


▼ Dog Breed Classification


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

▼ Load Dataset Files

```
%tensorflow_version 2.x
```

 TensorFlow 2.x selected.

```
import tensorflow as tf  
tf.__version__
```

 '2.1.0-rc1'

```
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")

```
# Initialize the random number generator  
import random  
random.seed(0)
```

```
import warnings  
warnings.filterwarnings("ignore")
```

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

```
project_path = "/content/drive/My Drive/Great Learning Residency 8.1 CNN/Project 2/"
```

Run the below code to extract all the images in the train.zip files given in the dataset. We are going to use the train and test 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

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

Repeat the same step for labels.csv.zip

```
with ZipFile(project_path+'labels.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

▼ Read labels.csv file using pandas

```
import pandas as pd

labels = pd.read_csv('/content/labels.csv')


labels.head(10)
```



	id	breed
0	000bec180eb18c7604dcecc8fe0dba07	boston_bull
1	001513dfcb2ffafc82cccf4d8bbaba97	dingo
2	001cdf01b096e06d78e9e5112d419397	pekinese
3	00214f311d5d2247d5dfe4fe24b2303d	bluetick
4	0021f9ceb3235effd7fcde7f7538ed62	golden_retriever
5	002211c81b498ef88e1b40b9abf84e1d	bedlington_terrier
6	00290d3e1fdd27226ba27a8ce248ce85	bedlington_terrier
7	002a283a315af96eaea0e28e7163b21b	borzoi
8	003df8b8a8b05244b1d920bb6cf451f9	basenji
9	0042188c895a2f14ef64a918ed9c7b64	scottish_deerhound

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

```
print('Total count of dogs: ', labels.shape[0])
print('Number of dog Category: ', len(labels.breed.unique()))
```



Total count of dogs: 10222
Number of dog Category: 120

```
breed_count = labels['breed'].value_counts()
breed_count.head()
```



```

scottish_deerhound    126
maltese_dog           117
afghan_hound          116
entlebucher           115
bernese_mountain_dog  114
Name: breed, dtype: int64

```

```
breed_count.shape
```

```
(120,)
```

▼ Get one-hot encodings of labels

```

from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
breed_encoded = encoder.fit_transform(labels['breed'])
print(breed_encoded)

```

```
[19 37 85 ... 3 75 28]
```

```
import tensorflow.keras
```

```
y = tensorflow.keras.utils.to_categorical(breed_encoded,num_classes=None,dtype='int')
```

```
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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])

```

▼ 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)
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_channel = 1

```

```


from tqdm import tqdm
import cv2

```


```
> feature =[]
```

```
x_feature = []  
y_feature = []
```

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

 100%|██████████| 10222/10222 [00:28<00:00, 354.25it/s]

```
y_feature[1]
```

 'dingo'

```
x_feature[1]
```



```

array([[ 35,  45,  63],
       [ 19,  33,  57],
       [ 22,  42,  74],
       ...,
       [ 37,  69, 112],
       [ 16,  48,  91],
       [ 25,  45,  76]],

       [[ 19,  33,  55],
        [ 16,  31,  57],
        [ 17,  35,  62],
        ...,
        [ 19,  34,  58],
        [  4,  16,  39],
        [ 28,  36,  51]],

       [[ 15,  35,  67],
        [ 17,  34,  63],
        [ 22,  35,  61],
        ...,
        [  5,  13,  32],
        [ 26,  40,  59],
        [ 17,  18,  31]],

       ...,

       [[ 32,  95, 169],
        [ 45, 117, 187],
        [ 15,  70, 152],
        ...,
        [  9,  20,  47],
        [ 17,  24,  48],
        [ 12,  21,  35]],

       [[ 27,  99, 179],
        [ 34, 109, 180],
        [ 35,  79, 158],
        ...,
        [ 21,  30,  50],
        [ 17,  21,  48],
        [ 23,  26,  47]],

       [[ 52, 124, 203],
        [ 50, 124, 195],
        [ 20,  65, 145],
        ...,
        [  5,  16,  42],
        [  1,   5,  38],
        [ 19,  20,  49]]], dtype=uint8)

```

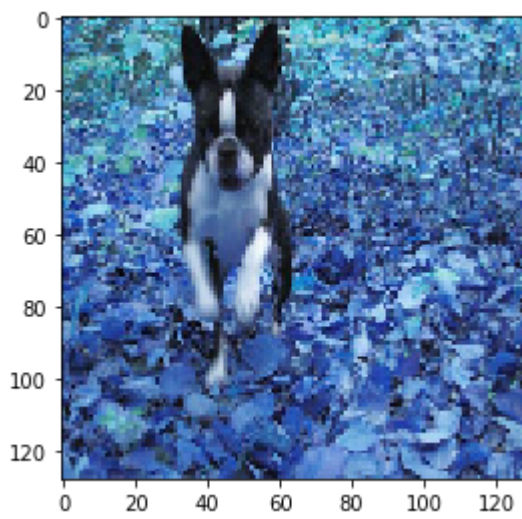
```

import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(50,50))

for i in range(1):
    plt.subplot(10,10,i+1)
    plt.imshow(x_feature[i], cmap=plt.cm.binary)

```





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

```
x_feature = np.array(x_feature, dtype=np.float32)
```

```
x_feature /= 255
print('x_feature shape:', x_feature.shape)
```

```
x_feature shape: (10222, 128, 128, 3)
```

```
x_feature[1]
```



```

array([[0.13725491, 0.1764706 , 0.24705882],
       [0.07450981, 0.12941177, 0.22352941],
       [0.08627451, 0.16470589, 0.2901961 ],
       ...,
       [0.14509805, 0.27058825, 0.4392157 ],
       [0.0627451 , 0.1882353 , 0.35686275],
       [0.09803922, 0.1764706 , 0.29803923]],

       [[0.07450981, 0.12941177, 0.21568628],
       [0.0627451 , 0.12156863, 0.22352941],
       [0.06666667, 0.13725491, 0.24313726],
       ...,
       [0.07450981, 0.13333334, 0.22745098],
       [0.01568628, 0.0627451 , 0.15294118],
       [0.10980392, 0.14117648, 0.2          ]],

       [[0.05882353, 0.13725491, 0.2627451 ],
       [0.06666667, 0.13333334, 0.24705882],
       [0.08627451, 0.13725491, 0.23921569],
       ...,
       [0.01960784, 0.05098039, 0.1254902 ],
       [0.10196079, 0.15686275, 0.23137255],
       [0.06666667, 0.07058824, 0.12156863]],

       ...,

       [[0.1254902 , 0.37254903, 0.6627451 ],
       [0.1764706 , 0.45882353, 0.73333335],
       [0.05882353, 0.27450982, 0.59607846],
       ...,
       [0.03529412, 0.07843138, 0.18431373],
       [0.06666667, 0.09411765, 0.1882353 ],
       [0.04705882, 0.08235294, 0.13725491]],

       [[0.10588235, 0.3882353 , 0.7019608 ],
       [0.13333334, 0.42745098, 0.7058824 ],
       [0.13725491, 0.30980393, 0.61960787],
       ...,
       [0.08235294, 0.11764706, 0.19607843],
       [0.06666667, 0.08235294, 0.1882353 ],
       [0.09019608, 0.10196079, 0.18431373]],

       [[0.20392157, 0.4862745 , 0.79607844],
       [0.19607843, 0.4862745 , 0.7647059 ],
       [0.07843138, 0.25490198, 0.5686275 ],
       ...,
       [0.01960784, 0.0627451 , 0.16470589],
       [0.00392157, 0.01960784, 0.14901961],
       [0.07450981, 0.07843138, 0.19215687]]], dtype=float32)

```

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

```

encoder = LabelEncoder()
y_feature = encoder.fit_transform(y_feature)
print(y_feature)

```



[19 37 85 ... 3 75 28]

```
y_feature = tensorflow.keras.utils.to_categorical(y_feature,num_classes=None,dtype='int')
```

```
y_feature[0]
```

```
array([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, 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])
```

```
x_train_data=x_feature
```

```
y_train_data = y_feature
```

▼ Split the training and validation data from x_train_data and y_train_data obtained from

```
from sklearn.model_selection import train_test_split
trainX, validationX,trainY,validationY = train_test_split(x_train_data,y_train_data, test_size=0.3,
```

```
trainX.shape
```

```
(7155, 128, 128, 3)
```

```
validationX.shape
```

```
(3067, 128, 128, 3)
```

```
trainY.shape
```

```
(7155, 120)
```

```
validationY.shape
```

```
(3067, 120)
```

▼ Loading the test data

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

```
test_img = pd.read_csv("/content/sample_submission.csv" , usecols = ["id"])
```

```
test_img.shape
```

```
(10357, 1)
```


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

```
format(test_img.values)
```




"F'000621fb3cbb32d8935728e48679680e' '00102ee9d8eb90812350685311fe5890'\n '0012a730dfa437f5f3613fb75efcd4ce'

test_img.head()

 0 000621fb3cbb32d8935728e48679680e
1 00102ee9d8eb90812350685311fe5890
2 0012a730dfa437f5f3613fb75efcd4ce
3 001510bc8570bbeee98c8d80c8a95ec1
4 001a5f3114548acdefa3d4da05474c2e
Name: id, dtype: object

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

```
x_test_feature = []  
i = 0 # initialisation  
  
for t in tqdm(test_img.values): # f for format ,jpg  
    img = cv2.imread('./test/{}.jpg'.format(t), 1)  
    img_resize = cv2.resize(img, (img_rows, img_cols))  
    x_test_feature.append(img_resize)
```

 100%|██████████| 10357/10357 [00:28<00:00, 367.93it/s]

x_test_feature[1]



```

array([[ 1, 1, 1],
       [ 1, 1, 1],
       [ 1, 1, 1],
       ...,
       [ 1, 1, 1],
       [ 1, 1, 1],
       [ 1, 1, 1]],

       [[ 1, 1, 1],
        [ 1, 1, 1],
        [ 1, 1, 1],
        ...,
        [ 1, 1, 1],
        [ 1, 1, 1],
        [ 1, 1, 1]],

       [[ 1, 1, 1],
        [ 1, 1, 1],
        [ 1, 1, 1],
        ...,
        [ 1, 1, 1],
        [ 1, 1, 1],
        [ 1, 1, 1]],

       ...,

       [[105, 110, 107],
        [ 86, 91, 88],
        [101, 106, 103],
        ...,
        [ 99, 109, 110],
        [ 92, 102, 103],
        [104, 107, 109]],

       [[113, 118, 113],
        [122, 128, 122],
        [124, 129, 126],
        ...,
        [120, 126, 123],
        [113, 119, 116],
        [115, 118, 122]],

       [[116, 122, 117],
        [114, 119, 117],
        [127, 132, 131],
        ...,
        [126, 129, 127],
        [120, 123, 121],
        [108, 110, 111]]], dtype=uint8)

```

Normalize the test data and convert it into 4 dimensions

```
x_test_feature_ar = np.array(x_test_feature, dtype=np.float32)
```

```
x_test_feature_ar /= 255
```

```
x_test_feature_ar.shape[0]
```



10357

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

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

```
from tensorflow.keras.models import Sequential,Model
from tensorflow.keras.layers import Input, Dense, Dropout, Flatten, Activation
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import categorical_crossentropy
from tensorflow.keras.layers import LeakyReLU

model = Sequential()
model.add(Conv2D(filters=32, input_shape = (128,128,3), kernel_size=5))
model.add(Conv2D(filters=64, kernel_size=3))

model.add(Flatten())

# fully connected layer
model.add(Dense(units=256, kernel_initializer = 'he_normal', activation = 'relu'))
model.add(Dense(units = 120, activation = 'softmax'))
```

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

```
model.compile(optimizer='adam', loss = 'categorical_crossentropy',metrics = ['accuracy'])

history = model.fit(trainX,trainY,
                    epochs=10,
                    validation_data=(validationX,validationY),
                    verbose = 1,
                    batch_size=128)
```



Train on 7155 samples, validate on 3067 samples

Epoch 1/10

7155/7155 [=====] - 17s 2ms/sample - loss: 16.4091 - accuracy: 0.0095

Epoch 2/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7862 - accuracy: 0.0101

Epoch 3/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7834 - accuracy: 0.0098

Epoch 4/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7823 - accuracy: 0.0109

Epoch 5/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7825 - accuracy: 0.0099

Epoch 6/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7809 - accuracy: 0.0115

Epoch 7/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7802 - accuracy: 0.0103

Epoch 8/10

7155/7155 [=====] - 12s 2ms/sample - loss: 4.7789 - accuracy: 0.0117

Epoch 9/10

7155/7155 [=====] - 13s 2ms/sample - loss: 4.7775 - accuracy: 0.0105

Epoch 10/10

7155/7155 [=====] - 13s 2ms/sample - loss: 4.7748 - accuracy: 0.0120

▼ 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 ImageDataGenerator
```

```
train_datagen = ImageDataGenerator( rotation_range=90,
                                     width_shift_range=0.1, height_shift_range=0.1,
                                     horizontal_flip=True)
train_datagen.fit(trainX)
```

```
val_datagen = ImageDataGenerator( rotation_range=90,
                                   width_shift_range=0.1, height_shift_range=0.1,
                                   horizontal_flip=True)
val_datagen.fit(validationX)
```

▼ Using the above objects, create the image generators with variable names train_generator and val_generator

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

```
train_generator = train_datagen.flow(trainX,trainY, batch_size=9)
val_generator = val_datagen.flow(validationX,validationY, batch_size=9)
```

▼ Fit the model using fit_generator() using train_generator and val_generator from the above

```
model.fit_generator(train_generator,\
                    epochs=10, steps_per_epoch=300, \
                    verbose=1,validation_data=val_generator, validation_steps = 300)
```



```
WARNING:tensorflow:From <ipython-input-61-cbaa13ca61c1>:1: Model.fit_generator (from tensorflow
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 300 steps, validate for 300 steps
Epoch 1/10
300/300 [=====] - 30s 99ms/step - loss: 4.8076 - accuracy: 0.0093 - va
Epoch 2/10
300/300 [=====] - 29s 98ms/step - loss: 4.7942 - accuracy: 0.0104 - va
Epoch 3/10
300/300 [=====] - 30s 99ms/step - loss: 4.8485 - accuracy: 0.0093 - va
Epoch 4/10
300/300 [=====] - 29s 98ms/step - loss: 4.7798 - accuracy: 0.0100 - va
Epoch 5/10
300/300 [=====] - 29s 97ms/step - loss: 4.7788 - accuracy: 0.0085 - va
Epoch 6/10
300/300 [=====] - 29s 97ms/step - loss: 4.7796 - accuracy: 0.0085 - va
Epoch 7/10
300/300 [=====] - 29s 97ms/step - loss: 4.7776 - accuracy: 0.0104 - va
Epoch 8/10
300/300 [=====] - 29s 96ms/step - loss: 4.7775 - accuracy: 0.0093 - va
Epoch 9/10
300/300 [=====] - 29s 96ms/step - loss: 4.7779 - accuracy: 0.0078 - va
Epoch 10/10
300/300 [=====] - 29s 97ms/step - loss: 4.7786 - accuracy: 0.0081 - va
<tensorflow.python.keras.callbacks.History at 0x7f5e403abb00>
```

- 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

```
import keras.backend.common as k
k.set_image_dim_ordering('th')
```

```
project_path = "/content/drive/My Drive/Great Learning Residency 8.1 CNN/Project 2/vgg16_weights_tf_
```

Use the below code to load VGG16 weights trained on ImageNet

```
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,
                  include_top=False, pooling='avg')
```

Print the summary of the base_model

```
base_model.summary()
```



▼ 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.layers import Input
input = Input(shape=(128,128,3),name = 'image_input')
output_vgg16 = base_model(input)

x = base_model.output
#x = Flatten()(x)
x = Dense(1024, activation='relu')(x) # let's add a fully-connected layer
x = Dropout(0.25)(x)
x = Dense(256, activation='relu')(x) # let's add a fully-connected layer
x = Dropout(0.25)(x)
predictions = Dense(120, activation='softmax')(x)

# this is the model we will train
m = Model(inputs=base_model.input, outputs=predictions)
```

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

```
#Module to print colourful statements
from termcolor import colored

#Check which layers have been frozen
for layer in m.layers:
    print (colored(layer.name, 'blue'))
    print (colored(layer.trainable, 'red'))
```



```
for layer in m.layers:  
    m.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%

