dog_app

April 18, 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 [2]:
```
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

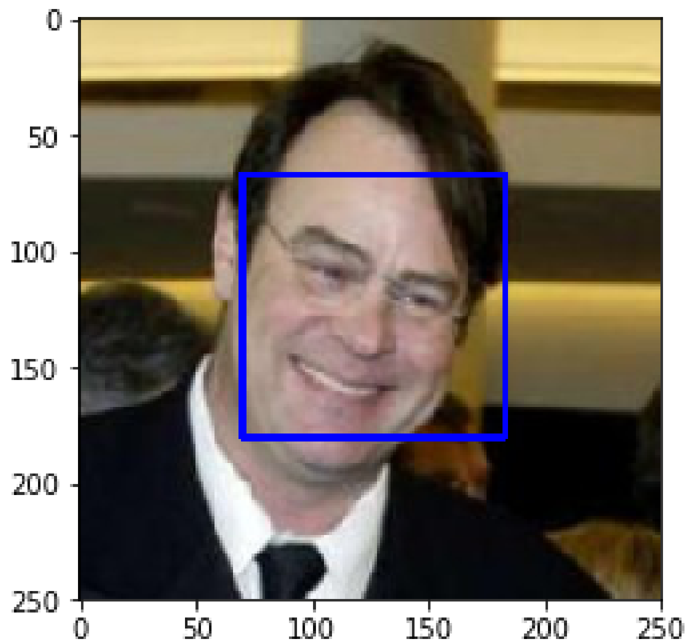
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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 [3]:
```
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))
```

```python
# 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 [4]: # 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 [5]: 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.

        count_humans = 0
        count_dogs = 0

        for file in human_files_short:
            if face_detector(file) == True:
                count_humans +=1

        for file in dog_files_short:
            if face_detector(file) == True:
                count_dogs +=1
        print('%.1f%% images of the first 100 human_files were detected as human face.' % count_
        print('%.1f%% images of the first 100 dog_files were detected as human face.' % count_do

98.0% images of the first 100 human_files were detected as human face.
17.0% images of the first 100 dog_files were detected as human face.
```

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, 100624516.48it/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 load_image(img_path):
            image = Image.open(img_path).convert('RGB')
            # resize the input image into 224x224 because VGG16 takes only 224x224 pixel image
            in_transform = transforms.Compose([transforms.Resize(size=(224,224)),
                                                transforms.ToTensor()
                                                ])
            image = in_transform(image)[:3,:,:].unsqueeze(0)
            return image
```

```
In [8]: from PIL import Image
        import torchvision.transforms as transforms

        from PIL import ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True

        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
            img = load_image(img_path)
            if use_cuda:
                img = img.cuda()
            ret = VGG16(img)

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

```
In [9]: VGG16_predict(dog_files_short[0])
```

```
Out[9]: 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 [10]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             idx = VGG16_predict(img_path)
             return  idx>=151 and idx<=268
```

```
In [11]: print(dog_detector(dog_files_short[0]))
         print(dog_detector(human_files_short[0]))
```

```
True
False
```

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: 0% of dogs in human_files_short and 94% of dogs in dog_files_short

```
In [12]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         def dog_detector_test(files):
             detection_cnt = 0;
             total_cnt = len(files)
             for file in files:
                 detection_cnt += dog_detector(file)
             return detection_cnt, total_cnt
```

```
In [13]: print("detect a dog in human_files: {} / {}".format(dog_detector_test(human_files_short
         print("detect a dog in dog_files: {} / {}".format(dog_detector_test(dog_files_short)[0]
```

```
detect a dog in human_files: 0 / 100
detect a dog in dog_files: 94 / 100
```

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

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 [14]: import os
         from torchvision import datasets

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes
         ImageFile.LOAD_TRUNCATED_IMAGES = True
```

```
batch_size = 20
num_workers = 0 # default is 0

data_dir = '/data/dog_images/'
train_dir = os.path.join(data_dir,'train')
valid_dir = os.path.join(data_dir,'valid')
test_dir = os.path.join(data_dir,'test')


standard_normalization = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0

data_transforms = {'train': transforms.Compose([transforms.RandomResizedCrop(224),
                                                transforms.RandomHorizontalFlip(),
                                                 transforms.ToTensor(),
                                                 standard_normalization
                                                ]),

                      'val': transforms.Compose([transforms.Resize(256),
                                                transforms.CenterCrop(224),
                                                transforms.ToTensor(),
                                                standard_normalization]),

                      'test': transforms.Compose([transforms.Resize(size=(224,224)),
                                                transforms.ToTensor(),
                                                standard_normalization])

                  }
```

```
In [15]: train_data = datasets.ImageFolder(train_dir, transform=data_transforms['train'])
         valid_data = datasets.ImageFolder(valid_dir, transform=data_transforms['val'])
         test_data = datasets.ImageFolder(test_dir, transform = data_transforms['test'])

         train_loader = torch.utils.data.DataLoader(train_data,batch_size=batch_size, num_worker
         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

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

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:As resizing the image data is one of the important part of preprocessing because different images have different pixel sizes,so i resize my images dataset using RandomResizedCrop and i set the resize value to be 224. Augmenting the data also helps when we have imbalanced dataset problem. So i applied RandomHorizontalClip function to our training data only because we will train our data on that train dataset only rest for valid and test dataset we will not require to do augmentation.

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [23]:
```
num_classes = 133
```

In [24]:
```
import torch.nn as nn
import torch.nn.functional as F
import numpy as np

# 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, 32, 3, stride=2, padding=1)
        self.conv2 = nn.Conv2d(32, 64, 3, stride=2, padding=1)
        self.conv3 = nn.Conv2d(64, 128, 3, padding=1)

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

        # fully-connected
        self.fc1 = nn.Linear(7*7*128, 500)
        self.fc2 = nn.Linear(500, num_classes)

        # drop-out
        self.dropout = nn.Dropout(0.3)

    def forward(self, x):
        ## Define forward behavior
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x = F.relu(self.conv2(x))
        x = self.pool(x)
        x = F.relu(self.conv3(x))
        x = self.pool(x)
        (_, C, H, W) = x.data.size()

        # flatten
        x = x.view( -1 , C * H * W)

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

        x = self.dropout(x)
        x = self.fc2(x)
        return x
```

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

        # instantiate the CNN
        model_scratch = Net()
        print(model_scratch)
        # move tensors to GPU if CUDA is available
        if use_cuda:
            model_scratch.cuda()
```

```
Net(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (conv3): Conv2d(64, 128, 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=6272, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=133, bias=True)
  (dropout): Dropout(p=0.3)
)
```

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

Answer: I have used 3 conv2d layer for architecture with kernel size = 3,stride = 2, padding = 1. The first 2 layer implemented with a kernel size of 3 and stride 2 and padding of 1. The 3rd layer is implemented with kernal size of 3 and padding of 1 but i have not implemented stride operation on 3rd layer.After each layer i implemented the maxpooling layer and at last i have used dropout regularization with value 0.3.Dropout prevents our algorithm from overfitting. I have used RELU activation function at the hidden layers of our CNN architecture. RELU activation function gives values between 0 and 1.I have used 2 fully connected layers. Last fully connected layer gives the predictions from one of the 133 classes.

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 [25]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.002)
```

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 [26]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path, last_val
             """returns trained model"""
             # initialize tracker for minimum validation loss
             if last_validation_loss is not None:
                 valid_loss_min = last_validation_loss
             else:
                 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

                     # initialize weights to zero
                     optimizer.zero_grad()

                     output = model(data)

                     # calculate loss
                     loss = criterion(output, target)

                     # back prop
                     loss.backward()

                     # grad
                     optimizer.step()

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

                     if batch_idx % 100 == 0:
                         print('Epoch %d, Batch %d loss: %.6f' %
                           (epoch, batch_idx + 1, train_loss))

                 ######################
                 # validate the model #
                 ######################
```

```
            model.eval()
            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)
                loss = criterion(output, target)
                valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)


            # 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 [28]: model_scratch = train(40, loader_scratch, model_scratch, optimizer_scratch,  criterion_
```

```
Epoch 1, Batch 1 loss: 4.880376
Epoch 1, Batch 101 loss: 4.892124
Epoch 1, Batch 201 loss: 4.865727
Epoch 1, Batch 301 loss: 4.830857
Epoch: 1        Training Loss: 4.819205         Validation Loss: 4.645087
Validation loss decreased (inf --> 4.645087).  Saving model ...
Epoch 2, Batch 1 loss: 4.675576
Epoch 2, Batch 101 loss: 4.688949
Epoch 2, Batch 201 loss: 4.664219
Epoch 2, Batch 301 loss: 4.624367
Epoch: 2        Training Loss: 4.621480         Validation Loss: 4.397635
Validation loss decreased (4.645087 --> 4.397635).  Saving model ...
Epoch 3, Batch 1 loss: 4.610833
Epoch 3, Batch 101 loss: 4.516422
Epoch 3, Batch 201 loss: 4.512268
Epoch 3, Batch 301 loss: 4.494890
Epoch: 3        Training Loss: 4.493062         Validation Loss: 4.285367
```

```
Validation loss decreased (4.397635 --> 4.285367).  Saving model ...
Epoch 4, Batch 1 loss: 4.651677
Epoch 4, Batch 101 loss: 4.440221
Epoch 4, Batch 201 loss: 4.434040
Epoch 4, Batch 301 loss: 4.434682
Epoch: 4         Training Loss: 4.432982         Validation Loss: 4.222027
Validation loss decreased (4.285367 --> 4.222027).  Saving model ...
Epoch 5, Batch 1 loss: 4.354278
Epoch 5, Batch 101 loss: 4.389802
Epoch 5, Batch 201 loss: 4.394581
Epoch 5, Batch 301 loss: 4.380628
Epoch: 5         Training Loss: 4.383595         Validation Loss: 4.141426
Validation loss decreased (4.222027 --> 4.141426).  Saving model ...
Epoch 6, Batch 1 loss: 3.984164
Epoch 6, Batch 101 loss: 4.320390
Epoch 6, Batch 201 loss: 4.315139
Epoch 6, Batch 301 loss: 4.333007
Epoch: 6         Training Loss: 4.334670         Validation Loss: 4.187063
Epoch 7, Batch 1 loss: 4.265858
Epoch 7, Batch 101 loss: 4.281908
Epoch 7, Batch 201 loss: 4.288800
Epoch 7, Batch 301 loss: 4.288730
Epoch: 7         Training Loss: 4.289967         Validation Loss: 4.064446
Validation loss decreased (4.141426 --> 4.064446).  Saving model ...
Epoch 8, Batch 1 loss: 4.359960
Epoch 8, Batch 101 loss: 4.256014
Epoch 8, Batch 201 loss: 4.267797
Epoch 8, Batch 301 loss: 4.270120
Epoch: 8         Training Loss: 4.268560         Validation Loss: 4.051850
Validation loss decreased (4.064446 --> 4.051850).  Saving model ...
Epoch 9, Batch 1 loss: 3.993916
Epoch 9, Batch 101 loss: 4.209431
Epoch 9, Batch 201 loss: 4.230379
Epoch 9, Batch 301 loss: 4.240817
Epoch: 9         Training Loss: 4.246354         Validation Loss: 4.055290
Epoch 10, Batch 1 loss: 4.138025
Epoch 10, Batch 101 loss: 4.217835
Epoch 10, Batch 201 loss: 4.224414
Epoch 10, Batch 301 loss: 4.234032
Epoch: 10         Training Loss: 4.234851         Validation Loss: 4.043916
Validation loss decreased (4.051850 --> 4.043916).  Saving model ...
Epoch 11, Batch 1 loss: 4.204412
Epoch 11, Batch 101 loss: 4.185291
Epoch 11, Batch 201 loss: 4.181698
Epoch 11, Batch 301 loss: 4.189135
Epoch: 11         Training Loss: 4.194087         Validation Loss: 4.139400
Epoch 12, Batch 1 loss: 3.711044
Epoch 12, Batch 101 loss: 4.191503
```

```
Epoch 12, Batch 201 loss: 4.190087
Epoch 12, Batch 301 loss: 4.197142
Epoch: 12        Training Loss: 4.199644        Validation Loss: 4.010719
Validation loss decreased (4.043916 --> 4.010719).  Saving model ...
Epoch 13, Batch 1 loss: 4.292813
Epoch 13, Batch 101 loss: 4.156364
Epoch 13, Batch 201 loss: 4.174941
Epoch 13, Batch 301 loss: 4.190215
Epoch: 13        Training Loss: 4.187249        Validation Loss: 3.992157
Validation loss decreased (4.010719 --> 3.992157).  Saving model ...
Epoch 14, Batch 1 loss: 4.114443
Epoch 14, Batch 101 loss: 4.185062
Epoch 14, Batch 201 loss: 4.162474
Epoch 14, Batch 301 loss: 4.165208
Epoch: 14        Training Loss: 4.170358        Validation Loss: 3.978343
Validation loss decreased (3.992157 --> 3.978343).  Saving model ...
Epoch 15, Batch 1 loss: 3.557680
Epoch 15, Batch 101 loss: 4.142726
Epoch 15, Batch 201 loss: 4.161064
Epoch 15, Batch 301 loss: 4.173584
Epoch: 15        Training Loss: 4.173562        Validation Loss: 4.009115
Epoch 16, Batch 1 loss: 4.133609
Epoch 16, Batch 101 loss: 4.159767
Epoch 16, Batch 201 loss: 4.161564
Epoch 16, Batch 301 loss: 4.163648
Epoch: 16        Training Loss: 4.163361        Validation Loss: 4.019470
Epoch 17, Batch 1 loss: 3.793711
Epoch 17, Batch 101 loss: 4.134758
Epoch 17, Batch 201 loss: 4.116159
Epoch 17, Batch 301 loss: 4.130571
Epoch: 17        Training Loss: 4.134736        Validation Loss: 3.998801
Epoch 18, Batch 1 loss: 4.363779
Epoch 18, Batch 101 loss: 4.111971
Epoch 18, Batch 201 loss: 4.092103
Epoch 18, Batch 301 loss: 4.104073
Epoch: 18        Training Loss: 4.117477        Validation Loss: 4.000218
Epoch 19, Batch 1 loss: 4.046420
Epoch 19, Batch 101 loss: 4.095998
Epoch 19, Batch 201 loss: 4.114415
Epoch 19, Batch 301 loss: 4.122773
Epoch: 19        Training Loss: 4.127980        Validation Loss: 3.992518
Epoch 20, Batch 1 loss: 4.171683
Epoch 20, Batch 101 loss: 4.092900
Epoch 20, Batch 201 loss: 4.116925
Epoch 20, Batch 301 loss: 4.124427
Epoch: 20        Training Loss: 4.130503        Validation Loss: 3.944509
Validation loss decreased (3.978343 --> 3.944509).  Saving model ...
Epoch 21, Batch 1 loss: 3.987177
```

```
Epoch 21, Batch 101 loss: 4.131769
Epoch 21, Batch 201 loss: 4.128146
Epoch 21, Batch 301 loss: 4.121715
Epoch: 21         Training Loss: 4.124859         Validation Loss: 3.888182
Validation loss decreased (3.944509 --> 3.888182).  Saving model ...
Epoch 22, Batch 1 loss: 3.796560
Epoch 22, Batch 101 loss: 4.037601
Epoch 22, Batch 201 loss: 4.089409
Epoch 22, Batch 301 loss: 4.101123
Epoch: 22         Training Loss: 4.092000         Validation Loss: 3.913833
Epoch 23, Batch 1 loss: 4.356958
Epoch 23, Batch 101 loss: 4.109727
Epoch 23, Batch 201 loss: 4.109988
Epoch 23, Batch 301 loss: 4.103276
Epoch: 23         Training Loss: 4.106902         Validation Loss: 3.899242
Epoch 24, Batch 1 loss: 4.257855
Epoch 24, Batch 101 loss: 4.033718
Epoch 24, Batch 201 loss: 4.059278
Epoch 24, Batch 301 loss: 4.061814
Epoch: 24         Training Loss: 4.067706         Validation Loss: 3.938845
Epoch 25, Batch 1 loss: 4.387321
Epoch 25, Batch 101 loss: 4.068182
Epoch 25, Batch 201 loss: 4.085292
Epoch 25, Batch 301 loss: 4.092345
Epoch: 25         Training Loss: 4.090805         Validation Loss: 3.894534
Epoch 26, Batch 1 loss: 4.069507
Epoch 26, Batch 101 loss: 4.045637
Epoch 26, Batch 201 loss: 4.071591
Epoch 26, Batch 301 loss: 4.081798
Epoch: 26         Training Loss: 4.082880         Validation Loss: 3.933674
Epoch 27, Batch 1 loss: 3.961185
Epoch 27, Batch 101 loss: 4.059009
Epoch 27, Batch 201 loss: 4.071114
Epoch 27, Batch 301 loss: 4.062493
Epoch: 27         Training Loss: 4.065426         Validation Loss: 3.890086
Epoch 28, Batch 1 loss: 4.059380
Epoch 28, Batch 101 loss: 4.022579
Epoch 28, Batch 201 loss: 4.055151
Epoch 28, Batch 301 loss: 4.070765
Epoch: 28         Training Loss: 4.076953         Validation Loss: 3.919895
Epoch 29, Batch 1 loss: 4.289463
Epoch 29, Batch 101 loss: 4.001369
Epoch 29, Batch 201 loss: 4.026670
Epoch 29, Batch 301 loss: 4.047438
Epoch: 29         Training Loss: 4.051985         Validation Loss: 3.910012
Epoch 30, Batch 1 loss: 3.703373
Epoch 30, Batch 101 loss: 4.033245
Epoch 30, Batch 201 loss: 4.024643
```

```
Epoch 30, Batch 301 loss: 4.019840
Epoch: 30        Training Loss: 4.018717        Validation Loss: 3.898215
Epoch 31, Batch 1 loss: 3.864375
Epoch 31, Batch 101 loss: 4.047602
Epoch 31, Batch 201 loss: 4.052174
Epoch 31, Batch 301 loss: 4.043049
Epoch: 31        Training Loss: 4.045265        Validation Loss: 4.041333
Epoch 32, Batch 1 loss: 4.008075
Epoch 32, Batch 101 loss: 4.023729
Epoch 32, Batch 201 loss: 4.011748
Epoch 32, Batch 301 loss: 4.021887
Epoch: 32        Training Loss: 4.023514        Validation Loss: 3.890668
Epoch 33, Batch 1 loss: 3.814862
Epoch 33, Batch 101 loss: 4.018108
Epoch 33, Batch 201 loss: 4.041087
Epoch 33, Batch 301 loss: 4.021194
Epoch: 33        Training Loss: 4.021971        Validation Loss: 3.861955
Validation loss decreased (3.888182 --> 3.861955).  Saving model ...
Epoch 34, Batch 1 loss: 3.821235
Epoch 34, Batch 101 loss: 4.020109
Epoch 34, Batch 201 loss: 4.001233
Epoch 34, Batch 301 loss: 4.015042
Epoch: 34        Training Loss: 4.014979        Validation Loss: 3.861820
Validation loss decreased (3.861955 --> 3.861820).  Saving model ...
Epoch 35, Batch 1 loss: 4.003522
Epoch 35, Batch 101 loss: 4.023411
Epoch 35, Batch 201 loss: 4.005120
Epoch 35, Batch 301 loss: 4.003310
Epoch: 35        Training Loss: 4.004262        Validation Loss: 3.862421
Epoch 36, Batch 1 loss: 3.647422
Epoch 36, Batch 101 loss: 4.017648
Epoch 36, Batch 201 loss: 4.019085
Epoch 36, Batch 301 loss: 4.024241
Epoch: 36        Training Loss: 4.033803        Validation Loss: 3.886848
Epoch 37, Batch 1 loss: 3.722945
Epoch 37, Batch 101 loss: 3.997901
Epoch 37, Batch 201 loss: 3.981230
Epoch 37, Batch 301 loss: 3.990685
Epoch: 37        Training Loss: 3.989128        Validation Loss: 3.891833
Epoch 38, Batch 1 loss: 4.454162
Epoch 38, Batch 101 loss: 3.971361
Epoch 38, Batch 201 loss: 3.941253
Epoch 38, Batch 301 loss: 3.978968
Epoch: 38        Training Loss: 3.980290        Validation Loss: 3.840586
Validation loss decreased (3.861820 --> 3.840586).  Saving model ...
Epoch 39, Batch 1 loss: 4.057964
Epoch 39, Batch 101 loss: 3.919207
Epoch 39, Batch 201 loss: 3.955767
```

```
Epoch 39, Batch 301 loss: 3.965198
Epoch: 39 	Training Loss: 3.972845 	Validation Loss: 3.868381
Epoch 40, Batch 1 loss: 3.807726
Epoch 40, Batch 101 loss: 3.941514
Epoch 40, Batch 201 loss: 3.949837
Epoch 40, Batch 301 loss: 3.966057
Epoch: 40 	Training Loss: 3.964358 	Validation Loss: 3.863968
```

```
In [30]: # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('model_scratches.pt'))
```

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 [31]: 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(loader_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.983341


Test Accuracy: 11% (93/836)
```

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 [32]:
```
## TODO: Specify data loaders
loader_transfer = loader_scratch.copy()
```

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 [33]:
```
import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
model_transfer = models.resnet50(pretrained=True)

for param in model_transfer.parameters():
    param.requires_grad = False

model_transfer.fc = nn.Linear(2048,133,bias=True)

fc_parameters = model_transfer.fc.parameters()

for param in fc_parameters:
    param.requires_grad = True

model_transfer

if use_cuda:
    model_transfer = model_transfer.cuda()
```

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:01<00:00, 93925726.16it/s]
```

In [34]:
```
model_transfer
```

Out[34]:
```
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): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (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=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (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=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (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=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
```

```
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
        (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): Bottleneck(
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (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
        (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
      )
      (2): Bottleneck(
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (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
        (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
      )
      (3): Bottleneck(
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (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
        (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (relu): ReLU(inplace)
      )
    )
    (layer3): Sequential(
      (0): Bottleneck(
        (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        (relu): ReLU(inplace)
        (downsample): Sequential(
```

```
      (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (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
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (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
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (3): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (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
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (4): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (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
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (5): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (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
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
```

```
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (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
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (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
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
  )
  (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
  (fc): Linear(in_features=2048, 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: After trying using VGG16 pretrained model for our custom CNN i get less accuracy but when i used Transfer Learning with resnet50 pretrained model even after less epochs i get great accuracy as compare to our custom CNN.In our custom CNN even after 40 epochs i get accuracy of 11% and when i used transfer learning even with epoch=10 i get accuracy of 75%. reset also prevents overfitting problems so i think it is the best possible solution to our 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 [49]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(model_transfer.fc.parameters(),lr = 0.02)
```

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 [50]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""

             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)

                     if batch_idx % 100 == 0:
                         print('Epoch %d, Batch %d loss: %.6f' %
                           (epoch, batch_idx + 1, 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)



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


            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 [51]: # train the model
         model_transfer = train(10, loader_transfer, model_transfer, optimizer_transfer, criteri

         # 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, Batch 1 loss: 34.209389
Epoch 1, Batch 101 loss: 37.500393
Epoch 1, Batch 201 loss: 24.466619
Epoch 1, Batch 301 loss: 19.698641
Epoch: 1         Training Loss: 18.799641         Validation Loss: 7.198446
Validation loss decreased (inf --> 7.198446).  Saving model ...
Epoch 2, Batch 1 loss: 3.557804
Epoch 2, Batch 101 loss: 9.666421
Epoch 2, Batch 201 loss: 10.218366
Epoch 2, Batch 301 loss: 10.551362
Epoch: 2         Training Loss: 10.627810         Validation Loss: 7.723756
```

```
Epoch 3, Batch 1 loss: 7.565480
Epoch 3, Batch 101 loss: 9.572866
Epoch 3, Batch 201 loss: 10.244462
Epoch 3, Batch 301 loss: 10.460735
Epoch: 3 	Training Loss: 10.512556 	Validation Loss: 7.977457
Epoch 4, Batch 1 loss: 10.587145
Epoch 4, Batch 101 loss: 9.581202
Epoch 4, Batch 201 loss: 10.382877
Epoch 4, Batch 301 loss: 10.275661
Epoch: 4 	Training Loss: 10.419001 	Validation Loss: 8.017649
Epoch 5, Batch 1 loss: 16.640640
Epoch 5, Batch 101 loss: 10.866409
Epoch 5, Batch 201 loss: 11.022018
Epoch 5, Batch 301 loss: 11.252077
Epoch: 5 	Training Loss: 11.300002 	Validation Loss: 6.176461
Validation loss decreased (7.198446 --> 6.176461).  Saving model ...
Epoch 6, Batch 1 loss: 1.961773
Epoch 6, Batch 101 loss: 10.411688
Epoch 6, Batch 201 loss: 10.536411
Epoch 6, Batch 301 loss: 10.708339
Epoch: 6 	Training Loss: 10.749020 	Validation Loss: 8.280869
Epoch 7, Batch 1 loss: 6.480914
Epoch 7, Batch 101 loss: 11.145477
Epoch 7, Batch 201 loss: 10.780931
Epoch 7, Batch 301 loss: 11.103426
Epoch: 7 	Training Loss: 11.181463 	Validation Loss: 7.321775
Epoch 8, Batch 1 loss: 12.596926
Epoch 8, Batch 101 loss: 10.833867
Epoch 8, Batch 201 loss: 10.775551
Epoch 8, Batch 301 loss: 10.610254
Epoch: 8 	Training Loss: 10.753158 	Validation Loss: 6.962005
Epoch 9, Batch 1 loss: 5.360072
Epoch 9, Batch 101 loss: 10.191726
Epoch 9, Batch 201 loss: 10.829884
Epoch 9, Batch 301 loss: 11.028337
Epoch: 9 	Training Loss: 11.140327 	Validation Loss: 7.453637
Epoch 10, Batch 1 loss: 11.529467
Epoch 10, Batch 101 loss: 10.795544
Epoch 10, Batch 201 loss: 11.106572
Epoch 10, Batch 301 loss: 10.919391
Epoch: 10 	Training Loss: 11.074163 	Validation Loss: 7.244518
```

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 [53]: test(loader_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 9.373858


Test Accuracy: 75% (635/836)
```

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.

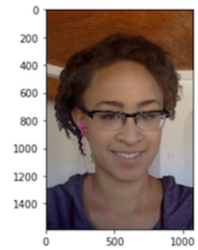
```
In [60]: from PIL import Image
         import torchvision.transforms as transforms

         def load_image(img_path):
             image = Image.open(img_path).convert('RGB')
             # resize the input image into 224x224 because VGG16 takes only 224x224 pixel image
             prediction_transform = transforms.Compose([transforms.Resize(size=(224,224)),
                                                  transforms.ToTensor()
                                                  ])
             image = prediction_transform(image)[:3,:,:].unsqueeze(0)
             return image
```

```
In [61]: ### 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]
         class_names = [item[4:].replace("_", " ") for item in loader_transfer['train'].dataset.

         def predict_breed_transfer(model,class_names,img_path):
             # load the image and return the predicted breed
             img = load_image(img_path)
             model = model.cpu()
             model.eval()
             idx = torch.argmax(model(img))
             return class_names[idx]
```

```
In [62]: for img_file in os.listdir('./images'):
             img_path = os.path.join('./images', img_file)
             predition = predict_breed_transfer(model_transfer, class_names, img_path)
             print("image_file_name: {0}, \t predition breed: {1}".format(img_path, predition))
```

```
image_file_name: ./images/Welsh_springer_spaniel_08203.jpg,          predition breed: Afghan hou
image_file_name: ./images/sample_human_output.png,          predition breed: Portuguese water do
image_file_name: ./images/Labrador_retriever_06457.jpg,          predition breed: Giant schnauze
image_file_name: ./images/Curly-coated_retriever_03896.jpg,          predition breed: Portuguese
image_file_name: ./images/sample_cnn.png,          predition breed: Portuguese water dog
```

hello, human!



You look like a ...
Chinese_shar-pei

Sample Human Output

```
image_file_name: ./images/Brittany_02625.jpg,          predition breed: Brittany
image_file_name: ./images/Labrador_retriever_06449.jpg,          predition breed: Giant schnauze
image_file_name: ./images/American_water_spaniel_00648.jpg,          predition breed: Portuguese
image_file_name: ./images/sample_dog_output.png,          predition breed: Xoloitzcuintli
image_file_name: ./images/Labrador_retriever_06455.jpg,          predition breed: Neapolitan mas
```

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.

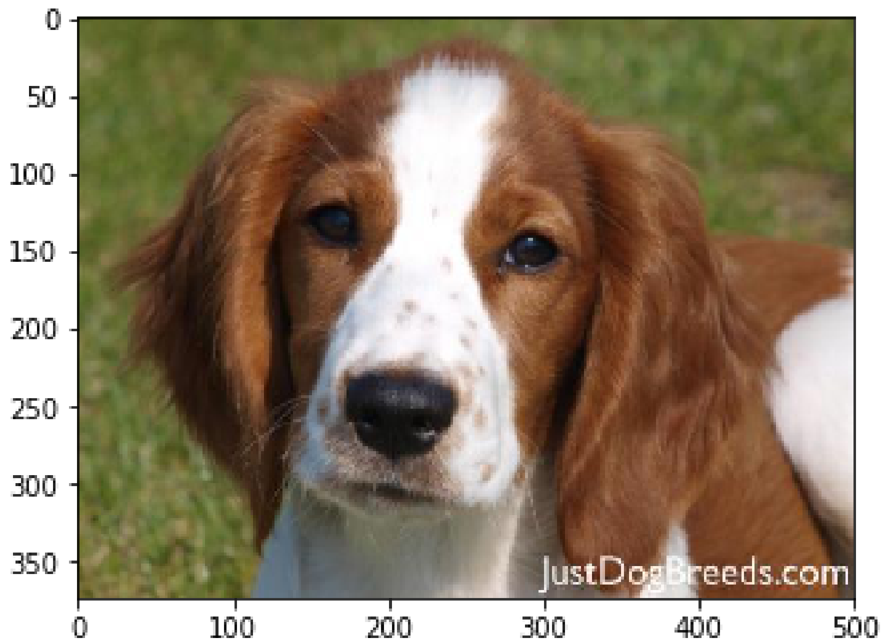
You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

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

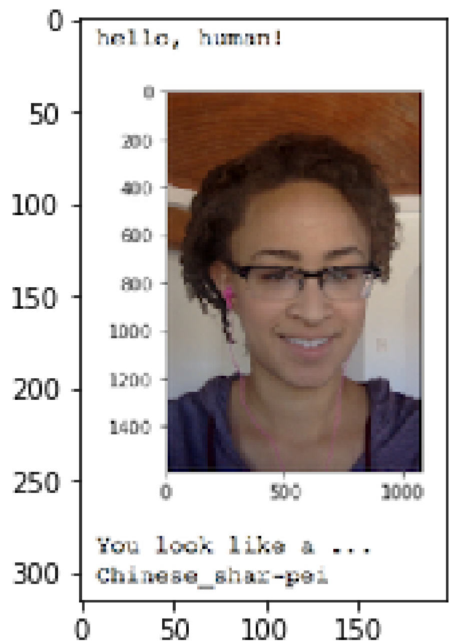
1.1.18 (IMPLEMENTATION) Write your Algorithm

In [67]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
import matplotlib.pyplot as plt
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(model_transfer, class_names,img_path)
        print('Dog is detected !!!!!! Ohh i think it looks {0}'.format(prediction))
    elif face_detector(img_path) > 0:
        prediction = predict_breed_transfer(model_transfer, class_names, img_path)
```

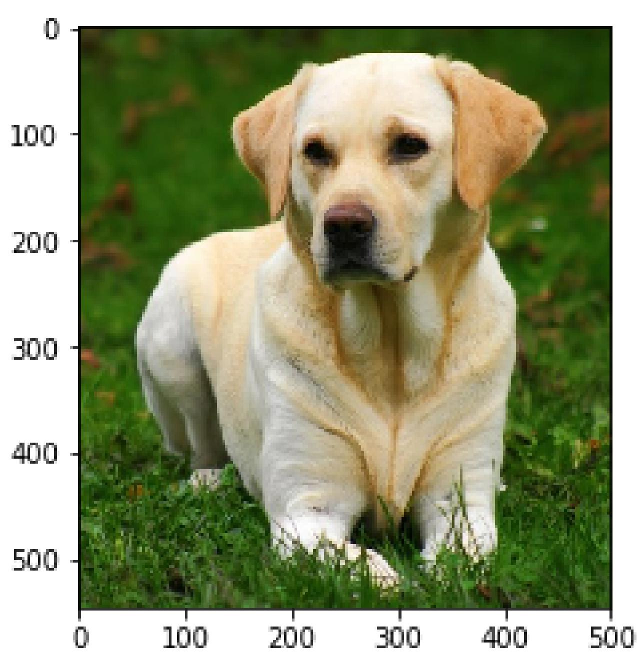
```python
            print("Ohh Human is detected!!!!! Human looks like {0}". format(prediction))
        else:
            print("Error!!!! Neither Dogs are found nor Human in the given supplied image")


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



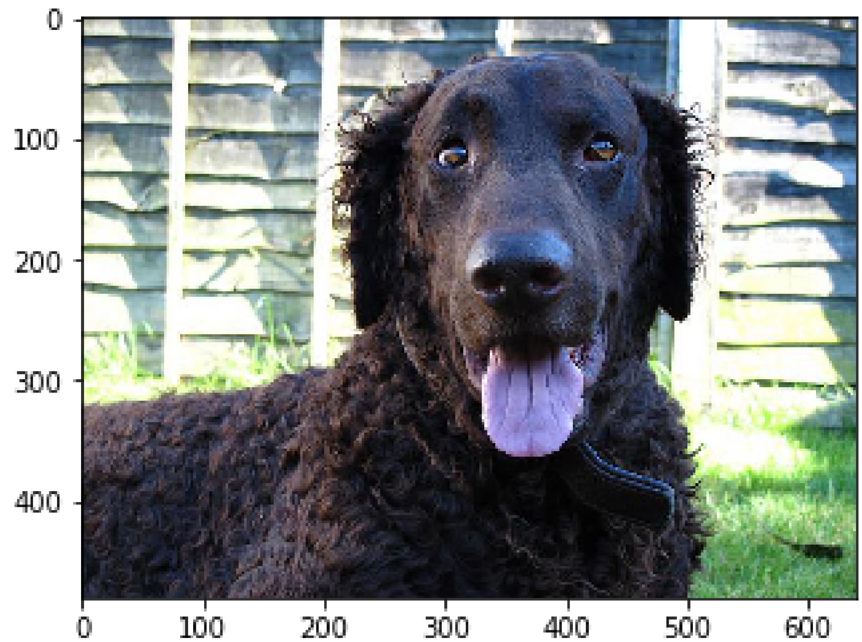

```
Dog is detected !!!!!! Ohh i think it looks Afghan hound
```



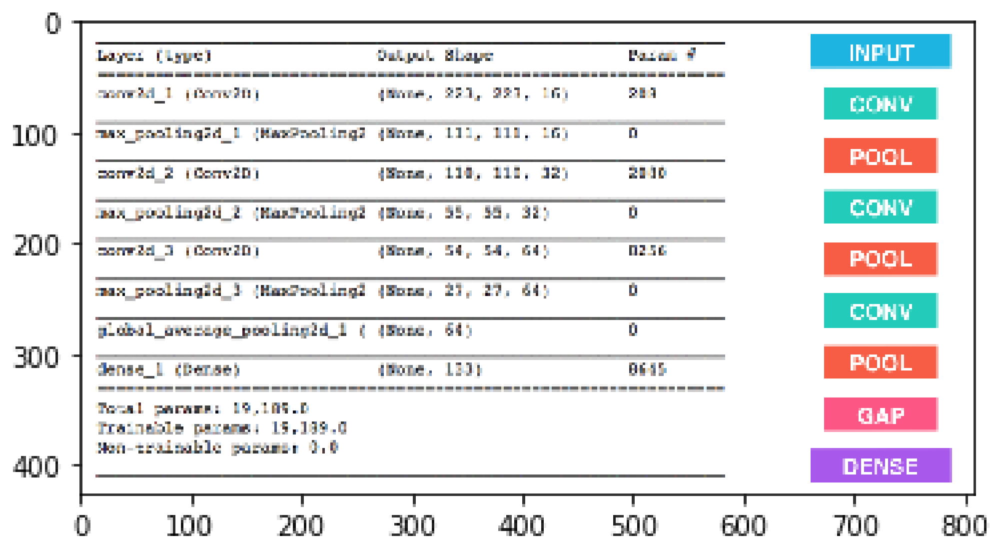

```
Ohh Human is detected!!!!! Human looks like Portuguese water dog
```



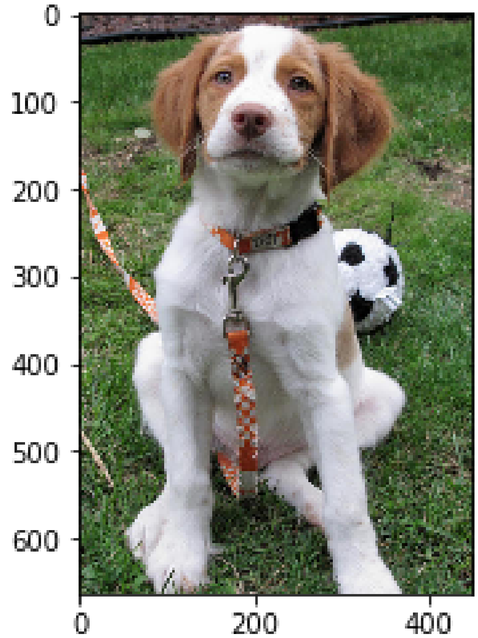
Dog is detected !!!!!! Ohh i think it looks Giant schnauzer



Dog is detected !!!!!! Ohh i think it looks Portuguese water dog



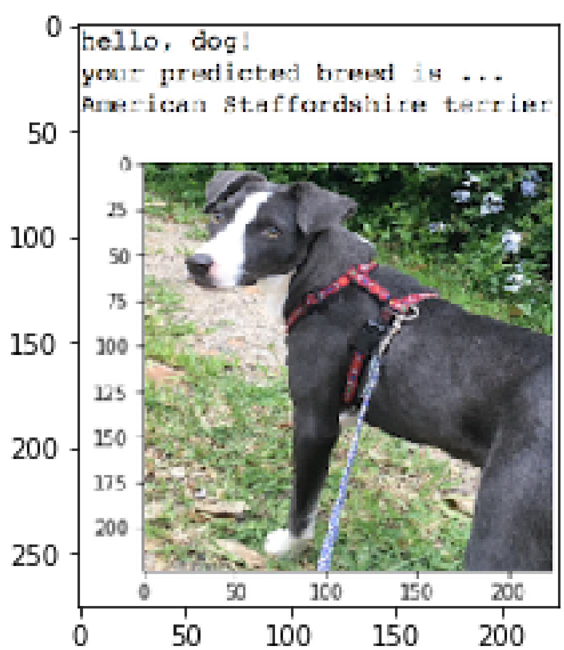
Error!!!! Neither Dogs are found nor Human in the given supplied image



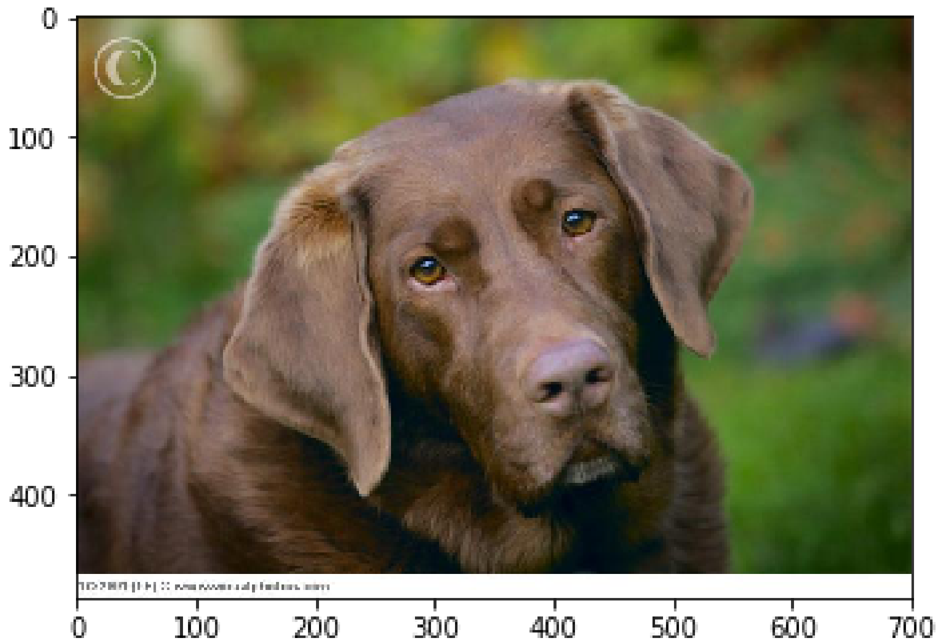
Dog is detected !!!!!! Ohh i think it looks Brittany

Dog is detected !!!!!! Ohh i think it looks Giant schnauzer

Dog is detected !!!!!! Ohh i think it looks Portuguese water dog



```
Error!!!! Neither Dogs are found nor Human in the given supplied image
```




```
Dog is detected !!!!!! Ohh i think it looks Neapolitan mastiff
```

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!

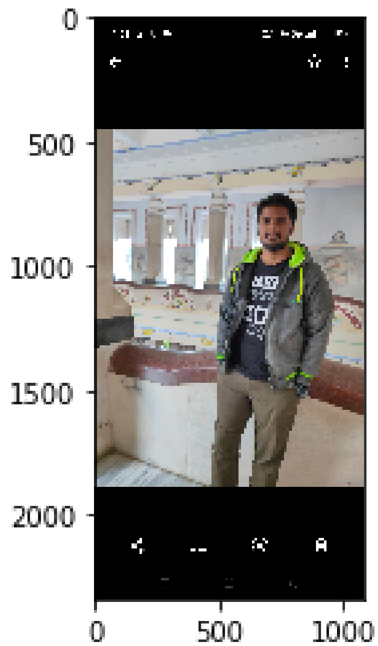
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

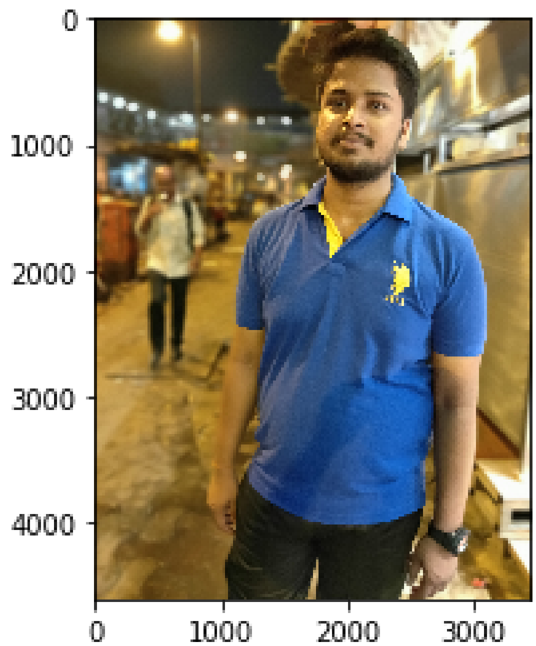
Answer: I tested my algorithm on atleast 7 images out of which 3 images is of human and 2 images is of cat and 2 is of dog. I got the results as expected. My algorithm accurately predicting the dogs breed as well as predicting the human's breed. For further testing i uploaded 2 images of cats in my dog folder. And my algorithm accurately predicts of that given image.It shows its niether human nor dogs. 1).For improving our model we can do hyperparameters changes to get better and more accurate model. 2).We can do more epochs to get even better accuracy for most complex images of dog's breed.

```
In [84]: human_files = ['./test_images/dp.jpg','./test_images/test_images_1.jpg','./test_images/
         dog_files = ['./test_images/dog_1.jpg','./test_images/dog_2.jpg','./test_images/cat_1.j
```

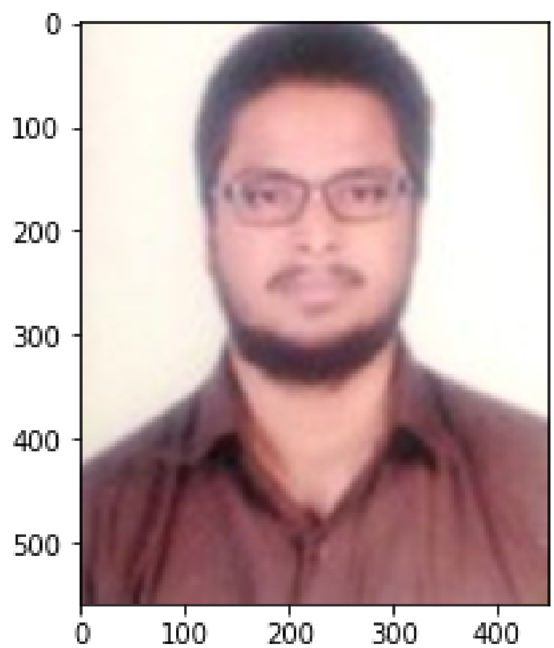
```
In [86]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

         ## suggested code, below
         for file in np.hstack((human_files[:3], dog_files[:4])):
             run_app(file)
```



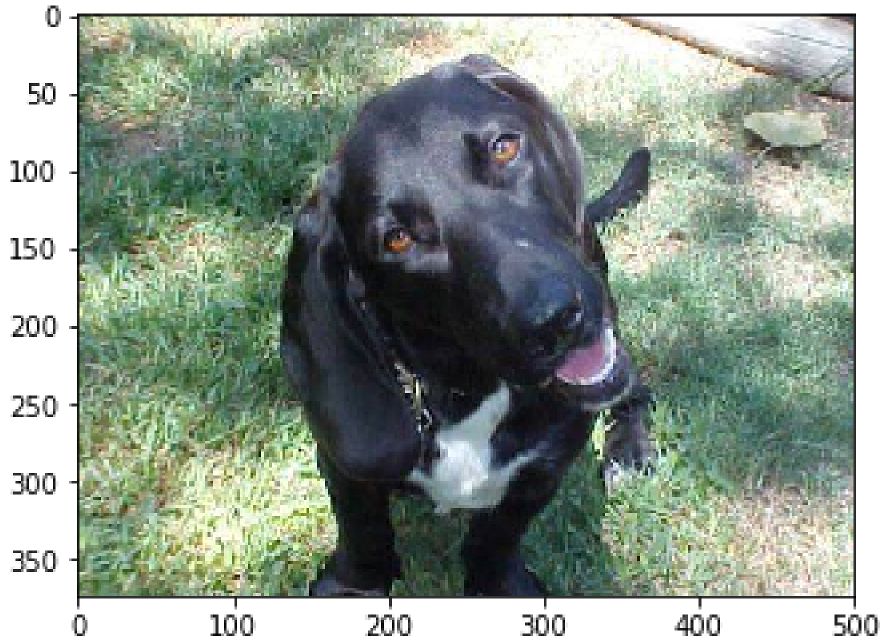
```
Ohh Human is detected!!!!! Human looks like Portuguese water dog
```



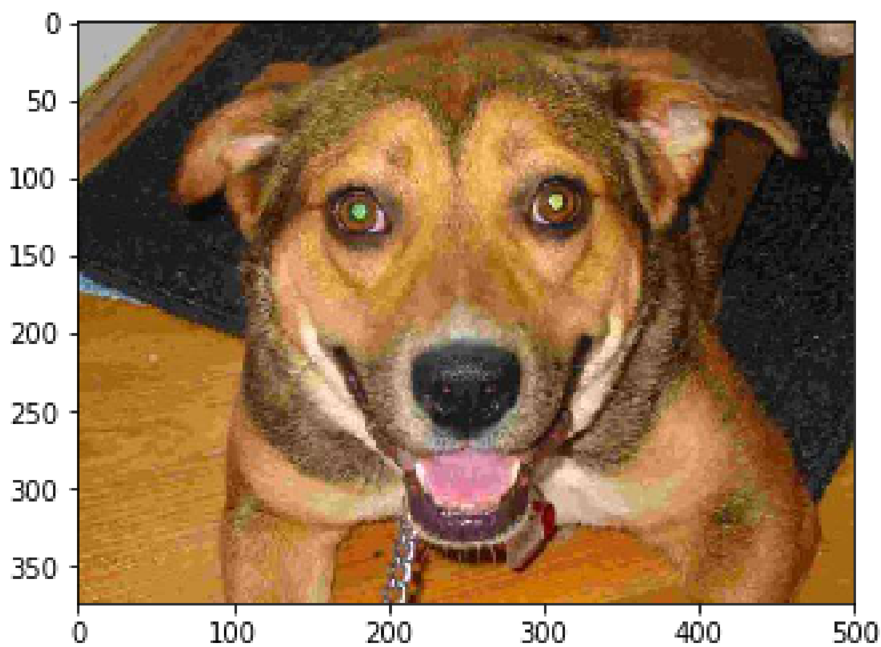

```
Ohh Human is detected!!!!! Human looks like Lowchen
```



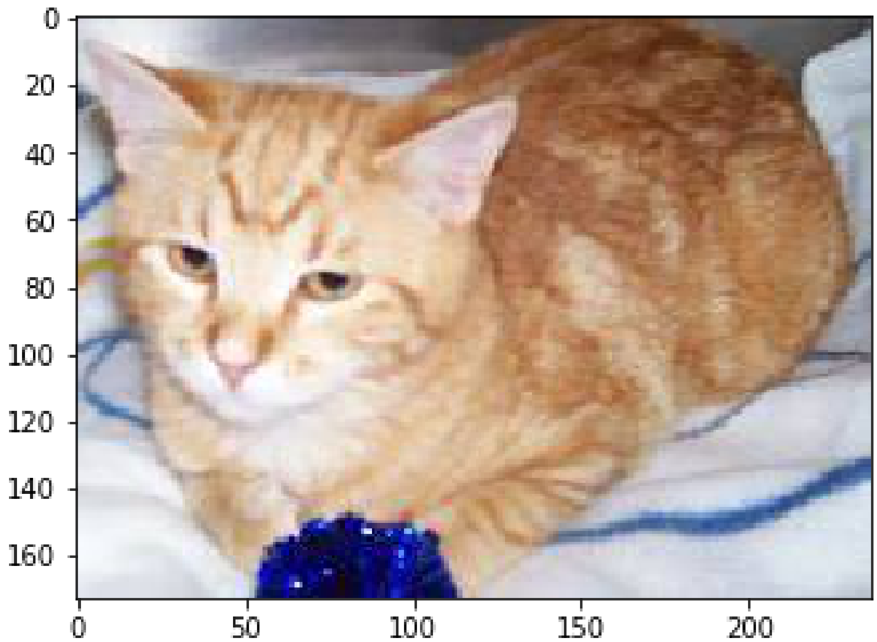
```
Ohh Human is detected!!!!! Human looks like Afghan hound
```



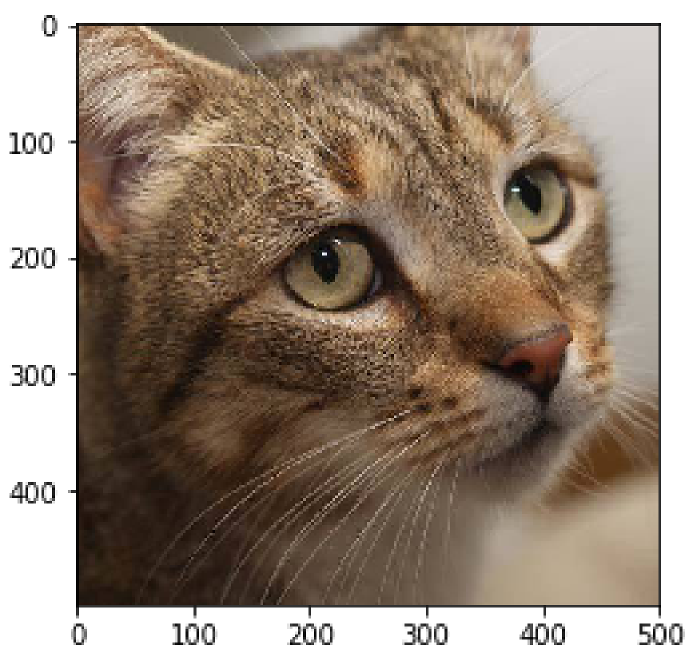

```
Dog is detected !!!!!! Ohh i think it looks Cane corso
```



```
Dog is detected !!!!!! Ohh i think it looks Greyhound
```




```
Error!!!! Neither Dogs are found nor Human in the given supplied image
```



```
Error!!!! Neither Dogs are found nor Human in the given supplied image
```

```
In [ ]:
```