Dog Breed Classification

In this project we will use traditional CNN, CNN with data augmentation and finally transfer Learning by VGG16 model with weights pre-on Imagenet to solve the dog breed classification problem

Load Dataset Files

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

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491h

Enter your authorization code:
··········
Mounted at /content/drive
```

Now, upload the given dataset file shared with you in your google drive and give its path for the below given `project_path` variable. For example, a path is given below according to the file path in our google drive. You need to change this to match the path of yours.

```
project_path = "/content/drive/My Drive/Conv-Project-2/"
```

```
import os
```

```
os.chdir(project_path)
```

Run the below code to extract all the images in the train.zip files given in the dataset. We are going to use these images as train and va sets and their labels in further steps.

```
from zipfile import ZipFile
with ZipFile(project_path+'train.zip', 'r') as z:
  z.extractall()
```

Repeat the same step for test.zip

```
with ZipFile(project_path+'test.zip', 'r') as z:
  z.extractall()
```

Repeat the same step for sample_submission.csv.zip

```
from zipfile import ZipFile
with ZipFile(project_path+'sample_submission.csv.zip', 'r') as z:
  z.extractall()
```

Repeat the same step for labels.csv.zip

```
with ZipFile(project_path+'labels.csv.zip', 'r') as z:
  z.extractall()
```

After this process, we will have 4 files - Train folder, test folder and labels.csv and sample_submission.csv as part of your google drive

Read labels.csv file using pandas

```
import pandas as pd
```

```
labels=pd.read_csv('labels.csv')
```

Print the count of each category of Dogs given in the dataset

```
labels['breed'].value_counts()
```

```
scottish_deerhound      126
maltese_dog             117
afghan_hound            116
entlebucher             115
bernese_mountain_dog    114
                       ...
golden_retriever         67
brabancon_griffon        67
komondor                 67
briard                   66
eskimo_dog               66
Name: breed, Length: 120, dtype: int64
```

Get one-hot encodings of labels

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
```

```
label_encoder=LabelEncoder()
```

```
labels_decoded=label_encoder.fit_transform(labels['breed'])
```

```
%tensorflow_version 2.x
import tensorflow as tf
import numpy as np
y = tf.keras.utils.to_categorical(labels_decoded, dtype='float32')
y=np.array(y)
```

```
TensorFlow 2.x selected.
```

```
y[0]
```

```
array([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., 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.], dtype=float32)
```

Preparing training dataset

1. Write a code which reads each and every id from labels.csv file and loads the corresponding image (in RGB - 128, 128, 3) from the train folder.
2. Create 2 variables
   a. x_train - Should have all the images of the dogs from train folder
   b. y_train - Corresponding label of the dog
   Note: The id of the dog images and its corresponding labels are available in labels.csv file
   Hint: Watch the video shared on "Preparing the training dataset" if you face issue on creating the training dataset

```
img_rows=128
img_cols=128
num_channels=3
```

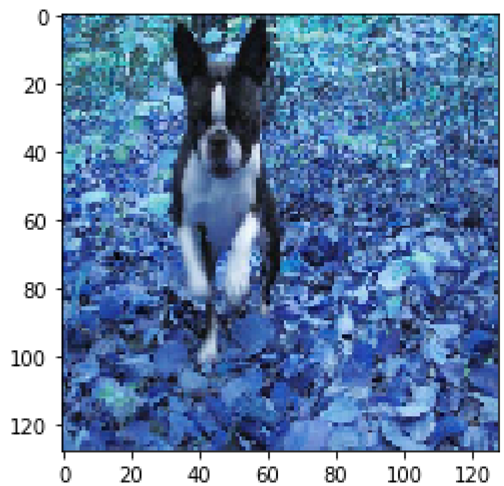
```
from tqdm import tqdm
import cv2
x_feature=[]
y_feature=[]

for dogid, img in tqdm(labels.values):
  train_img=cv2.imread('./train/{}.jpg'.format(dogid), 1)
  train_img_resize=cv2.resize(train_img, (img_rows, img_cols))
```

```
    train_img_resize=cv2.resize(train_img, (img_rows, img_cols))
    x_feature.append(train_img_resize)
    y_feature.append(img)
```

```
100%|██████████| 10222/10222 [36:38<00:00,  5.52it/s]
```

```
import matplotlib.pyplot as plt
plt.imshow(x_feature[0])
```

```
<matplotlib.image.AxesImage at 0x7fadf11689b0>
```




```
import numpy as np
```

```
x_feature=np.asarray(x_feature)
```

```
x_feature.shape
```

```
(10222, 128, 128, 3)
```

Normalize the training data and convert into 4 dimensions so that it can be used as an input to conv layers in the model

```
X = x_feature.astype('float32')
```

```
X /= 255
```

```
X=X.reshape(X.shape[0],128,128,3)
```

```
X.shape
```

```
(10222, 128, 128, 3)
```

Split the training and validation data from `x_train_data` and `y_train_data` obtained from above step

```
from sklearn.model_selection import train_test_split

X_train_data , X_val, y_train_data, y_val = train_test_split(X, y, test_size=0.2, random_state=2)
print ("No. of images in train dataset: ", len(X_train_data))
print ("No. of images in Validation dataset: ", len(X_val))
```

```
No. of images in train dataset:  8177
No. of images in Validation dataset:  2045
```

```
X_train_data.shape
```

```
(8177, 128, 128, 3)
```

Loading the test data

Read the id column from the samples_submission.csv and store it in test_img

```
sample_sub=pd.read_csv('sample_submission.csv')
```

```
test_img=sample_sub['id']
```

```
import cv2
from tqdm import tqdm
```

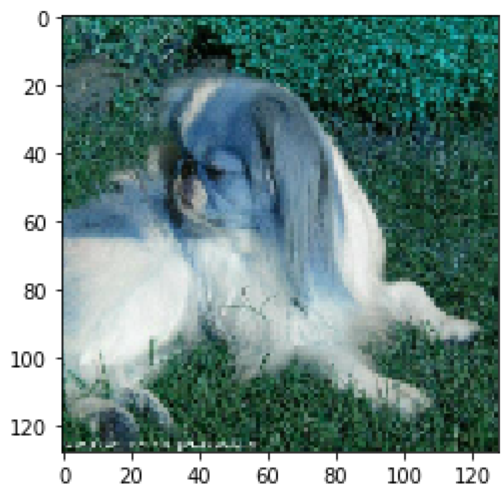
Run the below code to load the test image files in x_test_feature

```
x_test_feature = []

for dogtestid in tqdm(test_img.values):
  test_img=cv2.imread('./test/{}.jpg'.format(dogtestid), 1)
  test_img_resize=cv2.resize(test_img, (img_rows, img_cols))
  x_test_feature.append(test_img_resize)
```

```
100%|██████████| 10357/10357 [37:12<00:00,  7.12it/s]
```

```
import matplotlib.pyplot as plt
plt.imshow(x_test_feature[0])
```

```
<matplotlib.image.AxesImage at 0x7fca0c71f940>
```



Normalize the test data and convert it into 4 dimensions

```
x_test_feature=np.asarray(x_test_feature)
```

```
x_test_feature=np.asarray(x_test_feature)
X_test= x_test_feature.astype('float32')
X_test /= 255
```

Build a basic conv neural network with 2 conv layers (kernel sizes - 5 and 3) add layers as mentioned below classification.

1. Add a Dense layer with 256 neurons with `relu` activation
2. Add a Dense layer with 120 neurons as final layer (as there are 120 classes in the given dataset) with `softmax` activation for classifiaction.

```
import tensorflow.keras
import keras
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
input_shape = (img_rows, img_cols, 3)
```

```
Using TensorFlow backend.
```

```
num_classes=120
#Initialize the model
model = Sequential()
#Add a Convolutional Layer with 32 filters of size 3X3 and activation function as 'ReLU'
model.add(Conv2D(32, kernel_size=(5, 5),
                 activation='relu',
                 input_shape=input_shape,name='conv_1'))
model.add(MaxPooling2D(pool_size=(2, 2),name='max_1', input_shape=(128,128,3)))

#Add a Convolutional Layer with 64 filters of size 3X3 and activation function as 'ReLU'
model.add(Conv2D(64, (3, 3), activation='relu',name='conv_2'))

#Add a MaxPooling Layer of size 2X2
model.add(MaxPooling2D(pool_size=(2, 2),name='max_2'))
```

```
model.add(Flatten())

model.add(Dense(256, activation='relu',name='dense_11'))

model.add(Dense(120, activation='softmax',name='dense_12'))


from tensorflow.keras.optimizers import SGD
from tensorflow.keras.losses import categorical_crossentropy


#To use adam optimizer for learning weights with learning rate = 0.001
optimizer = SGD(lr=0.001)
#Set the loss function and optimizer for the model training
model.compile(loss=categorical_crossentropy,optimizer=optimizer,metrics=['accuracy'])


model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv_1 (Conv2D)              (None, 124, 124, 32)      2432
_________________________________________________________________
max_1 (MaxPooling2D)         (None, 62, 62, 32)        0
_________________________________________________________________
conv_2 (Conv2D)              (None, 60, 60, 64)        18496
_________________________________________________________________
max_2 (MaxPooling2D)         (None, 30, 30, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 57600)             0
_________________________________________________________________
dense_11 (Dense)             (None, 256)               14745856
_________________________________________________________________
dense_12 (Dense)             (None, 120)               30840
=================================================================
Total params: 14,797,624
Trainable params: 14,797,624
Non-trainable params: 0
_________________________________________________________________
```

Use batch_size = 128 and epochs = 10 and execute the model

```
batch_size=128
epochs=10
model.fit(X_train_data, y_train_data,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(X_val, y_val))
```

```
Train on 8177 samples, validate on 2045 samples
Epoch 1/10
8177/8177 [==============================] - 4s 548us/sample - loss: 4.7566 - accuracy: 0.0212 - val_loss: 4.7746 - val
Epoch 2/10
8177/8177 [==============================] - 4s 539us/sample - loss: 4.7535 - accuracy: 0.0204 - val_loss: 4.7728 - val
Epoch 3/10
8177/8177 [==============================] - 4s 534us/sample - loss: 4.7497 - accuracy: 0.0218 - val_loss: 4.7702 - val
Epoch 4/10
8177/8177 [==============================] - 4s 534us/sample - loss: 4.7457 - accuracy: 0.0207 - val_loss: 4.7676 - val
Epoch 5/10
8177/8177 [==============================] - 4s 539us/sample - loss: 4.7413 - accuracy: 0.0219 - val_loss: 4.7645 - val
Epoch 6/10
8177/8177 [==============================] - 4s 540us/sample - loss: 4.7364 - accuracy: 0.0234 - val_loss: 4.7617 - val
Epoch 7/10
8177/8177 [==============================] - 4s 543us/sample - loss: 4.7309 - accuracy: 0.0225 - val_loss: 4.7581 - val
Epoch 8/10
8177/8177 [==============================] - 4s 540us/sample - loss: 4.7254 - accuracy: 0.0227 - val_loss: 4.7546 - val
Epoch 9/10
8177/8177 [==============================] - 4s 537us/sample - loss: 4.7190 - accuracy: 0.0240 - val_loss: 4.7517 - val
Epoch 10/10
8177/8177 [==============================] - 4s 541us/sample - loss: 4.7121 - accuracy: 0.0246 - val_loss: 4.7458 - val
<tensorflow.python.keras.callbacks.History at 0x7fadca3f2390>
```

```
score = model.evaluate(X_val, y_val)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
2045/2045 [==============================] - 1s 287us/sample - loss: 4.7458 - accuracy: 0.0181
Test loss: 4.745807010911788
Test accuracy: 0.01809291
```

The model accuracy is very poor !!!!

Use Data Augmentation in the above model to see if the accuracy improves

```
from tensorflow.keras.preprocessing.image import img_to_array,load_img,ImageDataGenerator
from tensorflow.keras.layers import ZeroPadding2D
```

```
train_datagen=ImageDataGenerator(
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)
```

Using the above objects, create the image generators with variable names `train_generator` and `val_gener`

You need to use train_datagen.flow() and val_datagen.flow()

```
train_generator=train_datagen.flow(X_train_data, y=y_train_data, batch_size=32)
val_generator=train_datagen.flow(X_val, y=y_val, batch_size=32)
```

Fit the model using fit_generator() using `train_generator` and `val_generator` from the above step with 10

```
model.fit_generator(
        train_generator,
        epochs=10,
        validation_data=val_generator)
```

```
WARNING:tensorflow:From <ipython-input-42-8bb277a3b951>:4: Model.fit_generator (from tensorflow.python.keras.engine.tra
```

Model accuracy is still poor!!!

Lets use Transfer Learning

Download the vgg wieght file from here : https://github.com/MinerKasch/applied_deep_learning/blob/master/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5

```
Train for 256 steps, validate for 64 steps
```

Use the below code to load VGG16 weights trained on ImageNet

```
Epoch 2/10
```

```
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input
# Instantiate the model with the pre-trained weights (no top)
base_model= VGG16(weights=(project_path+'vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5'),
                 include_top=False, pooling='avg')
```

```
Epoch 5/10


256/256 [==============================] - 36s 140ms/step - loss: 4.7854 - accuracy: 0.0125 - val_loss: 4.7865 - val_ac
```

Print the summary of the base_model

```
Epoch 8/10
```

```
base_model.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_2 (InputLayer)         [(None, None, None, 3)]   0         
_________________________________________________________________
block1_conv1 (Conv2D)        (None, None, None, 64)    1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, None, None, 64)    36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, None, None, 64)    0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, None, None, 128)   73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, None, None, 128)   147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, None, None, 128)   0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, None, None, 256)   295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, None, None, 256)   590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, None, None, 256)   590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, None, None, 256)   0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, None, None, 512)   1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, None, None, 512)   0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, None, None, 512)   0         
_________________________________________________________________
global_average_pooling2d_1 ( (None, 512)               0         
```

```
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

Add the following classification layers to the imported VGG Model

1. Flatten Layer
2. Dense layer with 1024 neurons with activation as Relu
3. Dense layer with 256 neurons with activation as Relu
4. Dense layer with 120 neurons with activation as Softmax

```
from tensorflow.keras.models import Model


x=base_model.output
x=Flatten()(x)
x=Dense(1024,activation='relu')(x) #we add dense layers so that the model can learn more complex functions and classify for
x=Dense(256,activation='relu')(x) #dense layer 2
preds=Dense(120,activation='softmax')(x) #final layer with softmax activation


vgmodel=Model(inputs=base_model.input,outputs=preds)



for i,layer in enumerate(vgmodel.layers):
  print(i,layer.name)
```

```
0 input_2
1 block1_conv1
2 block1_conv2
3 block1_pool
4 block2_conv1
5 block2_conv2
6 block2_pool
7 block3_conv1
8 block3_conv2
9 block3_conv3
10 block3_pool
11 block4_conv1
12 block4_conv2
13 block4_conv3
14 block4_pool
15 block5_conv1
16 block5_conv2
17 block5_conv3
18 block5_pool
19 global_average_pooling2d_1
20 flatten_4
21 dense_6
22 dense_7
23 dense_8
```

```
#To use adam optimizer for learning weights with learning rate = 0.001
optimizer = SGD(lr=0.001)
#Set the loss function and optimizer for the model training
vgmodel.compile(loss=categorical_crossentropy,optimizer=optimizer,metrics=['accuracy'])
```

Make all the layers in the base_model (VGG16) to be non-trainable

```
for layer in vgmodel.layers:
  if('dense' not in layer.name): #prefix detection to freeze layers which does not have dense
    #Freezing a layer
    layer.trainable = False
```

Fit and compile the model with batch_size = 128 and epochs = 10 and execute the model

Try to get training and validation accuracy to be more than 90%

```
batch_size=128
epochs=10
vgmodel.fit(train_generator,
          epochs=epochs,
          verbose=1,
          validation_data=(val_generator))
```

```
WARNING:tensorflow:sample_weight modes were coerced from
  ...
    to
  ['...']
WARNING:tensorflow:sample_weight modes were coerced from
  ...
    to
  ['...']
Train for 256 steps, validate for 64 steps
Epoch 1/10
256/256 [==============================] - 57s 225ms/step - loss: 4.7908 - accuracy: 0.0108 - val_loss: 4.7945 - val_ac
Epoch 2/10
256/256 [==============================] - 49s 193ms/step - loss: 4.7854 - accuracy: 0.0110 - val_loss: 4.7935 - val_ac
Epoch 3/10
256/256 [==============================] - 50s 194ms/step - loss: 4.7829 - accuracy: 0.0105 - val_loss: 4.7925 - val_ac
Epoch 4/10
256/256 [==============================] - 49s 193ms/step - loss: 4.7816 - accuracy: 0.0108 - val_loss: 4.7914 - val_ac
Epoch 5/10
256/256 [==============================] - 50s 194ms/step - loss: 4.7808 - accuracy: 0.0108 - val_loss: 4.7919 - val_ac
Epoch 6/10
256/256 [==============================] - 49s 192ms/step - loss: 4.7800 - accuracy: 0.0115 - val_loss: 4.7915 - val_ac
Epoch 7/10
256/256 [==============================] - 50s 194ms/step - loss: 4.7797 - accuracy: 0.0117 - val_loss: 4.7917 - val_ac
Epoch 8/10
256/256 [==============================] - 50s 195ms/step - loss: 4.7793 - accuracy: 0.0122 - val_loss: 4.7919 - val_ac
Epoch 9/10
256/256 [==============================] - 50s 194ms/step - loss: 4.7789 - accuracy: 0.0109 - val_loss: 4.7920 - val_ac
Epoch 10/10
256/256 [==============================] - 50s 194ms/step - loss: 4.7785 - accuracy: 0.0113 - val_loss: 4.7916 - val_ac
<tensorflow.python.keras.callbacks.History at 0x7fadc25f9b00>
```