels[0]
```

```
[0]: array([False, False, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False,
                                                                   False, True, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False,
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                                                                   False, False, False, False, False, False, False, False,
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                                                                   False, False, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False,
                                                                   False, False, False, False, False, False, False, False, False,
                                                                    False, False, False, False, False, False, False, False,
                                                                   False, False, False])
[0]: boolean labels[0].astype(int)
0, 0, 0, 0, 0, 0, 0, 0, 0])
[0]: print(labels[0])
                            print(np.where(unique_breeds==labels[0]))
                            print(boolean_labels[0].astype(int))
                            print(boolean_labels[0])
                        boston_bull
                          (array([19]),)
                          0 0 0 0 0 0 0 0 0]
                           [False False False
                              False False False False False False True False False False False
                              False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False 
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                              False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False 
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                              False False False False False False False False False False False False
                              False False False False False False False False False False False
[0]: ## Setup X and y
```

```
x=filenames
    y=boolean_labels
    len(x), len(y)
[0]: (10222, 10222)
    NUM_IMAGES=1000 #@param{type:"slider", min:1000, max:5000, step:1000}
[0]: from sklearn.model selection import train test split
    x_train, x_val, y_train,y_val=train_test_split(x[:NUM_IMAGES],y[:
     →NUM_IMAGES],test_size=0.2, random_state=44)
[0]: len(x_train), len(x_val)
[0]: (800, 200)
[0]: x_train[:2], y_train[:2]
[0]: (['drive/My Drive/Kaggle-Dog-Vision/train/0140b05bfc2fd43f2819fab3d8566109.jpg',
      'drive/My Drive/Kaggle-Dog-
    Vision/train/0b6da522f27c115716285a4f7187969e.jpg'],
      [array([False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, True,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False,
             False, False, False]),
      array([False, False, False, False, False, False, True, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
             False, False, False, False, False, False, False, False, False,
```

```
False, Fa
```

### 1.4 Preprocessing Images (Turning images into tensors)

### 1)Take the File path as input ### 2) Use the tensorflow to read the image and save into a variable 'image' ### 3) Transfer the variable 'image' (.jpg) into a tensor ### 4) Resize the 'image' to a a shape (244,244) ### 5) Retirn the modified 'image'

##### First Check the Image- how it look like

```
[0]: from matplotlib.pyplot import imread
     image=imread(filenames[44])
     image.shape
[0]: (333, 500, 3)
[0]:
     image
[0]: array([[[ 79,
                     81,
                           60],
              [ 87,
                     88,
                           70],
              [ 98,
                     99, 81],
              [221, 219, 222],
              [217, 215, 218],
              [216, 214, 217]],
             [[ 83,
                     84,
                           66],
              [ 89,
                     90,
                          72],
              [ 98,
                     99,
                          81],
              [220, 218, 221],
              [216, 214, 217],
              [214, 212, 215]],
             [[ 89,
                     90,
                           72],
              [ 93,
                     94,
                           76],
              [100, 101,
                           85],
              [218, 216, 219],
              [214, 212, 215],
              [213, 211, 214]],
             ...,
             [[210, 212, 198],
```

```
[166, 168, 154],
             [101, 103, 90],
             [197, 195, 200],
             [192, 190, 195],
             [192, 190, 195]],
            [[181, 184, 165],
             [189, 192, 173],
             [159, 161, 147],
             ...,
             [199, 197, 200],
             [192, 190, 193],
             [195, 193, 196]],
            [[172, 176, 153],
             [192, 195, 174],
             [184, 187, 168],
             [192, 190, 193],
             [183, 181, 184],
             [189, 187, 190]]], dtype=uint8)
[0]: image[:2]
[0]: array([[[ 79,
                    81,
                         60],
             [87,
                    88, 70],
             [ 98,
                    99, 81],
             [221, 219, 222],
             [217, 215, 218],
             [216, 214, 217]],
            [[ 83,
                    84, 66],
             [89,
                    90,
                        72],
             [ 98,
                    99, 81],
             [220, 218, 221],
             [216, 214, 217],
             [214, 212, 215]]], dtype=uint8)
[0]: ## Turn image into tensor
     tensor=tf.constant(image)
     tensor[:2]
[0]: <tf.Tensor: shape=(2, 500, 3), dtype=uint8, numpy=
     array([[[ 79, 81, 60],
```

```
[ 87, 88, 70],
[ 98, 99, 81],
...,
[221, 219, 222],
[217, 215, 218],
[216, 214, 217]],

[[ 83, 84, 66],
[ 89, 90, 72],
[ 98, 99, 81],
...,
[220, 218, 221],
[216, 214, 217],
[214, 212, 215]]], dtype=uint8)>
```

Turning our Data into batches -to fit the data into memory (RAM)

```
[0]: # 1) To use tenserflow effectively turn the data into tuples of form (image, □ → label)

def get_image_label(image_path, label):
   image=process_image(image_path, IMG_SIZE)
   return image, label
```

```
[0]: # 2) Turn the data into Batches

BATCH_SIZE=32

def create_data_batches(x, y=None, batch_size=BATCH_SIZE, valid_data=False, u

→test_data=False):

if test_data:
```

```
print("Creating batches of test data...")
         data=tf.data.Dataset.from_tensor_slices((tf.constant(x)))
         data_batch=data.map(process_image).batch(BATCH_SIZE) ## convert our data_
      \rightarrow into n(BATCH_SIZE) batches
         return data batch
       elif valid data:
         print("Creating Batches of valid data...")
         data=tf.data.Dataset.from_tensor_slices((tf.constant(x), tf.constant(y)))
         data_batch=data.map(get_image_label).batch(batch_size)
         return data_batch
       else:
         print("Creating Batches of train data....")
         data=tf.data.Dataset.from_tensor_slices((tf.constant(x), tf.constant(y)))
         data=data.shuffle(buffer_size=len(x))
         data_batch=data.map(get_image_label).batch(batch_size)
         return data_batch
[0]: # 3) Creating training and valid data
     train_data=create_data_batches(x_train, y_train)
     val_data=create_data_batches(x_val,y_val, valid_data=True)
    Creating Batches of train data...
    Creating Batches of valid data...
[0]: train_data.element_spec, val_data.element_spec
[0]: ((TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name=None),
       TensorSpec(shape=(None, 120), dtype=tf.bool, name=None)),
      (TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name=None),
       TensorSpec(shape=(None, 120), dtype=tf.bool, name=None)))
[0]: # 4) Visualization Function
     import matplotlib.pyplot as plt
     def show_images(images, label):
      plt.figure(figsize=(10,10))
      for i in range(25):
         ax=plt.subplot(5,5,i+1)
         plt.imshow(images[i])
         plt.title(unique_breeds[label[i].argmax()])
         plt.axis("off")
[0]: train_data
[0]: <BatchDataset shapes: ((None, 224, 224, 3), (None, 120)), types: (tf.float32,
     tf.bool)>
```

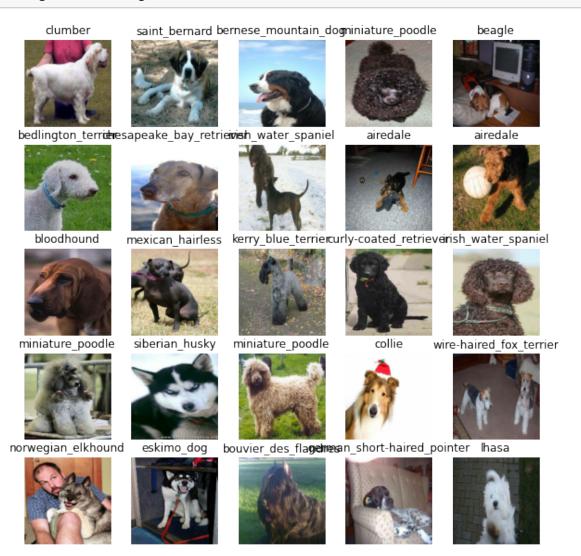
[0]: # 5) Make the data displayable- converting from batches to images and labels train\_images,train\_labels=next(train\_data.as\_numpy\_iterator()) len(train\_images), len(train\_labels)

[0]: (32, 32)

[0]: show\_images(train\_images, train\_labels) ### when 36 instead of 25

File "<ipython-input-54-c5fb8f0574b5>", line 1
 `show\_images(train\_images, train\_labels) ### when 36 instead of 25
 `
SyntaxError: invalid syntax

## [0]: show\_images(train\_images, train\_labels)



- [0]: val\_images, val\_labels=next(val\_data.as\_numpy\_iterator())
- [0]: show\_images(val\_images, val\_labels)



## 1.5 Building the Model

### 1) Define the input shape and Output shape ### 2) Define the Model

[0]: ## 1) Define the input and output shape of the Model

INPUT\_SHAPE=[None,IMG\_SIZE,IMG\_SIZE,3] ## batch\_size, height, width, channels

OUTPUT\_SHAPE=len(unique\_breeds)

```
[0]: ## 2) Define the model-Model URL

MODEL_URL="https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/

⇔classification/4"
```

#### 1.5.1 Create a function in which:

- takes input shape, output shape and model url
- Define the layers in keras model in sequential fashion
- Compile the model
- Build the model
- Return the Model

```
[0]: ## Create a function which build a keras model
     def create_model(input_shape=INPUT_SHAPE, output_shape=OUTPUT_SHAPE,__
      →model_url=MODEL_URL):
      print("Building the model with :", model_url)
       ## Setup model layers
      model=tf.keras.Sequential([
                                  hub.KerasLayer(model_url), ## Layer 1(input layer)
                                  tf.keras.layers.Dense(units=output_shape,__
      →activation="softmax") ## Layer 2 -output layer
                                  ])
      model.compile(
           loss=tf.keras.losses.CategoricalCrossentropy(),
           optimizer=tf.keras.optimizers.Adam(),
           metrics=["accuracy"]
       model.build(input_shape)
       return model
[0]: model=create_model()
    model.summary()
    Building the model with:
    https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/classification/4
```

```
Non-trainable params: 5,432,713
```

#### 1.5.2 Creating a Callbacks

callbacks are functions which monitor the progress, save the progress, stop training the model at early stage if model stops improving

```
[0]: ## 1) Monitor the progress of the model----TensorBoard()
## 2) Early stop the training if the model traing takes too
□
□ long--EarlyStopping()
```

```
[0]: %load_ext tensorboard
```

```
[0]: import datetime

def create_tensorboard_callback():
    logdir=os.path.join("drive/My Drive/Kaggle-Dog-Vision/logs", datetime.
    →datetime.now().strftime("%Y%m%d-%H%M%S"))
    return tf.keras.callbacks.TensorBoard(logdir)

early_stopping=tf.keras.callbacks.EarlyStopping(monitor="val_accuracy",
    →patience=3)
```

#### 1.5.3 Training the model

• First tain only 1000 images to make sure the model is working fine

```
[0]: NUM_EPOCHS=100 #@param{type:"slider", min:10,max:100, step:10}

[0]: ## Check the GPU Availability once again

print("GPU is abailabe" if tf.config.list_physical_devices("GPU") else "Not⊔

→Available")
```

GPU is abailabe

```
[0]: ## Creating the Function to train model data

def train_model():
    ## 1) create model
    model=create_model()

## Create tensorboard callback

tensorboard=create_tensorboard_callback()

## Fit the model by passing it the callbacks
```

#### [0]: model=train\_model()

```
Building the model with:
https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/classification/4
Epoch 1/100
accuracy: 0.1063 - val_loss: 3.3004 - val_accuracy: 0.3050
Epoch 2/100
accuracy: 0.6662 - val_loss: 1.9643 - val_accuracy: 0.5400
accuracy: 0.9350 - val_loss: 1.5070 - val_accuracy: 0.6300
Epoch 4/100
accuracy: 0.9862 - val_loss: 1.3311 - val_accuracy: 0.6950
Epoch 5/100
25/25 [============ ] - 6s 228ms/step - loss: 0.1481 -
accuracy: 0.9987 - val_loss: 1.2502 - val_accuracy: 0.6850
accuracy: 1.0000 - val_loss: 1.2004 - val_accuracy: 0.7050
Epoch 7/100
accuracy: 1.0000 - val_loss: 1.1697 - val_accuracy: 0.7200
Epoch 8/100
25/25 [============== ] - 6s 227ms/step - loss: 0.0606 -
accuracy: 1.0000 - val_loss: 1.1418 - val_accuracy: 0.7100
Epoch 9/100
accuracy: 1.0000 - val_loss: 1.1200 - val_accuracy: 0.7200
Epoch 10/100
accuracy: 1.0000 - val_loss: 1.0984 - val_accuracy: 0.7200
```

```
[0]: ## Checking the tensorboard logs
     %tensorboard --logdir drive/My\ Drive/Kaggle-Dog-Vision/logs
    Output hidden; open in https://colab.research.google.com to view.
[0]: perdictions=model.predict(val_data, verbose=1)
    7/7 [======== ] - 1s 133ms/step
[0]: perdictions
[0]: array([[3.1904652e-04, 2.8376055e-05, 2.1039024e-05, ..., 7.0034504e-05,
            2.1644725e-04, 3.5363206e-04],
            [1.0917850e-03, 4.4810784e-04, 1.4270380e-05, ..., 1.9621334e-04,
            4.0214852e-04, 2.5536679e-04],
            [4.3971950e-04, 8.1442040e-04, 1.1172935e-04, ..., 1.8473429e-03,
            9.8125951e-05, 7.1198934e-05],
            [1.8317510e-04, 2.0304467e-06, 3.6325215e-05, ..., 2.2910845e-04,
            1.5076550e-05, 2.2900448e-04],
            [1.7741120e-05, 7.7323847e-07, 1.3393277e-04, ..., 9.4005583e-05,
            2.5561139e-06, 3.5640312e-04],
            [7.2058372e-04, 2.5633842e-04, 1.9855145e-04, ..., 7.4380354e-05,
            5.7517154e-05, 1.0176528e-03]], dtype=float32)
[0]: perdictions.shape
[0]: (200, 120)
[0]: val_data.shape
     AttributeError
                                                Traceback (most recent call last)
     <ipython-input-74-b9596635893d> in <module>()
     ---> 1 val data.shape
     AttributeError: 'BatchDataset' object has no attribute 'shape'
[0]: len(y_val)
[0]: 200
[0]: perdictions [44]
[0]: array([1.98651198e-03, 1.93281309e-03, 1.57560586e-04, 4.12486435e-04,
            1.40574458e-03, 4.29102947e-04, 3.41883046e-04, 2.18705341e-01,
            1.38233521e-03, 7.97442510e-04, 4.86103399e-03, 1.06555117e-05,
```

```
2.13659205e-03, 3.40142986e-04, 7.89339840e-03, 4.61865362e-04,
            1.60252632e-04, 1.11369975e-01, 3.44525877e-04, 3.67033324e-04,
            4.38945543e-04, 3.19684128e-04, 1.09810918e-03, 1.22309336e-02,
            2.27288567e-02, 2.33945344e-03, 4.58094431e-03, 1.23660534e-03,
            1.38698024e-05, 2.13134638e-03, 1.05463827e-04, 2.29030338e-05,
            1.38204268e-04, 8.03836528e-03, 4.15253676e-02, 4.15996066e-04,
            1.62155728e-03, 1.65151607e-04, 1.16658525e-03, 4.14367057e-02,
            7.80138420e-04, 3.02970438e-04, 4.04646125e-05, 4.96969114e-05,
            1.08808708e-04, 1.96785922e-03, 5.91442995e-06, 4.01035920e-02,
            8.15987494e-03, 9.02750326e-05, 1.08540896e-03, 1.72411290e-03,
            1.69384468e-03, 1.48542560e-04, 5.34650986e-04, 5.80378342e-04,
            8.01953226e-02, 1.24251401e-05, 2.40069785e-05, 9.65381600e-03,
            1.46339741e-03, 1.16360570e-04, 1.89268636e-03, 4.75473562e-03,
            3.48220376e-04, 1.24447557e-04, 3.27480011e-05, 1.96899362e-02,
            1.10810054e-02, 1.51601867e-04, 5.04762447e-03, 2.19150744e-02,
            2.39428235e-04, 1.88543240e-03, 2.39102374e-05, 2.40050122e-05,
            4.51069391e-05, 2.22573326e-05, 5.83479559e-05, 6.22642619e-05,
            8.55999751e-05, 5.38775790e-03, 1.37331011e-03, 1.04204722e-04,
            1.99308456e-03, 3.10840132e-03, 1.14459600e-02, 1.83404947e-04,
            9.99714364e-04, 2.80952752e-02, 2.15469906e-03, 9.74333670e-04,
            1.51894841e-04, 8.67436233e-04, 3.11411731e-03, 3.34771525e-04,
            1.44628124e-04, 7.27058649e-02, 5.14603425e-06, 4.63304139e-04,
            7.39721023e-03, 4.37057053e-04, 1.33207499e-03, 1.86280267e-05,
            9.39052115e-05, 1.60227428e-04, 9.35323816e-03, 5.02452487e-03,
            1.22736406e-03, 2.68815644e-02, 8.23523005e-05, 2.11619044e-04,
            4.93823376e-04, 9.04424787e-02, 4.10740497e-03, 1.65232734e-04],
           dtype=float32)
    perdictions.max()
[0]: 0.98907566
[0]: index=4
     print(f"Max probability :", np.max(perdictions[index]))
     print(f"Index with Max probaility :", np.argmax(perdictions[index]))
     print(f" Dog breed name :", unique_breeds[np.argmax(perdictions[index])])
    Max probability: 0.7618544
    Index with Max probaility: 28
     Dog breed name : chesapeake_bay_retriever
[0]: ## Get prediction Probability into labels
     index=48
     def get_pred_label(prediction_probabilities):
        return unique_breeds[np.argmax(prediction_probabilities)]
     pred_labels=get_pred_label(perdictions[index])
```

2.67881970e-03, 4.26700353e-07, 2.63938215e-03, 6.73842951e-05,

```
pred_labels
```

[0]: 'walker\_hound'

```
1.5.4 Unbatch Function
[0]: def unbatchify(data):
       images_=[]
      labels_=[]
      for image, label in data.unbatch().as_numpy_iterator():
           images_.append(image)
          labels_.append(unique_breeds[np.argmax(label)])
      return images_, labels_
    val images, val labels=unbatchify(val data)
    val_images[0], val_labels[0]
[0]: (array([[[0.38253656, 0.33005056, 0.39671725],
              [0.39007288, 0.33761382, 0.4041996],
              [0.3882505, 0.33652484, 0.4009104],
              [0.6425558, 0.5580867, 0.42135274],
              [0.64060557, 0.5465585, 0.37419435],
              [0.6989901 , 0.5822008 , 0.400487 ]],
             [[0.23527732, 0.22053643, 0.26486418],
              [0.26317158, 0.24654026, 0.29140618],
              [0.30117124, 0.274853, 0.3158876],
              [0.591317 , 0.5246922 , 0.388734 ],
              [0.60727173, 0.52386594, 0.3482765],
              [0.6351768, 0.53510714, 0.34835058]],
             [[0.24187677, 0.2657213, 0.31404063],
              [0.24192405, 0.26956236, 0.3097672],
              [0.24611345, 0.26242998, 0.30113798],
              [0.47172153, 0.4274753, 0.30893174],
              [0.6263348, 0.568551, 0.40058115],
              [0.591305, 0.51581454, 0.33219227]],
             [[0.7795137 , 0.6720558 , 0.494955 ],
              [0.73814404, 0.6306861, 0.4535853],
              [0.70882916, 0.6013713, 0.4242705],
```

```
[0.03302119, 0.03694276, 0.01733491],
        [0.03980222, 0.04372379, 0.02411595],
        [0.04552821, 0.04944978, 0.02984194]],
       [[0.7726975, 0.66180956, 0.48411128],
        [0.80110955, 0.68805355, 0.5136074],
       [0.79248595, 0.6814494, 0.5039739],
       [0.02868533, 0.0326069, 0.01299905],
        [0.03525044, 0.039172, 0.01956416],
        [0.04181555, 0.04573712, 0.02612927]],
       [[0.73340476, 0.62360084, 0.43928713],
        [0.7443359, 0.634532, 0.45021826],
        [0.79445696, 0.684653, 0.50033927],
        [0.02868533, 0.0326069, 0.01299905],
        [0.03525044, 0.039172, 0.01956416],
        [0.04181555, 0.04573712, 0.02612927]]], dtype=float32),
'bernese_mountain_dog')
```

#### 1.6 Plot Prediction Probabilities

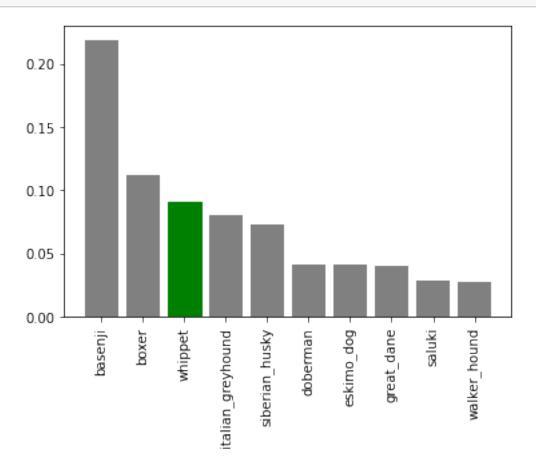
[0]: plot\_pred(perdictions, images=val\_images, labels=val\_labels, n=47)

## Predicted Breed: groenendael True Breed: groenendael Probability: 89.37%



pass

[0]: plot\_pred\_conf(prediction\_probabilities=perdictions, labels=val\_labels, n=44)



```
plt.tight_layout(h_pad=1.0)
plt.show();
```



## 1.7 Saving and Re-Loading the Model

```
[0]: def load_model(model_path):
    print(f"Loading saved model")
    model=tf.keras.models.load_model(model_path, custom_objects={"KerasLayer":
    →hub.KerasLayer})
```

```
return model
[192]: save model(model=model, suffix="1000-images-mobilenet-Adam")
     Saving model to : drive/My Drive/Kaggle-Dog-
     Vision/models/20200506-221442-1000-images-mobilenet-Adam.h5
[192]: 'drive/My Drive/Kaggle-Dog-Vision/models/20200506-221442-1000-images-mobilenet-
      Adam.h5'
[194]: loaded_1000_images_model=load_model("drive/My Drive/Kaggle-Dog-Vision/models/
       \hookrightarrow 20200506-220916-1000-images-mobilenet-Adam.h5")
     Loading saved model
[195]: model.evaluate(val data)
     0.7200
[195]: [1.098382830619812, 0.7200000286102295]
[196]: loaded_1000_images_model.evaluate(val_data)
     0.7200
[196]: [1.098382830619812, 0.7200000286102295]
          Train the model on full data
[197]: len(x), len(y)
[197]: (10222, 10222)
[198]: ### Create batches of the full data
      full_data=create_data_batches(x,y)
     Creating Batches of train data...
[199]: full_model=create_model()
     Building the model with:
     https://tfhub.dev/google/imagenet/mobilenet_v2_130_224/classification/4
 [0]: full_model_tensorboard=create_tensorboard_callback()
      full_model_early_stopping=tf.keras.callbacks.EarlyStopping(monitor="accuracy", u
       →patience=3)
```

```
[201]: full_model.fit(x=full_data,epochs=NUM_EPOCHS,__ 

--callbacks=[full_model_tensorboard,full_model_early_stopping])
```

```
Epoch 1/100
accuracy: 0.6771
Epoch 2/100
320/320 [============== ] - 55s 172ms/step - loss: 0.3972 -
accuracy: 0.8846
Epoch 3/100
320/320 [============= ] - 54s 169ms/step - loss: 0.2342 -
accuracy: 0.9360
Epoch 4/100
accuracy: 0.9651
Epoch 5/100
320/320 [=============== ] - 55s 173ms/step - loss: 0.1065 -
accuracy: 0.9777
Epoch 6/100
accuracy: 0.9862
Epoch 7/100
320/320 [============== ] - 55s 173ms/step - loss: 0.0582 -
accuracy: 0.9912
Epoch 8/100
accuracy: 0.9936
Epoch 9/100
accuracy: 0.9964
Epoch 10/100
320/320 [============ ] - 55s 171ms/step - loss: 0.0309 -
accuracy: 0.9976
Epoch 11/100
accuracy: 0.9976
Epoch 12/100
accuracy: 0.9980
Epoch 13/100
320/320 [============ ] - 57s 177ms/step - loss: 0.0188 -
accuracy: 0.9986
Epoch 14/100
accuracy: 0.9985
Epoch 15/100
accuracy: 0.9989
```

```
320/320 [============== ] - 57s 178ms/step - loss: 0.0156 -
     accuracy: 0.9985
     Epoch 17/100
     accuracy: 0.9985
     Epoch 18/100
     accuracy: 0.9986
[201]: <tensorflow.python.keras.callbacks.History at 0x7f2147e4da58>
     1.9 Testing predictions on test data
 [0]: test_path="drive/My Drive/Kaggle-Dog-Vision/test/"
[211]: test_filenames=[test_path +fname for fname in os.listdir(test_path)]
      test filenames[:10]
[211]: ['drive/My Drive/Kaggle-Dog-Vision/test/ea4a775ecbf81b2cd2967cc34ce4e52b.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/ef4b59cdb6485917a71f2c40df9c8d47.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/f16eed64196d24c423f0a68d7ebf287d.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/eb0f81618a71ccf82982d70879464d89.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/f3aac2f76dfbfa4df96d63227c2c9390.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/f5787e3574a4af6a19ff825cf0c32366.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/e91ffd67dd303f59029d041ff4fb65b8.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/f4db24d71e6f3100614eb4543f98394f.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/e8319b1410a984291d71a3e60c84d86c.jpg',
       'drive/My Drive/Kaggle-Dog-Vision/test/eb9e89f5c0f1717f290360fec6f2a160.jpg']
[212]: test_data=create_data_batches(test_filenames,test_data=True)
     Creating batches of test data...
[213]: test_data
[213]: <BatchDataset shapes: (None, 224, 224, 3), types: tf.float32>
[206]: ## First save the full model
      save_model(model=full_model,suffix="full_images_mobilenet_Adam")
     Saving model to : drive/My Drive/Kaggle-Dog-
     Vision/models/20200507-012311-full_images_mobilenet_Adam.h5
[206]: 'drive/My Drive/Kaggle-Dog-
      Vision/models/20200507-012311-full_images_mobilenet_Adam.h5'
[214]: loaded_full_model=load_model("drive/My Drive/Kaggle-Dog-Vision/models/
       →20200507-012311-full_images_mobilenet_Adam.h5")
```

Epoch 16/100

```
Loading saved model
```

```
[215]: ### Make prediction on full model
      test_predictions=loaded_full_model.predict(test_data,verbose=1)
      [216]: test_predictions
[216]: array([[1.79608162e-06, 1.23005547e-03, 1.62111480e-08, ...,
              6.97953365e-05, 3.86809447e-08, 1.89875244e-08],
             [1.83567117e-09, 1.22392674e-09, 7.97013955e-10, ...,
              2.16934515e-09, 5.85569015e-09, 6.32938566e-07],
             [1.42523311e-11, 1.85392646e-10, 2.75590488e-11, ...,
              3.89042087e-09, 1.02380191e-07, 1.18577315e-10],
             [5.65643802e-07, 3.39985901e-10, 1.04329327e-08, ...,
              1.19955977e-04, 3.99673263e-06, 5.45388926e-03],
             [1.66609532e-10, 4.44898091e-04, 1.70764425e-09, ...,
              1.55636770e-09, 2.86497825e-10, 2.47329908e-08],
             [1.30986795e-08, 1.27479481e-07, 1.64474534e-06, ...,
              3.30079741e-09, 5.22824848e-07, 2.25895008e-07]], dtype=float32)
[217]: test_predictions[:10]
[217]: array([[1.7960816e-06, 1.2300555e-03, 1.6211148e-08, ..., 6.9795336e-05,
              3.8680945e-08, 1.8987524e-08],
             [1.8356712e-09, 1.2239267e-09, 7.9701395e-10, ..., 2.1693451e-09,
              5.8556902e-09, 6.3293857e-07],
             [1.4252331e-11, 1.8539265e-10, 2.7559049e-11, ..., 3.8904209e-09,
              1.0238019e-07, 1.1857731e-10],
             [4.5562548e-10, 2.0066428e-10, 4.7072589e-07, ..., 4.1608400e-06,
              5.7118815e-10, 5.1432680e-09],
             [5.4503340e-07, 1.0682242e-08, 1.8309745e-08, ..., 3.6779824e-07,
              1.9849319e-08, 6.5907098e-09],
             [6.5860689e-08, 1.0820182e-10, 4.9200262e-11, ..., 1.8008982e-12,
              9.0674979e-09, 4.4159798e-08]], dtype=float32)
[218]: test_predictions1=loaded_full_model.predict(test_data,verbose=1)
      324/324 [============ ] - 61s 189ms/step
[219]: test_predictions.shape
[219]: (10357, 120)
 [0]: preds_df=pd.DataFrame(columns=["id"]+list(unique_breeds))
```

```
[231]: preds_df
[231]: Empty DataFrame
       Columns: [id, affenpinscher, afghan_hound, african_hunting_dog, airedale,
       american staffordshire terrier, appenzeller, australian terrier, basenji,
       basset, beagle, bedlington_terrier, bernese_mountain_dog, black-and-
       tan_coonhound, blenheim_spaniel, bloodhound, bluetick, border_collie,
       border_terrier, borzoi, boston_bull, bouvier_des_flandres, boxer,
       brabancon griffon, briard, brittany spaniel, bull mastiff, cairn, cardigan,
       chesapeake bay retriever, chihuahua, chow, clumber, cocker spaniel, collie,
       curly-coated_retriever, dandie_dinmont, dhole, dingo, doberman,
       english foxhound, english setter, english springer, entlebucher, eskimo_dog,
       flat-coated_retriever, french_bulldog, german_shepherd, german_short-
      haired_pointer, giant_schnauzer, golden_retriever, gordon_setter, great_dane,
       great_pyrenees, greater_swiss_mountain_dog, groenendael, ibizan_hound,
       irish setter, irish terrier, irish water spaniel, irish wolfhound,
       italian_greyhound, japanese_spaniel, keeshond, kelpie, kerry_blue_terrier,
      komondor, kuvasz, labrador_retriever, lakeland_terrier, leonberg, lhasa,
      malamute, malinois, maltese_dog, mexican_hairless, miniature_pinscher,
      miniature poodle, miniature schnauzer, newfoundland, norfolk terrier,
      norwegian_elkhound, norwich_terrier, old_english_sheepdog, otterhound, papillon,
      pekinese, pembroke, pomeranian, pug, redbone, rhodesian_ridgeback, rottweiler,
       saint_bernard, saluki, samoyed, schipperke, scotch_terrier, scottish_deerhound,
       sealyham_terrier, ...]
       Index: []
       [0 rows x 121 columns]
[232]: test_ids=[os.path.splitext(path)[0] for path in os.listdir(test_path)]
       test_ids[:10]
[232]: ['ea4a775ecbf81b2cd2967cc34ce4e52b',
        'ef4b59cdb6485917a71f2c40df9c8d47',
        'f16eed64196d24c423f0a68d7ebf287d',
        'eb0f81618a71ccf82982d70879464d89',
        'f3aac2f76dfbfa4df96d63227c2c9390',
        'f5787e3574a4af6a19ff825cf0c32366',
        'e91ffd67dd303f59029d041ff4fb65b8',
        'f4db24d71e6f3100614eb4543f98394f',
        'e8319b1410a984291d71a3e60c84d86c',
        'eb9e89f5c0f1717f290360fec6f2a160']
 [0]: preds_df["id"]=test_ids
[234]: preds_df
```

```
[234]:
                                                 ... yorkshire_terrier
              ea4a775ecbf81b2cd2967cc34ce4e52b
       0
                                                                  NaN
       1
              ef4b59cdb6485917a71f2c40df9c8d47
                                                                  NaN
       2
              f16eed64196d24c423f0a68d7ebf287d
                                                                  NaN
       3
              eb0f81618a71ccf82982d70879464d89
                                                                  NaN
       4
              f3aac2f76dfbfa4df96d63227c2c9390
                                                                  NaN
       10352
              0536a5378c2bb64f2d458b53994f1b32
                                                                  NaN
       10353
              055cb4e6ba1540c275d6ccd2c0b52c27
                                                                  NaN
       10354
              04ed8aeed03953dac6f575148bcb21e1
                                                                  NaN
       10355
              056eca95930e26c627c11e14cd9e1b3a
                                                                  NaN
       10356
              0552e89f6c0ffaaf0de95ee3fc40d68f
                                                                  NaN
       [10357 rows x 121 columns]
  [0]: preds_df[list(unique_breeds)]=test_predictions
[236]:
      preds_df
[236]:
                                             id
                                                 ... yorkshire_terrier
       0
              ea4a775ecbf81b2cd2967cc34ce4e52b
                                                          1.89875e-08
       1
              ef4b59cdb6485917a71f2c40df9c8d47
                                                          6.32939e-07
       2
              f16eed64196d24c423f0a68d7ebf287d
                                                          1.18577e-10
       3
              eb0f81618a71ccf82982d70879464d89
                                                          4.04296e-06
              f3aac2f76dfbfa4df96d63227c2c9390
                                                             0.998833
              0536a5378c2bb64f2d458b53994f1b32\\
       10352
                                                          2.10576e-10
       10353
              055cb4e6ba1540c275d6ccd2c0b52c27
                                                             0.999684
       10354
              04ed8aeed03953dac6f575148bcb21e1
                                                           0.00545389
              056eca95930e26c627c11e14cd9e1b3a
       10355
                                                           2.4733e-08
       10356
              0552e89f6c0ffaaf0de95ee3fc40d68f
                                                          2.25895e-07
       [10357 rows x 121 columns]
  [0]: preds_df.to_csv("drive/My Drive/Kaggle-Dog-Vision/
        →full_model_prediction_mobilenet.csv")
  [0]:
```