dog_app

May 8, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section, and the specifics of the implementation are marked in the code block with a 'TODO' statement. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.
Step 0: Import Datasets
Make sure that you've downloaded the required human and dog datasets:
Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

- Download the dog dataset. Unzip the folder and place it in this project's home directory, at the location /dog_images.
- Download the human dataset. Unzip the folder and place it in the home directory, at location /lfw.

Note: If you are using a Windows machine, you are encouraged to use 7zip to extract the folder.

In the code cell below, we save the file paths for both the human (LFW) dataset and dog dataset in the numpy arrays human_files and dog_files.

```
In [1]: import numpy as np
        from glob import glob

        # load filenames for human and dog images
        human_files = np.array(glob("/data/lfw/*/*"))
        dog_files = np.array(glob("/data/dog_images/*/*/*"))

        # print number of images in each dataset
        print('There are %d total human images.' % len(human_files))
        print('There are %d total dog images.' % len(dog_files))
```

```
There are 13233 total human images.
There are 8351 total dog images.
```

Step 1: Detect Humans

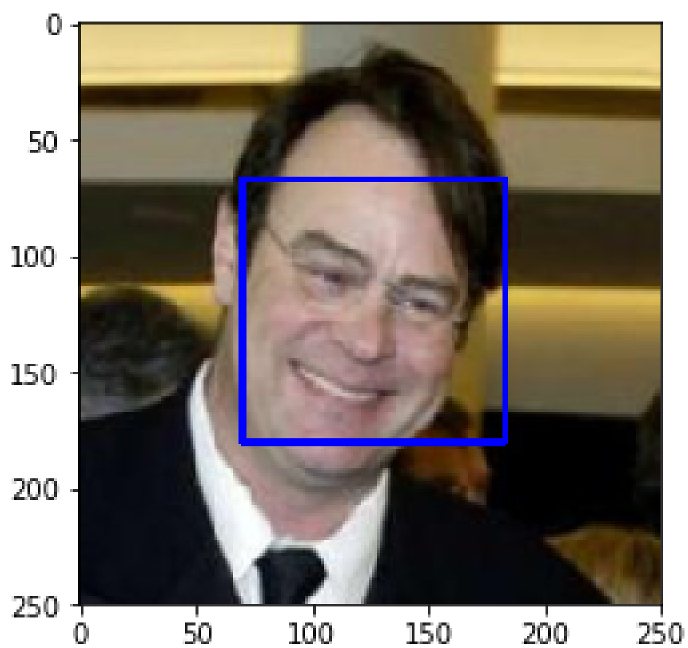
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

OpenCV provides many pre-trained face detectors, stored as XML files on github. We have downloaded one of these detectors and stored it in the haarcascades directory. In the next code cell, we demonstrate how to use this detector to find human faces in a sample image.

```
In [2]: import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline

        # extract pre-trained face detector
        face_cascade = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_alt.xml')

        # load color (BGR) image
        img = cv2.imread(human_files[0])
        # convert BGR image to grayscale
        gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # find faces in image
        faces = face_cascade.detectMultiScale(gray)

        # print number of faces detected in the image
        print('Number of faces detected:', len(faces))
```

```
# get bounding box for each detected face
for (x,y,w,h) in faces:
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)

# convert BGR image to RGB for plotting
cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

# display the image, along with bounding box
plt.imshow(cv_rgb)
plt.show()
```

```
Number of faces detected: 1
```



Before using any of the face detectors, it is standard procedure to convert the images to grayscale. The `detectMultiScale` function executes the classifier stored in `face_cascade` and takes the grayscale image as a parameter.

In the above code, `faces` is a numpy array of detected faces, where each row corresponds to a detected face. Each detected face is a 1D array with four entries that specifies the bounding box of the detected face. The first two entries in the array (extracted in the above code as `x` and `y`) specify the horizontal and vertical positions of the top left corner of the bounding box. The last two entries in the array (extracted here as `w` and `h`) specify the width and height of the box.

1.1.1 Write a Human Face Detector

We can use this procedure to write a function that returns `True` if a human face is detected in an image and `False` otherwise. This function, aptly named `face_detector`, takes a string-valued file path to an image as input and appears in the code block below.

```
In [3]: # returns "True" if face is detected in image stored at img_path
        def face_detector(img_path):
            img = cv2.imread(img_path)
            gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
            faces = face_cascade.detectMultiScale(gray)
            return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

Question 1: Use the code cell below to test the performance of the `face_detector` function.
- What percentage of the first 100 images in `human_files` have a detected human face?
- What percentage of the first 100 images in `dog_files` have a detected human face?

Ideally, we would like 100% of human images with a detected face and 0% of dog images with a detected face. You will see that our algorithm falls short of this goal, but still gives acceptable performance. We extract the file paths for the first 100 images from each of the datasets and store them in the numpy arrays `human_files_short` and `dog_files_short`.

Answer: (You can print out your results and/or write your percentages in this cell)

```
In [4]: from tqdm import tqdm

        human_files_short = human_files[:100]
        dog_files_short = dog_files[:100]

        #-#-# Do NOT modify the code above this line. #-#-#

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.

        def face_test(files):
            count=0
            for img in files:
                if (face_detector(img)):
                    count+=1
            return count

        print("Human face in HumanFiles = ", face_test(human_files_short))
        print("Human face in DogFiles = ", face_test(dog_files_short))

Human face in HumanFiles =  98
Human face in DogFiles =  17
```

We suggest the face detector from OpenCV as a potential way to detect human images in your algorithm, but you are free to explore other approaches, especially approaches that make use of deep learning :). Please use the code cell below to design and test your own face detection algorithm. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [5]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
```

Step 2: Detect Dogs
In this section, we use a pre-trained model to detect dogs in images.

1.1.3 Obtain Pre-trained VGG-16 Model

The code cell below downloads the VGG-16 model, along with weights that have been trained on ImageNet, a very large, very popular dataset used for image classification and other vision tasks. ImageNet contains over 10 million URLs, each linking to an image containing an object from one of 1000 categories.

```
In [6]: import torch
        import torchvision.models as models

        # define VGG16 model
        VGG16 = models.vgg16(pretrained=True)

        # check if CUDA is available
        use_cuda = torch.cuda.is_available()

        # move model to GPU if CUDA is available
        if use_cuda:
            VGG16 = VGG16.cuda()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 101601325.59it/s]
```

Given an image, this pre-trained VGG-16 model returns a prediction (derived from the 1000 possible categories in ImageNet) for the object that is contained in the image.

1.1.4 (IMPLEMENTATION) Making Predictions with a Pre-trained Model

In the next code cell, you will write a function that accepts a path to an image (such as `'dogImages/train/001.Affenpinscher/Affenpinscher_00001.jpg'`) as input and returns the index corresponding to the ImageNet class that is predicted by the pre-trained VGG-16 model. The output should always be an integer between 0 and 999, inclusive.

Before writing the function, make sure that you take the time to learn how to appropriately pre-process tensors for pre-trained models in the PyTorch documentation.

In [7]:
```
from PIL import Image
import torchvision.transforms as transforms

def PreProcess(img_path):
    image = Image.open(img_path).convert('RGB')

    img_transform = transforms.Compose([
        transforms.Resize(size=(224,224)),
        transforms.ToTensor()])

    image = img_transform(image)[:3,:,:].unsqueeze(0)
    return(image)
```

In [8]:
```
  def VGG16_predict(img_path):
    '''
    Use pre-trained VGG-16 model to obtain index corresponding to
    predicted ImageNet class for image at specified path

    Args:
        img_path: path to an image

    Returns:
        Index corresponding to VGG-16 model's prediction
    '''

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image

    image = PreProcess(img_path)

    if use_cuda:
        image = image.cuda()

    ret = VGG16(image)

    return torch.max(ret,1)[1].item() # predicted class index

VGG16_predict(dog_files_short[0])
```

Out[8]: 243

1.1.5 (IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary, you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from `'Chihuahua'` to `'Mexican hairless'`. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

Use these ideas to complete the `dog_detector` function below, which returns `True` if a dog is detected in an image (and `False` if not).

```
In [9]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.

            indx = VGG16_predict(img_path)
            if indx>151 and indx<268:
                return True # true/false
            else:
                return False
```

```
In [10]: print(dog_detector(dog_files_short[0]))
```

```
True
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.
- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

Answer:

```
In [11]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         def DogDetect_Test(files):
             count = 0
             for img in files:
                 if dog_detector(img):
                     count+=1
             return(count)
```

```
In [12]: print("Dog in HumanFiles = ", DogDetect_Test(human_files_short))
         print("Dog in DogFiles = ", DogDetect_Test(dog_files_short))
```

```
Dog in HumanFiles =  0
Dog in DogFiles =  92
```

We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as Inception-v3, ResNet-50, etc). Please use the code cell below to test other pre-trained PyTorch models. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [13]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.

         ResNet = models.resnet18(pretrained=True)
```

```
Downloading: "https://download.pytorch.org/models/resnet18-5c106cde.pth" to /root/.torch/models/
100%|| 46827520/46827520 [00:00<00:00, 31926144.11it/s]
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)

Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

We mention that the task of assigning breed to dogs from images is considered exceptionally challenging. To see why, consider that *even a human* would have trouble distinguishing between a Brittany and a Welsh Springer Spaniel.

Brittany	Welsh Springer Spaniel

It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).

Curly-Coated Retriever	American Water Spaniel

Likewise, recall that labradors come in yellow, chocolate, and black. Your vision-based algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.

Yellow Labrador	Chocolate Labrador

We also mention that random chance presents an exceptionally low bar: setting aside the fact that the classes are slightly imabalanced, a random guess will provide a correct answer roughly 1 in 133 times, which corresponds to an accuracy of less than 1%.

Remember that the practice is far ahead of the theory in deep learning. Experiment with many different architectures, and trust your intuition. And, of course, have fun!

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dog_images/train`, `dog_images/valid`, and `dog_images/test`, respectively). You may find this documentation on custom datasets to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms!

In [ ]:

In [14]:
```
import os
from torchvision import datasets
import torch
from torchvision.transforms import transforms
import numpy as np
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes

batch_size = 32
num_workers = 0

train_dir = "/data/dog_images/train"
valid_dir = "/data/dog_images/valid"
test_dir = "/data/dog_images/test"

transform = transforms.Compose([
    transforms.Resize(size=(256,256)),
    transforms.RandomResizedCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

train_transform = transforms.Compose([
    transforms.Resize(256),
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(), # randomly flip and rotate
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
```

In [15]:
```
train_data = datasets.ImageFolder(train_dir, transform=train_transform)
valid_data = datasets.ImageFolder(valid_dir, transform=transform)
test_data = datasets.ImageFolder(test_dir, transform=transform)

train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, num_worke
```

```
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, num_worke
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, num_workers

loaders_scratch = {
    'train': train_loader,
    'valid': valid_loader,
    'test': test_loader
}
```

In [16]:
```
len(iter(test_loader))
```

Out[16]: 27

Question 3: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why? - Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: 1. Yes, I resize am resizing the images to 256*256 dimension and then centre crop it to 224*224 dimension to make the size of all the images equal. 2. Yes, I have decided to augument the images using Horizontal flip, Random rotation of 10 degrees and using finally normalizing the images. I have only augumented the training images and for test & validation images I have only resized and normalized the images.

1.1.8 (IMPLEMENTATION) Model Architecture

Create a CNN to classify dog breed. Use the template in the code cell below.

In [60]:
```
import torch.nn as nn
import torch.nn.functional as F

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        self.conv2 = nn.Conv2d(16, 64, 3, padding=1)
        self.conv3 = nn.Conv2d(64, 128, 3, padding=1)
        self.conv4 = nn.Conv2d(128, 256, 3, padding=1)
        self.conv5 = nn.Conv2d(256, 512, 3, padding=1)

        self.pool = nn.MaxPool2d(2,2)

        self.fc1 = nn.Linear(7*7*512, 133)
        #self.fc2 = nn.Linear(1024, 133)
        #self.fc3 = nn.Linear(512, 133)

        self.dropout = nn.Dropout(0.3)
```

```
        #self.bn1 = nn.BatchNorm2d(224,3)
        self.bn2 = nn.BatchNorm2d(16)
        self.bn3 = nn.BatchNorm2d(64)
        self.bn4 = nn.BatchNorm2d(128)
        self.bn5 = nn.BatchNorm2d(256)
        self.bn6 = nn.BatchNorm2d(512)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.bn3(self.pool(F.relu(self.conv2(x))))
        x = self.bn4(self.pool(F.relu(self.conv3(x))))
        x = self.bn5(self.pool(F.relu(self.conv4(x))))
        x = self.bn6(self.pool(F.relu(self.conv5(x))))

        x = x.view(-1, 7*7*512)

        #x = self.dropout(x)
        #x = F.relu(self.fc1(x))
        #x = self.dropout(x)
        #x = F.relu(self.fc2(x))
        x= self.dropout(x)
        x = self.fc1(x)

        return x

#-#-# You so NOT have to modify the code below this line. #-#-#

# instantiate the CNN
model_scratch = Net()

# move tensors to GPU if CUDA is available
if use_cuda:
    model_scratch.cuda()
```

In [61]:
```
model_scratch
```

Out[61]:
```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv5): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=25088, out_features=133, bias=True)
  (dropout): Dropout(p=0.3)
  (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
```

```
    (bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (bn5): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (bn6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
  )
```

Question 4: Outline the steps you took to get to your final CNN architecture and your reasoning at each step.

Answer: I read different articles/blogs from various sources such as medium, etc and gained some imp info on hyperparameters and building models from scratch. Keeping the batch size of 20 I had decided to go with Adam optimizer rather than SGD keeping the value of learning rate 0.005.

Keeping the above things constant, I moved towards building my CNN architecture, I decided to move forward with hit & trial method.

I tried almost 12-15 different architectures and the lowest loss that i got on validation set is ---->3.999

Architecture -

Net((conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) (conv2): Conv2d(16, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) (conv4): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) (conv5): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)) (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) (fc1): Linear(in_features=25088, out_features=133, bias=True) (dropout): Dropout(p=0.3) (bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) (bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) (bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) (bn5): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) (bn6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True))

I tried to to implement a structure similar to VGG and sooo I have used 5 conv layer and 1 fully connected layer along with batch normalization and dropout of 0.3.

In each conv layer I have used padding of 1 to keep the size of image intact, and then used maxpool to reduce the size in half while increasing the depth at constant rate - 3,16,64, and soo on till 256.

I trained the model for 30 epochs and the validation loss started from ------> 4.9745 and the lowest loss recorded was -------->3.999

The accuracy which we got on test dataset is - 16%

1.1.9 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_scratch`, and the optimizer as `optimizer_scratch` below.

```
In [62]: import torch.optim as optim

         ### TODO: select loss function
         criterion_scratch = nn.CrossEntropyLoss()
```

```
    ### TODO: select optimizer
    optimizer_scratch = optim.Adam(model_scratch.parameters(), lr = 0.005)
```

1.1.10 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath 'model_scratch.pt'.

```
In [63]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

             for epoch in range(1, n_epochs+1):
                 # initialize variables to monitor training and validation loss
                 train_loss = 0.0
                 valid_loss = 0.0

                 ###################
                 # train the model #
                 ###################
                 model.train()
                 for batch_idx, (data, target) in enumerate(loaders['train']):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## find the loss and update the model parameters accordingly
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo

                     optimizer.zero_grad()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
                     optimizer.step()

                     train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

                 ######################
                 # validate the model #
                 ######################
                 model.eval()
                 acc=0
                 for batch_idx, (data, target) in enumerate(loaders['valid']):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## update the average validation loss
```

```
                output = model(data)
                _, predicted = torch.max(output.data, 1)
                acc = acc + (predicted==target).sum()/20
                loss = criterion(output, target)
                valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)

            print('Valid accuracy => ', acc)
            # print training/validation statistics
            print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
                epoch,
                train_loss,
                valid_loss
                ))

            ## TODO: save the model if validation loss has decreased
            if valid_loss < valid_loss_min:
                torch.save(model.state_dict(), save_path)
                print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                valid_loss_min = valid_loss

        # return trained model
        return model
```

In [64]:
```
# train the model
model_scratch = train(30, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

# load the model that got the best validation accuracy
model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

```
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 1         Training Loss: 10.730774        Validation Loss: 4.976345
Validation loss decreased (inf --> 4.976345).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 2         Training Loss: 4.779277         Validation Loss: 5.297732
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 3         Training Loss: 4.704033         Validation Loss: 4.774767
Validation loss decreased (4.976345 --> 4.774767).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 4         Training Loss: 4.609692         Validation Loss: 7.543745
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 5         Training Loss: 4.523286         Validation Loss: 4.684121
Validation loss decreased (4.774767 --> 4.684121).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 6         Training Loss: 4.450415         Validation Loss: 4.466932
```

```
Validation loss decreased (4.684121 --> 4.466932).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 7        Training Loss: 4.400684         Validation Loss: 4.662520
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 8        Training Loss: 4.479814         Validation Loss: 4.494042
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 9        Training Loss: 4.327785         Validation Loss: 8.113680
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 10        Training Loss: 4.259812         Validation Loss: 4.736894
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 11        Training Loss: 4.241324         Validation Loss: 4.536942
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 12        Training Loss: 4.161151         Validation Loss: 4.325546
Validation loss decreased (4.466932 --> 4.325546).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 13        Training Loss: 4.087121         Validation Loss: 5.116346
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 14        Training Loss: 4.035291         Validation Loss: 4.294696
Validation loss decreased (4.325546 --> 4.294696).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 15        Training Loss: 3.985561         Validation Loss: 4.502717
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 16        Training Loss: 3.961104         Validation Loss: 5.439846
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 17        Training Loss: 3.905993         Validation Loss: 13.969024
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 18        Training Loss: 3.859408         Validation Loss: 5.242236
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 19        Training Loss: 3.847363         Validation Loss: 4.307939
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 20        Training Loss: 3.806559         Validation Loss: 4.195688
Validation loss decreased (4.294696 --> 4.195688).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 21        Training Loss: 3.709044         Validation Loss: 4.181751
Validation loss decreased (4.195688 --> 4.181751).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 22        Training Loss: 3.703860         Validation Loss: 4.416534
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 23        Training Loss: 3.676540         Validation Loss: 4.376522
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 24        Training Loss: 3.653999         Validation Loss: 4.424244
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 25        Training Loss: 3.589655         Validation Loss: 4.263703
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 26        Training Loss: 3.566035         Validation Loss: 4.162456
Validation loss decreased (4.181751 --> 4.162456).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 27        Training Loss: 3.538579         Validation Loss: 4.275605
```

```
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 28         Training Loss: 3.509847         Validation Loss: 4.261285
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 29         Training Loss: 3.464432         Validation Loss: 3.999561
Validation loss decreased (4.162456 --> 3.999561).  Saving model ...
Valid accuracy =>  tensor(0, device='cuda:0')
Epoch: 30         Training Loss: 3.434175         Validation Loss: 20.233639
```

In [ ]:

1.1.11 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 10%.

In [65]:
```python
def test(loaders, model, criterion, use_cuda):

    # monitor test loss and accuracy
    test_loss = 0.

    correct = 0.
    total = 0.

    model.eval()
    for batch_idx, (data, target) in enumerate(loaders['test']):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)
        # calculate the loss
        loss = criterion(output, target)
        # update average test loss
        test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
        # convert output probabilities to predicted class
        pred = output.data.max(1, keepdim=True)[1]
        # compare predictions to true label
        correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
        total += data.size(0)

    print('Test Loss: {:.6f}\n'.format(test_loss))

    print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
        100. * correct / total, correct, total))

# call test function
test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 4.011351


Test Accuracy: 16% (137/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)

You will now use transfer learning to create a CNN that can identify dog breed from images. Your CNN must attain at least 60% accuracy on the test set.

1.1.12 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

```
In [89]: ## TODO: Specify data loaders
         import os
         from torchvision import datasets
         import torch
         from torchvision.transforms import transforms
         import numpy as np
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         batch_size = 20
         num_workers = 0

         train_dir = "/data/dog_images/train"
         valid_dir = "/data/dog_images/valid"
         test_dir = "/data/dog_images/test"

         train_transform = transforms.Compose([
             transforms.Resize(226),
             transforms.RandomResizedCrop(224),
             transforms.RandomHorizontalFlip(),
             transforms.RandomRotation(20),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
         ])

         transform = transforms.Compose([
```

```
        transforms.Resize(226),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ])

    image_datasets = {
        'train' : datasets.ImageFolder(root=train_dir,transform=train_transform),
        'valid' : datasets.ImageFolder(root=valid_dir,transform=transform),
        'test' : datasets.ImageFolder(root=test_dir,transform=transforms)
    }

    train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, num_worke
    valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, num_worke
    test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, num_workers

    loaders = {
        'train': train_loader,
        'valid': valid_loader,
        'test': test_loader
    }
```

1.1.13 (IMPLEMENTATION) Model Architecture

Use transfer learning to create a CNN to classify dog breed. Use the code cell below, and save your initialized model as the variable `model_transfer`.

```
In [77]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.resnet18(pretrained=True)

         if use_cuda:
             model_transfer = model_transfer.cuda()

         model_transfer
```

```
Out[77]: ResNet(
           (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
           (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
           (relu): ReLU(inplace)
           (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
           (layer1): Sequential(
             (0): BasicBlock(
               (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (relu): ReLU(inplace)
```

```
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
```

```
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (layer4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
    (fc): Linear(in_features=512, out_features=1000, bias=True)
  )
```

In [78]:
```python
for param in model_transfer.parameters():
    param.requires_grad = False

model_transfer.fc = nn.Linear(512, 133, bias=True)
fc_parameters = model_transfer.fc.parameters()

for param in fc_parameters:
    param.requires_grad = True

if use_cuda:
    model_transfer = model_transfer.cuda()

model_transfer
```

Out[78]:
```
ResNet(
    (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (relu): ReLU(inplace)
    (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (layer1): Sequential(
      (0): BasicBlock(
```

```
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (relu): ReLU(inplace)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
```

```
            (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
            (relu): ReLU(inplace)
            (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
            (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
          )
        )
        (layer4): Sequential(
          (0): BasicBlock(
            (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
            (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
            (relu): ReLU(inplace)
            (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
            (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
            (downsample): Sequential(
              (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
              (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
            )
          )
          (1): BasicBlock(
            (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
            (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
            (relu): ReLU(inplace)
            (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
            (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
          )
        )
        (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
        (fc): Linear(in_features=512, out_features=133, bias=True)
      )
```

Question 5: Outline the steps you took to get to your final CNN architecture and your reasoning at each step. Describe why you think the architecture is suitable for the current problem.

Answer: I chose ResNet or Residual Network as my pretrained model for transfer learning as ResNet outperformed oher CNN achitectures in ImageNet challenge and also it has interesting architecture with skip layers which helps in eliminating vanishing gradient problem

1.1.14 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_transfer`, and the optimizer as `optimizer_transfer` below.

```
In [90]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr=0.01)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath `'model_transfer.pt'`.

```
In [91]: import numpy as np
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         n_epochs = 5

         def train(n_epochs, loader, model, optimizer, criterion, use_cuda, save_path):

             valid_loss_min = np.Inf

             for epoch in range(1, (n_epochs+1)):

                 train_loss = 0.0
                 valid_loss = 0.0

                 model.train()

                 for batch_idx, (data, target) in enumerate(loaders['train']):

                     if use_cuda:
                         data, target = data.cuda(), target.cuda()

                     optimizer.zero_grad()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
                     optimizer.step()
                     train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

                     model.eval()
                 for batch_idx, (data, target) in enumerate(loaders['valid']):

                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     output = model(data)
                     loss = criterion(output, target)
                     valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)

                 train_loss = train_loss/len(loaders['train'].dataset)
                 valid_loss = valid_loss/len(loaders['valid'].dataset)

                 print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
                     epoch,
                     train_loss,
                     valid_loss
                     ))

                 if valid_loss <= valid_loss_min:
```

```
                print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss

        return model
```

```
In [92]: # train the model
         model_transfer = train(n_epochs, loaders, model_transfer, optimizer_transfer, criterion
         # load the model that got the best validation accuracy (uncomment the line below)
         # train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer, criterion_trans

         # load the model that got the best validation accuracy (uncomment the line below)
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1         Training Loss: 0.000210         Validation Loss: 0.001530
Validation loss decreased (inf --> 0.001530).  Saving model ...
Epoch: 2         Training Loss: 0.000193         Validation Loss: 0.001495
Validation loss decreased (0.001530 --> 0.001495).  Saving model ...
Epoch: 3         Training Loss: 0.000190         Validation Loss: 0.001450
Validation loss decreased (0.001495 --> 0.001450).  Saving model ...
Epoch: 4         Training Loss: 0.000184         Validation Loss: 0.001470
Epoch: 5         Training Loss: 0.000178         Validation Loss: 0.001426
Validation loss decreased (0.001450 --> 0.001426).  Saving model ...
```

1.1.16 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 60%.

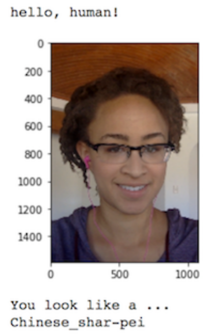
```
In [94]: test(loaders, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 1.187939


Test Accuracy: 70% (592/836)
```

1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

Write a function that takes an image path as input and returns the dog breed (`Affenpinscher`, `Afghan hound`, etc) that is predicted by your model.

```
In [97]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.

         # list of class names by index, i.e. a name can be accessed like class_names[0]
```



Sample Human Output

```
class_names = [item[4:].replace("_", " ") for item in image_datasets['train'].classes]

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    image = Image.open(img_path).convert('RGB')
    prediction_transform = transforms.Compose([transforms.Resize(size=(224, 224)),
                                    transforms.ToTensor(),
                                    transforms.Normalize(mean=[0.485, 0.456, 0.406], s

    # discard the transparent, alpha channel (that's the :3) and add the batch dimensio
    image = prediction_transform(image)[:3,:,:].unsqueeze(0)
    image = image.cuda()

    model_transfer.eval()
    idx = torch.argmax(model_transfer(image))

    return class_names[idx]
```

Step 5: Write your Algorithm

Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is detected in the image, provide output that indicates an error.

You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

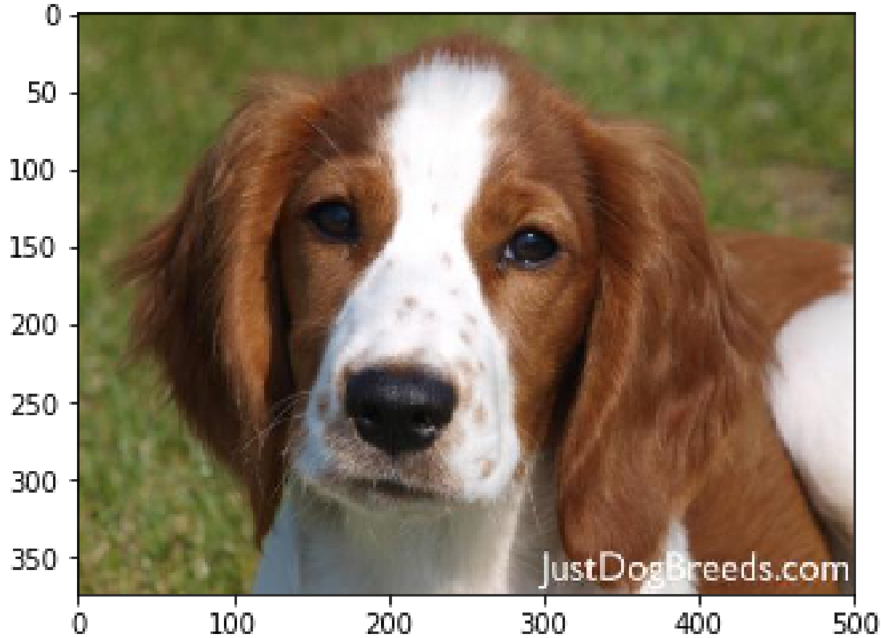
Some sample output for our algorithm is provided below, but feel free to design your own user experience!

1.1.18 (IMPLEMENTATION) Write your Algorithm

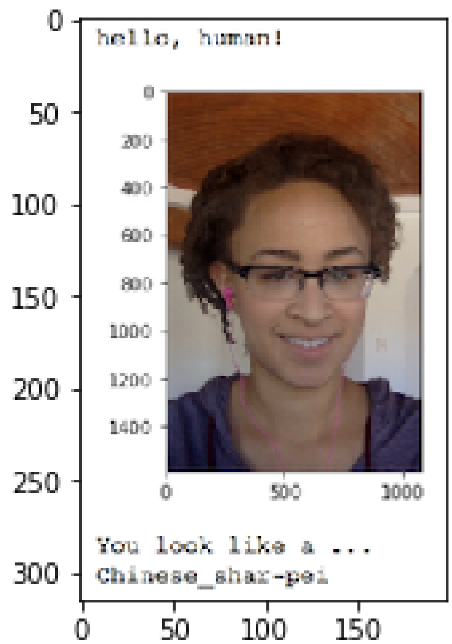
In [98]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
```

```
def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    img = Image.open(img_path)
    plt.imshow(img)
    plt.show()

    if dog_detector(img_path) is True:
        prediction = predict_breed_transfer(img_path)
        print("A dog has been detected which most likely to be {0} breed".format(predic
    else:
        prediction = predict_breed_transfer(img_path)
        print("This is a Human who looks like a {0}".format(prediction))
```

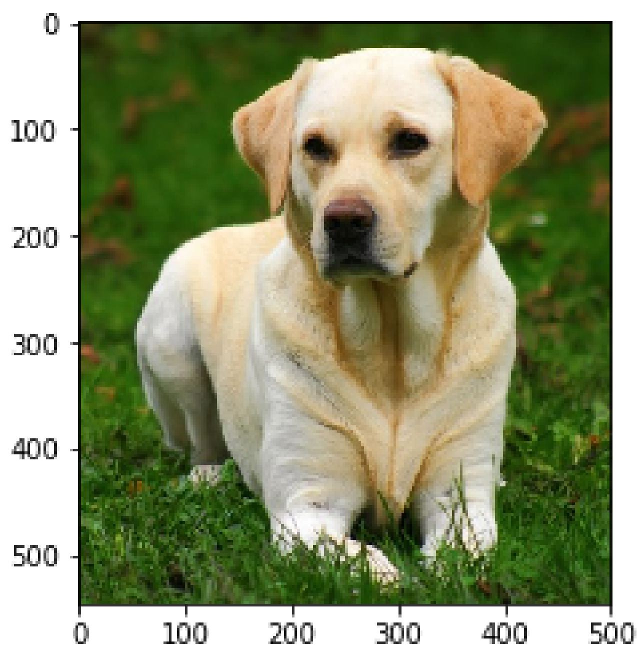
In [102]:
```
for img_file in os.listdir('./images'):
    img_path = os.path.join('./images', img_file)
    run_app(img_path)
```



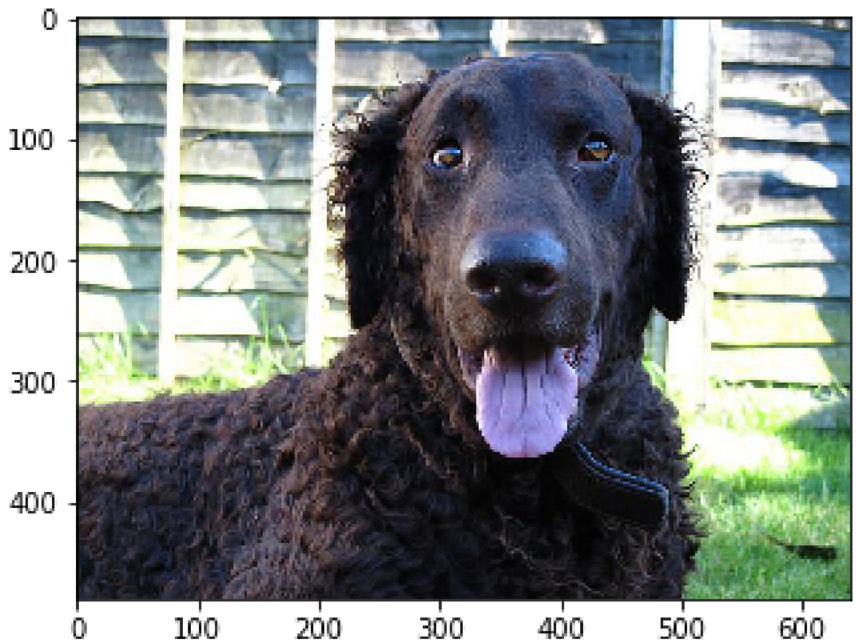

```
A dog has been detected which most likely to be Irish red and white setter breed
```



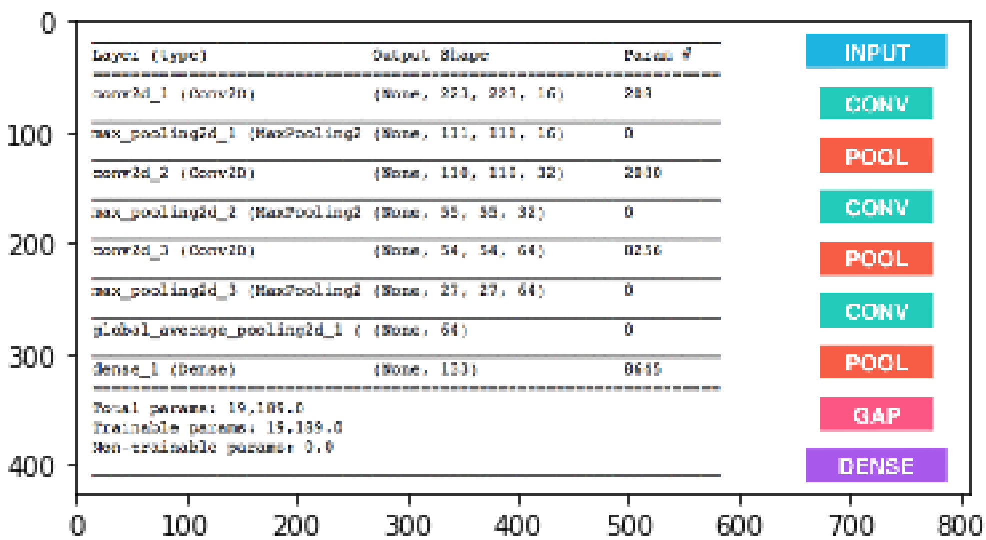
This is a Human who looks like a Bullmastiff



A dog has been detected which most likely to be Labrador retriever breed

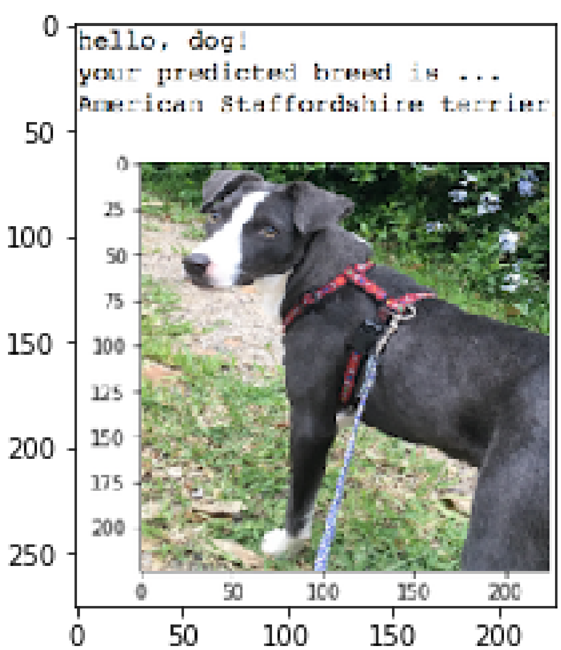


A dog has been detected which most likely to be Curly-coated retriever breed

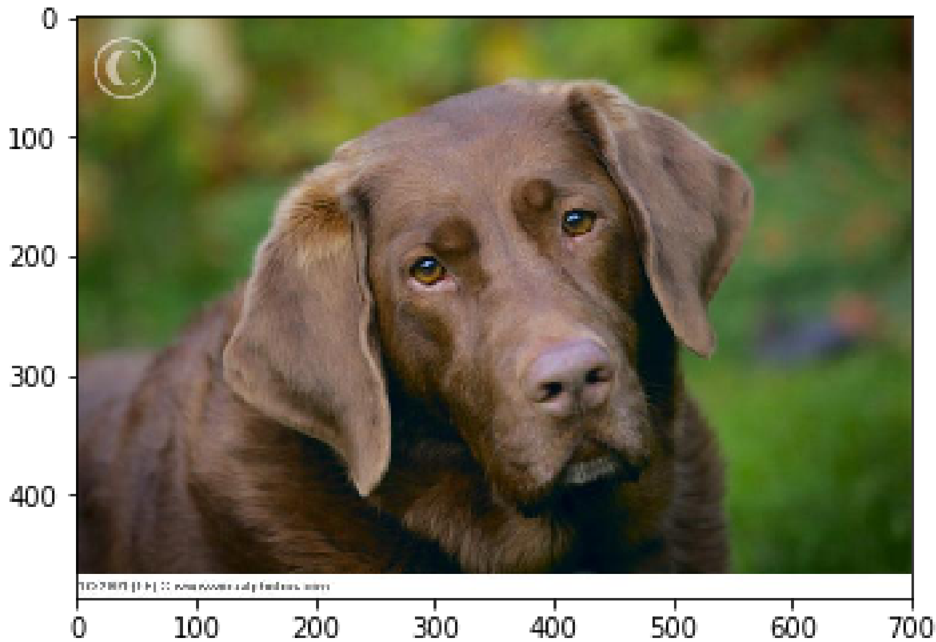


```
This is a Human who looks like a Affenpinscher
A dog has been detected which most likely to be Labrador retriever breed
```

```
A dog has been detected which most likely to be Boykin spaniel breed
```



```
A dog has been detected which most likely to be Entlebucher mountain dog breed
```



```
A dog has been detected which most likely to be Chesapeake bay retriever breed
```

Step 6: Test Your Algorithm
In this section, you will take your new algorithm for a spin! What kind of dog does the algorithm think that *you* look like? If you have a dog, does it predict your dog's breed accurately? If you have a cat, does it mistakenly think that your cat is a dog?

1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

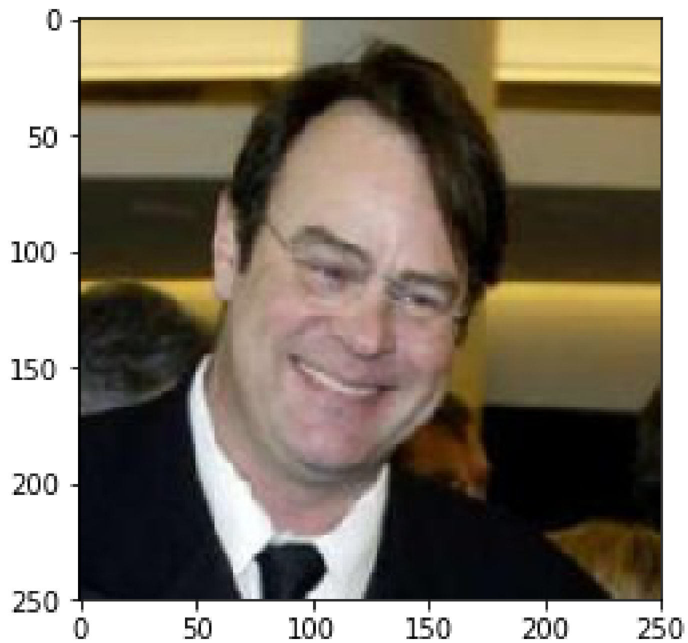
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

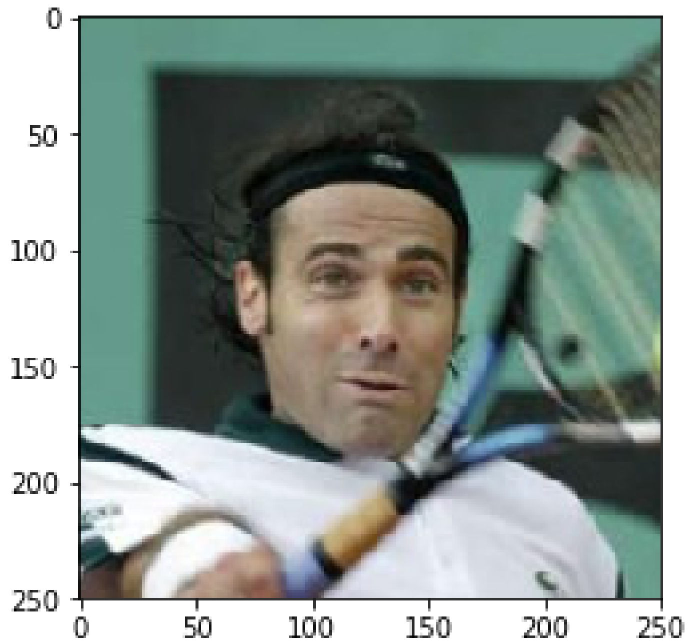
Answer: I am quite happy with the performance of the model on dogs.

Improvements- 1. Try different pre-trained model for transfer learning task. 2. Try tuning hyperparameters while training 3. Use augumantation to increase the size of dataset.

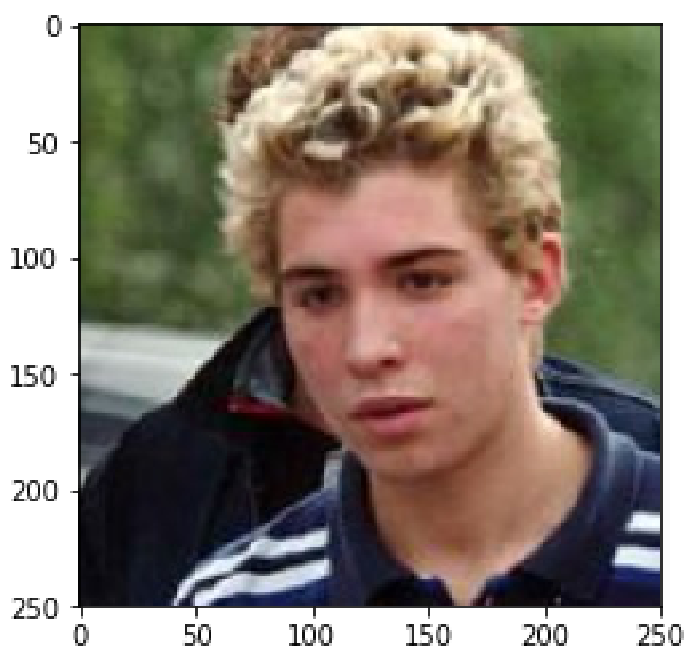
In [100]:
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.

## suggested code, below
for file in np.hstack((human_files[:3], dog_files[:3])):
    run_app(file)
```



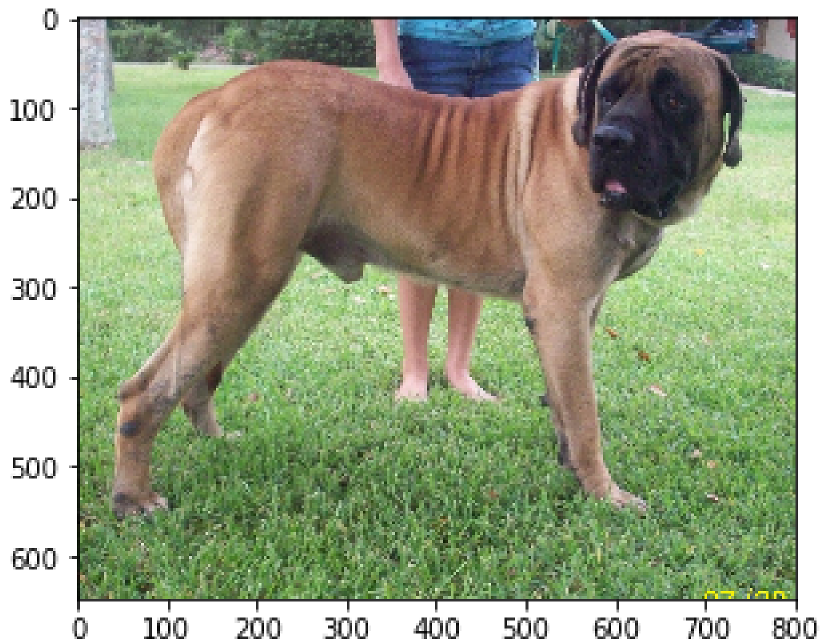
This is a Human who looks like a Chihuahua



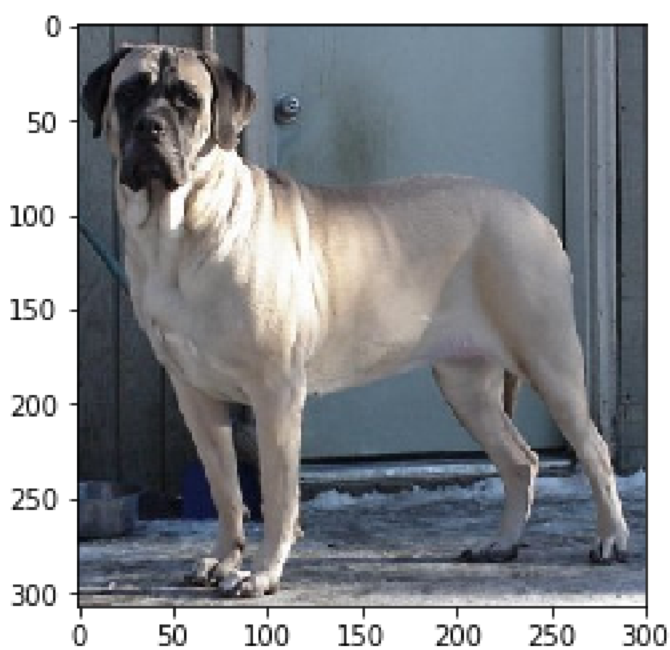
This is a Human who looks like a Dachshund



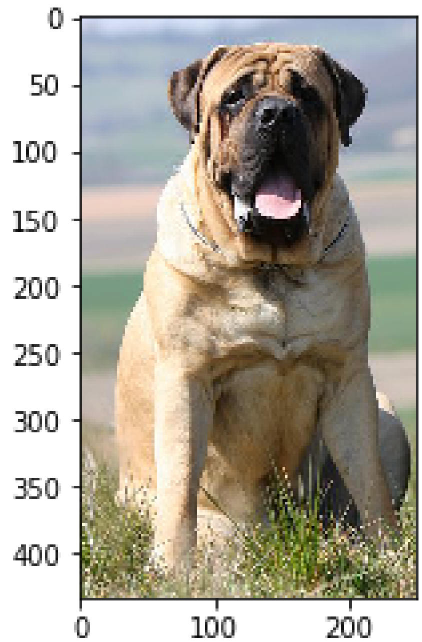
```
This is a Human who looks like a Dogue de bordeaux
```



```
A dog has been detected which most likely to be Bullmastiff breed
```



```
A dog has been detected which most likely to be Mastiff breed
```




```
A dog has been detected which most likely to be Bullmastiff breed
```

In [ ]: