# dog_app

March 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 [62]: 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

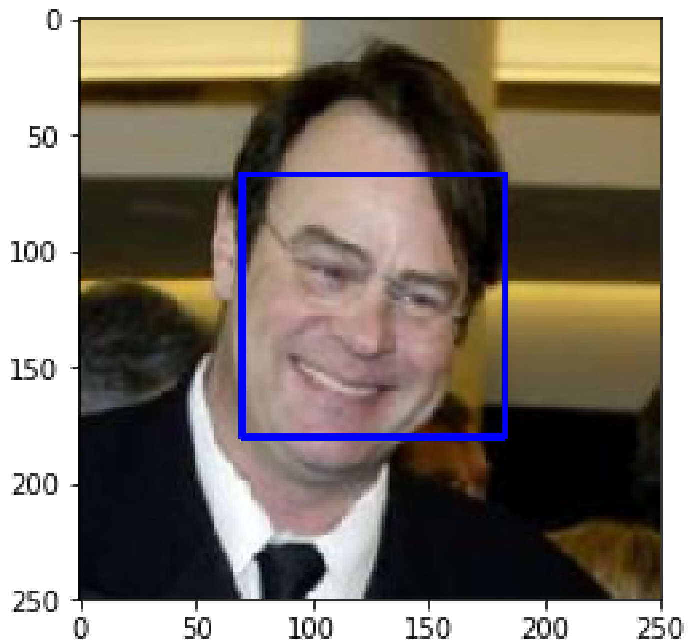
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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 [63]: 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 [64]: # 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:** * Detected human faces in humans = 98% * Detected human faces in dogs = 17%

```
In [65]: 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.
         correct_face_detected = 0 #Count for correctly detected human face
         for i in human_files_short:
             if face_detector(i):
                 correct_face_detected += 1
         face_in_dog_imgs = 0 #Count for human face detected in dog files
         for i in dog_files_short:
             if face_detector(i):
                 face_in_dog_imgs += 1

         print("Detected human faces in humans = {}%".format(correct_face_detected))

         print("Detected human faces in dogs = {}%".format(face_in_dog_imgs))

Detected human faces in humans = 98%
Detected human faces in dogs = 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 [ ]: ### (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 [66]: import torch
         import torchvision.models as models

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

```
In [67]: # define VGG16 model
         import os
         import numpy as np
         import torch

         import torchvision
         from torchvision import datasets, models, transforms
         import matplotlib.pyplot as plt

         %matplotlib inline

         VGG16 = models.vgg16(pretrained=True)

         # 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, 96808576.18it/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 [68]: import os
         import random
         import requests
         import time
         import ast
         import numpy as np
         from glob import glob
         import cv2
         from tqdm import tqdm
         from PIL import Image, ImageFile

         import torch
         import torchvision
         from torchvision import datasets
         import torchvision.transforms as transforms
         import torch.nn as nn
         import torch.nn.functional as F
         import torch.optim as optim
         import torchvision.models as models

         import matplotlib.pyplot as plt
         %matplotlib inline

         ImageFile.LOAD_TRUNCATED_IMAGES = True

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

```
In [69]: def image_to_tensor(img_path):
             '''
             As per Pytorch documentations: All pre-trained models expect input images normalize
             i.e. mini-batches of 3-channel RGB images
             of shape (3 x H x W), where H and W are expected to be at least 224.
             The images have to be loaded in to a range of [0, 1] and
             then normalized using mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225].
             You can use the following transform to normalize:
             '''
             img = Image.open(img_path).convert('RGB')
             transformations = transforms.Compose([transforms.Resize(size=224),
                                                   transforms.CenterCrop((224,224)),
```

```
                                             transforms.ToTensor(),
                                             transforms.Normalize(mean=[0.485, 0.456, 0.406
                                                                  std=[0.229, 0.224, 0.225]
    image_tensor = transformations(img)[:3,:,:].unsqueeze(0)
    return image_tensor


# helper function for un-normalizing an image  - from STYLE TRANSFER exercise
# and converting it from a Tensor image to a NumPy image for display
def im_convert(tensor):
    """ Display a tensor as an image. """

    image = tensor.to("cpu").clone().detach()
    image = image.numpy().squeeze()
    image = image.transpose(1,2,0)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = image.clip(0, 1)

    return image
```

In [70]:
```
def display_image(img_path, title="Title"):
    image = Image.open(img_path)
    plt.title(title)
    plt.imshow(image)
    plt.show()
```

In [71]:
```
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
    '''
    img = image_to_tensor(img_path)
    ## 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

    if use_cuda:
        img = img.cuda()
    ret = VGG16(img)
    return torch.max(ret,1)[1].item() # predicted class index
```

### 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 [72]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             ## TODO: Complete the function.
             pred = VGG16_predict(img_path)

             if pred > 150 and pred < 269:
                 return True
             else:
                 return 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:**

- Dogs detected in dog files = 100%
- Dogs detected in human files = 1%

```
In [73]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         dog_detected_in_dog_files = 0
         dog_detected_in_human_files = 0

         for i in dog_files_short:
             if dog_detector(i):
                 dog_detected_in_dog_files += 1

         for i in human_files_short:
             if dog_detector(i):
                 dog_detected_in_human_files += 1

         print("Dogs detected in dog files = {}%".format(dog_detected_in_dog_files))
         print("Dogs detected in human files = {}%".format(dog_detected_in_human_files))
```

```
Dogs detected in dog files = 100%
Dogs detected in human files = 1%
```

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 [ ]: ### (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 [1]:
```
import os
import torch
from torchvision import datasets
import torchvision.transforms as transforms
from PIL import Image, ImageFile
import numpy as np
from glob import glob
import cv2
import matplotlib.pyplot as plt
%matplotlib inline
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data.sampler import SubsetRandomSampler

ImageFile.LOAD_TRUNCATED_IMAGES = True

use_cuda = torch.cuda.is_available()
```

In [35]:
```
# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 16
# percentage of training set to use as validation
valid_size = 0.2

data_dir = '/data/dog_images/'

train_transform = transforms.Compose([
    transforms.Resize(size=258),
    transforms.RandomCrop((224,224)),
    transforms.RandomHorizontalFlip(), # randomly flip and rotate
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

testvalid_transform = transforms.Compose([
    transforms.Resize(size=258),
    transforms.CenterCrop((224,224)),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
```

```
        ])


# choose the training and test datasets
train_data = datasets.ImageFolder(os.path.join(data_dir, 'train'), train_transform)
test_data = datasets.ImageFolder(os.path.join(data_dir, 'test'), testvalid_transform)

# obtain training indices that will be used for validation
num_train = len(train_data)
indices = list(range(num_train))
np.random.shuffle(indices)
split = int(np.floor(valid_size * num_train))
train_idx, valid_idx = indices[split:], indices[:split]

# define samplers for obtaining training and validation batches
train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
    sampler=train_sampler, num_workers=num_workers)
valid_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
    sampler=valid_sampler, num_workers=num_workers)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
    num_workers=num_workers)
```

In [36]:
```
loaders_scratch = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

In [37]:
```
class_names = train_data.classes
nb_classes = len(class_names)

print("Number of classes:", nb_classes)
print("\nClass names: \n\n", class_names)
```

```
Number of classes: 133

Class names:

 ['001.Affenpinscher', '002.Afghan_hound', '003.Airedale_terrier', '004.Akita', '005.Alaskan_mal
```

**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**: * My code resizes the image first to 258 and then randomly crops it to size 224*224. I picked 224 based on what I had previously used in the class.* The data set is randomly rotated 10 degrees and randomly flipped horizontly as we saw in the previous class that how it diversifies the data set and helps generalise the model and reduce the validation loss.

### 1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [9]: # define the CNN architecture
        class Net(nn.Module):
            ### TODO: choose an architecture, and complete the class
            def __init__(self, constant_weight=None):
                super(Net, self).__init__()
                ## Define layers of a CNN

        #         self.conv1 = nn.Sequential(
        #             nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1),
        #             nn.BatchNorm2d(16),
        #             nn.ReLU())
        #         self.conv2 = nn.Sequential(
        #             nn.Conv2d(16, 32, kernel_size=3, stride=1, padding=1),
        #             nn.BatchNorm2d(32),
        #             nn.ReLU())
                self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
                # convolutional layer (sees 16x16x16 tensor)
                self.conv2 = nn.Conv2d(16, 32, 3, padding=1)

                # convolutional layer (sees 8x8x32 tensor)
                self.conv3 = nn.Conv2d(32, 64, 3, padding=1)

                # max pooling layer
                self.pool = nn.MaxPool2d(2, 2)
                # linear layer (64 * 28 * 28 -> 500)
                self.fc1 = nn.Linear(64 * 28 * 28, 500)
                # linear layer (500 -> 133)
                self.fc2 = nn.Linear(500, 133)
                # dropout layer (p=0.25)
                self.dropout = nn.Dropout(0.25)

                if(constant_weight is not None):
                    for m in self.modules():
                        if isinstance(m, nn.Linear):
                            nn.init.constant_(m.weight, constant_weight)
                            nn.init.constant_(m.bias, 0)

            def forward(self, x):
                ## Define forward behavior
                x = self.pool(F.relu(self.conv1(x)))

                # add dropout layer
                x = self.dropout(x)

                x = self.pool(F.relu(self.conv2(x)))
```

```
            # add dropout layer
            x = self.dropout(x)

            x = self.pool(F.relu(self.conv3(x)))

            # add dropout layer
            x = self.dropout(x)

            # flatten image input
            # 64 * 28 * 28
#             x = x.view(-1, 64 * 28 * 28)
            x = x.view(x.size(0), -1)

            # add 1st hidden layer, with relu activation function
            x = F.relu(self.fc1(x))

            # add dropout layer
            x = self.dropout(x)

            # add 2nd hidden layer, with relu activation function
            x = self.fc2(x)
            return x
```

In [10]:
```
def weights_init_normal(m):
    '''Takes in a module and initializes all linear layers with weight
       values taken from a normal distribution.'''

    classname = m.__class__.__name__
    # for every Linear layer in a model..
    if classname.find('Linear') != -1:
        # get the number of the inputs
        n = m.in_features
        y = 1.0/np.sqrt(n)
        m.weight.data.normal_(0, y)
        m.bias.data.fill_(0)
```

In [11]:
```
#-#-# You so NOT have to modify the code below this line. #-#-#

# instantiate the CNN
model_scratch = Net()
model_scratch.apply(weights_init_normal)

print(model_scratch)

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, 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=50176, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=133, bias=True)
  (dropout): Dropout(p=0.25)
)
```

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

**Answer:**
First layer has input shape of (224, 224, 3) and last layer should output 133 classes.

I started adding Convolutional layers and Maxpooling layers to reduce the x-y size of an input, keeping only the most active pixels from the previous layer as well as the usual Linear + Dropout layers to avoid overfitting and produce a 133-dim output.

MaxPool2d was a common choice as seen in the course.

First conv layer - input of (224,244,3)

Then pooling decreses the x-y dim by a factor of 2 as I use MaxPool2d(kernel_size=2, stride=2).

Second conv layer - input of (112, 112, 16) #no. of filters increased to 16

Then pooling decreses the x-y dim by a factor of 2.

Third conv layer - input of (56, 56, 32) #no. of filters increased to 32

I am adding two fully connected Linear Layer to produce a 133-dim output and a Dropout layer to avoid overfitting. Forward pass would give:

torch.Size([16, 3, 224, 224])

torch.Size([16, 16, 112, 112])

torch.Size([16, 32, 56, 56])

torch.Size([16, 64, 28, 28])

torch.Size([16, 50176])

torch.Size([16, 500])

torch.Size([16, 133])

#### 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 [12]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.Adam(model_scratch.parameters(), lr = 0.001)
```

### 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 [13]:
```
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

    if os.path.exists(save_path):
        model.load_state_dict(torch.load(save_path))

    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(train_loader):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()

            # clear the gradients of all optimized variables
            optimizer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to the model
            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # backward pass: compute gradient of the loss with respect to model paramet
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer.step()
            # update training loss
            train_loss += loss.item()*data.size(0)

        ######################
        # validate the model #
        ######################
        model.eval()
        for data, target in valid_loader:
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
```

```
                ## update the average validation loss

                # forward pass: compute predicted outputs by passing inputs to the model
                output = model(data)
                # calculate the batch loss
                loss = criterion(output, target)
                # update average validation loss
                valid_loss += loss.item()*data.size(0)

            # calculate average losses
            train_loss = train_loss/len(loaders['train'].dataset)
            valid_loss = valid_loss/len(loaders['valid'].dataset)

            # 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
                 # save model if validation loss has decreased
            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 trained model
        return model
```

In [14]:
```
# Train the model
model_scratch = train(15, loaders_scratch, model_scratch, optimizer_scratch, criterion_
```

```
Epoch: 1         Training Loss: 2.853741         Validation Loss: 0.680020
Validation loss decreased (inf --> 0.680020).  Saving model ...
Epoch: 2         Training Loss: 2.729676         Validation Loss: 0.674806
Validation loss decreased (0.680020 --> 0.674806).  Saving model ...
Epoch: 3         Training Loss: 2.659515         Validation Loss: 0.694465
Epoch: 4         Training Loss: 2.595203         Validation Loss: 0.708766
Epoch: 5         Training Loss: 2.562589         Validation Loss: 0.716930
Epoch: 6         Training Loss: 2.506903         Validation Loss: 0.691129
Epoch: 7         Training Loss: 2.470753         Validation Loss: 0.700542
Epoch: 8         Training Loss: 2.402373         Validation Loss: 0.700470
```

```
---------------------------------------------------------------------------
```

```
KeyboardInterrupt                         Traceback (most recent call last)

<ipython-input-14-291990b5ae52> in <module>()
      1 # Train the model
----> 2 model_scratch = train(15, loaders_scratch, model_scratch, optimizer_scratch, criteri


<ipython-input-13-794d47d8c7b2> in train(n_epochs, loaders, model, optimizer, criterion,
     17         ###################
     18         model.train()
---> 19         for batch_idx, (data, target) in enumerate(train_loader):
     20             # move to GPU
     21             if use_cuda:


/opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in __next__(self)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


/opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in <listcomp>(.0)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
     99         """
    100         path, target = self.samples[index]
--> 101         sample = self.loader(path)
    102         if self.transform is not None:
    103             sample = self.transform(sample)


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
    145         return accimage_loader(path)
    146     else:
--> 147         return pil_loader(path)
    148
    149
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
128     with open(path, 'rb') as f:
129         img = Image.open(f)
--> 130         return img.convert('RGB')
131
132


/opt/conda/lib/python3.6/site-packages/PIL/Image.py in convert(self, mode, matrix, dithe
890         """
891
--> 892         self.load()
893
894         if not mode and self.mode == "P":


/opt/conda/lib/python3.6/site-packages/PIL/ImageFile.py in load(self)
233
234                         b = b + s
--> 235                         n, err_code = decoder.decode(b)
236                         if n < 0:
237                             break


KeyboardInterrupt:
```

**Stopped the training beacuse the validation loss was not decreasing further and achieved the required accuracy.**

#### 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 [23]:
```python
# load the model that got the best validation accuracy
model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

In [26]:
```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 += loss.item()*data.size(0)
            # 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 testing statistics

        # calculate average loss
        test_loss = test_loss/len(loaders['test'].dataset)

        # print test statistics
        print('Testing Loss Average: {:.6f} '.format(test_loss))

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

In [38]:
```
# call test function
test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Testing Loss Average: 3.663056

Test Accuracy: 14% (121/836)
```

---

## 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 [39]:
```
import os
import torch
```

```
from torchvision import datasets
import torchvision.transforms as transforms
from PIL import Image, ImageFile
import numpy as np
from glob import glob
import cv2
import matplotlib.pyplot as plt
%matplotlib inline
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data.sampler import SubsetRandomSampler
import torch.optim as optim

ImageFile.LOAD_TRUNCATED_IMAGES = True

use_cuda = torch.cuda.is_available()
```

```
In [45]: loaders_transfer = loaders_scratch
         print(loaders_transfer)
```

```
{'train': <torch.utils.data.dataloader.DataLoader object at 0x7fa6ef63c8d0>, 'valid': <torch.uti
```

#### 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 [46]: import torchvision.models as models
         import torch.nn as nn

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

```
In [47]: print(model_transfer)
```

```
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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
```

```
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
```

```
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
  (fc): Linear(in_features=2048, out_features=1000, bias=True)
)
```

In [48]:
```
for param in model_transfer.parameters():
    param.requires_grad = False

#in_features -> 2048, out_features -> 133

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

if use_cuda:
    model_transfer = model_transfer.cuda()

print(model_transfer.fc)
print(model_transfer)
```

```
Linear(in_features=2048, out_features=133, bias=True)
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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
```

```
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
```

```
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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:**

- A trained architecture is very important for current problem as this problem is very complex and has 133 output classes so a trained architecture like resnet which has many layers pretrained helps predicting better output.
- These architectures have very deep features extraction layers and feature detectors which can be used for data sets for images they werent trained on.
- Here I am using resnet 50 available from torchvision. I could also have chosen other architectures but this had better and more layers for feature extraction than others.
- At the end of this architecture I added one fc layer with in_features=2048 and out_features=133 so it can be used for our task as our required output class has 133 features.

### 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 = 0.001)
```

### 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]: # train the model
         model_transfer =  train(15, loaders_transfer, model_transfer, optimizer_transfer, crite
         # 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: 0.558871         Validation Loss: 0.089295
Validation loss decreased (inf --> 0.089295).  Saving model ...
Epoch: 2        Training Loss: 0.462816         Validation Loss: 0.104021
Epoch: 3        Training Loss: 0.460797         Validation Loss: 0.120410
Epoch: 4        Training Loss: 0.447120         Validation Loss: 0.128349
Epoch: 5        Training Loss: 0.383410         Validation Loss: 0.111390
```

```
    ---------------------------------------------------------------------------

    KeyboardInterrupt                         Traceback (most recent call last)

    <ipython-input-50-b1d3b266ae0c> in <module>()
      1 # train the model
----> 2 model_transfer =  train(15, loaders_transfer, model_transfer, optimizer_transfer, cr
      3 # load the model that got the best validation accuracy (uncomment the line below)
      4 #model_transfer.load_state_dict(torch.load('model_transfer.pt'))


    <ipython-input-13-794d47d8c7b2> in train(n_epochs, loaders, model, optimizer, criterion,
     17         ###################
     18         model.train()
---> 19         for batch_idx, (data, target) in enumerate(train_loader):
     20             # move to GPU
     21             if use_cuda:


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in __next__(self)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in <listcomp>(.0)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
 99         """
100         path, target = self.samples[index]
--> 101         sample = self.loader(path)
102         if self.transform is not None:
103             sample = self.transform(sample)


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
145         return accimage_loader(path)
146     else:
--> 147         return pil_loader(path)
148 
149 


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
128     with open(path, 'rb') as f:
129         img = Image.open(f)
--> 130         return img.convert('RGB')
131 
132 


/opt/conda/lib/python3.6/site-packages/PIL/Image.py in convert(self, mode, matrix, dithe
890         """
891 
--> 892         self.load()
893 
894         if not mode and self.mode == "P":


/opt/conda/lib/python3.6/site-packages/PIL/ImageFile.py in load(self)
233 
234                             b = b + s
--> 235                             n, err_code = decoder.decode(b)
236                             if n < 0:
237                                 break


KeyboardInterrupt:
```

```
In [52]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

### 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(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

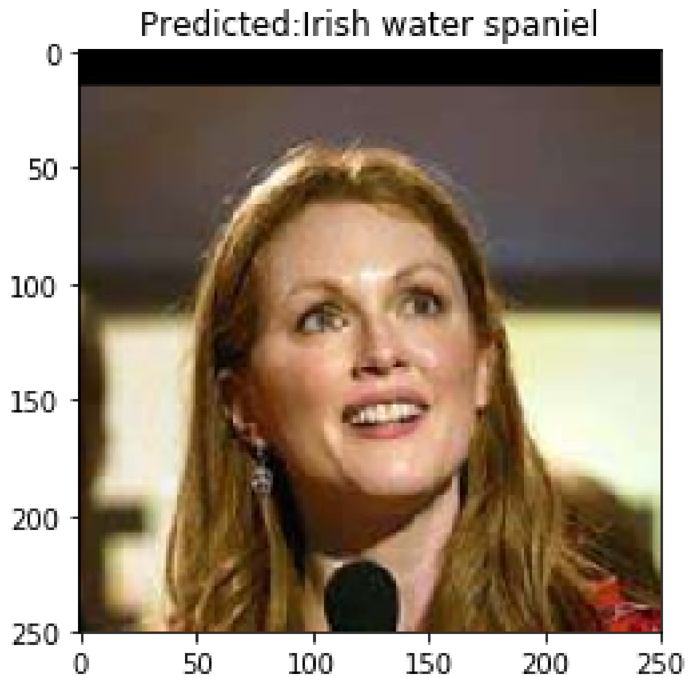
```
Testing Loss Average: 0.628658

Test Accuracy: 83% (700/836)
```

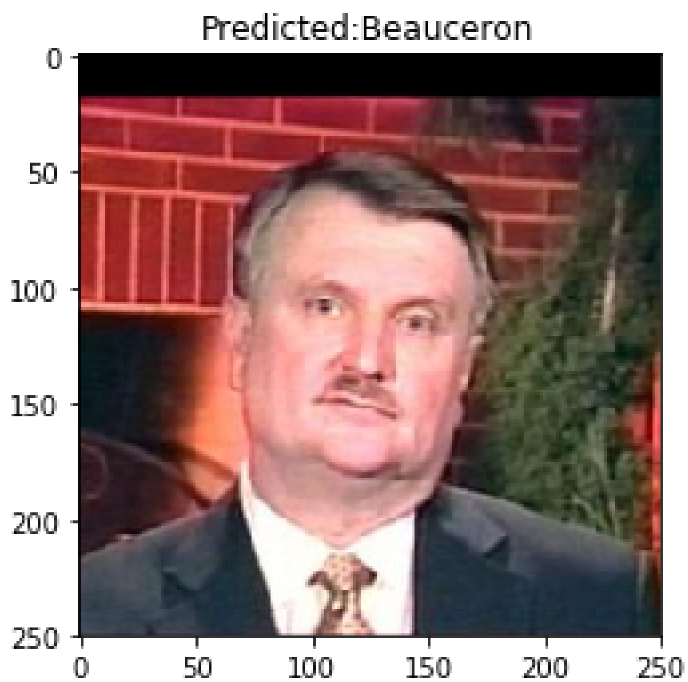
### 1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

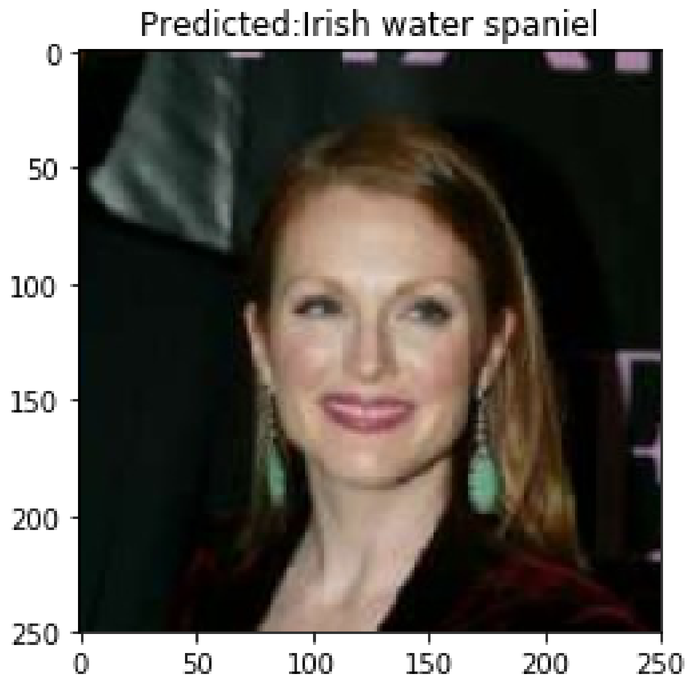
Write a function that takes an image path as input and returns the dog breed (`Affenpinscher`, `Afghan hound`, etc) that is predicted by your model.

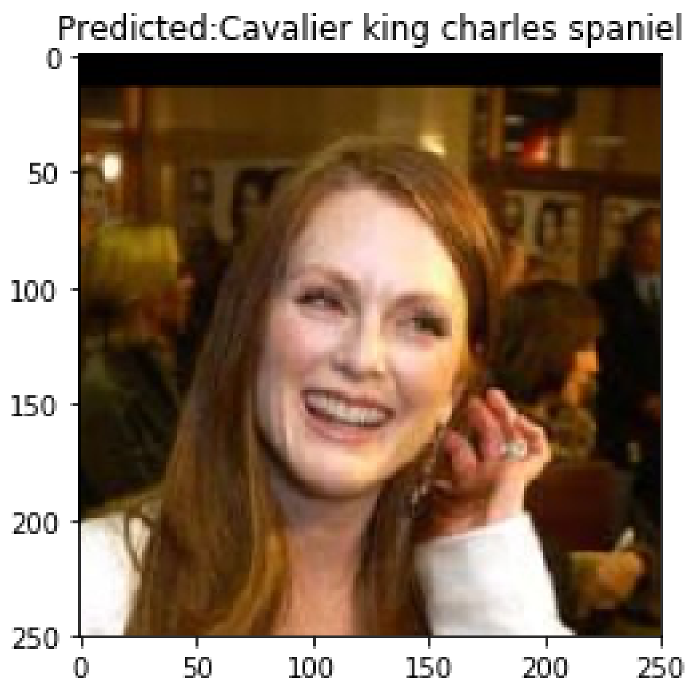
```
In [54]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.

         # 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 train_data.classes]

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             img = image_to_tensor(img_path)
             if use_cuda:
                 img = img.cuda()
             output = model_transfer(img)
             _, preds_tensor = torch.max(output, 1)
             pred = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso

             return class_names[pred]
```

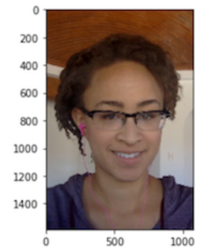
```
In [74]: import random

         # Try out the function
         for image in random.sample(list(human_files_short), 4):
             predicted_breed = predict_breed_transfer(image)
             display_image(image, title=f"Predicted:{predicted_breed}")
```


Predicted:Irish water spaniel
0
50
100
150
200
250
0
50
100
150
200
250


Predicted:Beauceron
0
50
100
150
200
250
0
50
100
150
200
250


Predicted:Irish water spaniel
0
50
100
150
200
250
0
50
100
150
200
250


Predicted:Cavalier king charles spaniel
0
50
100
150
200
250
0
50
100
150
200
250




Sample Human Output

## 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 [75]:
```
### 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
    if dog_detector(img_path):
        print("Hello Doggie!")
        predicted_breed = predict_breed_transfer(img_path)
        display_image(img_path, title=f"Predicted:{predicted_breed}")

    elif face_detector(img_path):
        print("Hello Human!")
        predicted_breed = predict_breed_transfer(img_path)
        display_image(img_path, title=f"Predicted:{predicted_breed}")

    else:
        print("Oh, we're sorry! We couldn't detect any dog or human face in the image."
        display_image(img_path, title="...")
        print("Try another!")
```

---

## 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.

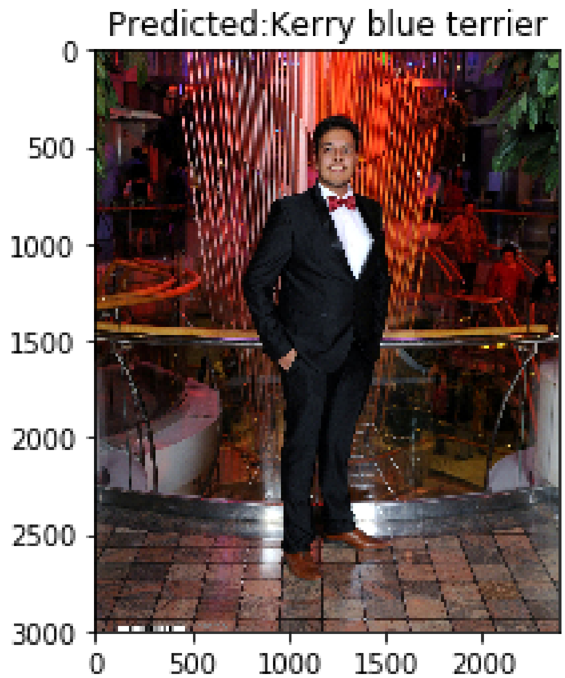
**Question 6:** Is the output better than you expected :) ? Or worse :( ? Provide at least three possible points of improvement for your algorithm.

**Answer:** The output is as expected. The network gave almost 75% accuracy and the human and dog detector gave very high accuracy so the output seems justified. * Fine tune the model to give a better accuracy by training it for more epochs, changing the optimizer and varying the learning rate.

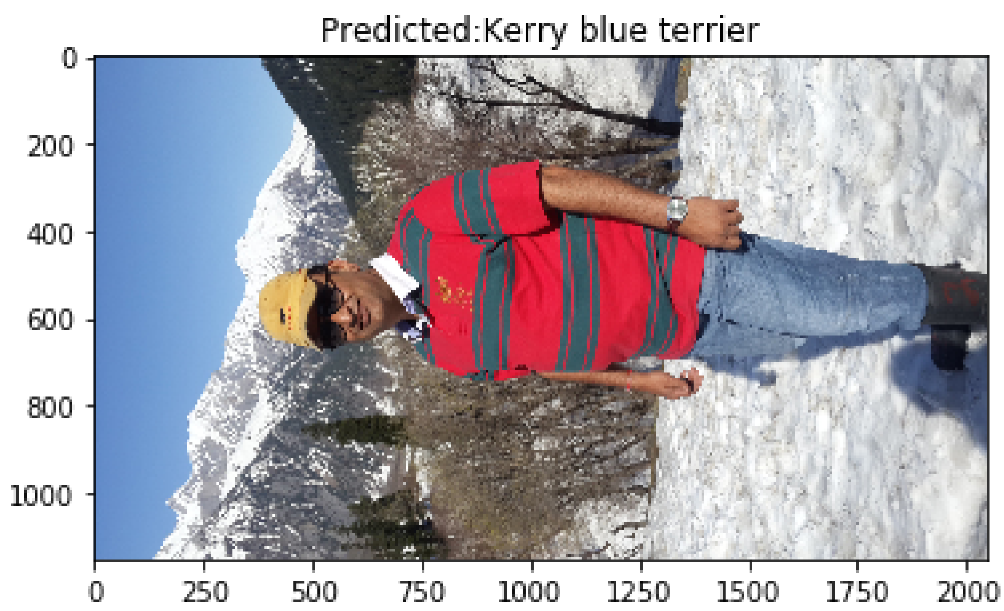
- Add multiple dog detector and add data set for the same.
- Try different data transorms, weight intialisation, image size, optimizers, loss function to get best accuracy.
- Clean up code and make it more modular

```
In [76]: run_app("test1.jpg")
         run_app("test2.jpg")
         run_app("test3.JPG")
         run_app("test4.jpeg")
         run_app("test5.jpeg")
         run_app("test6.jpeg")
```

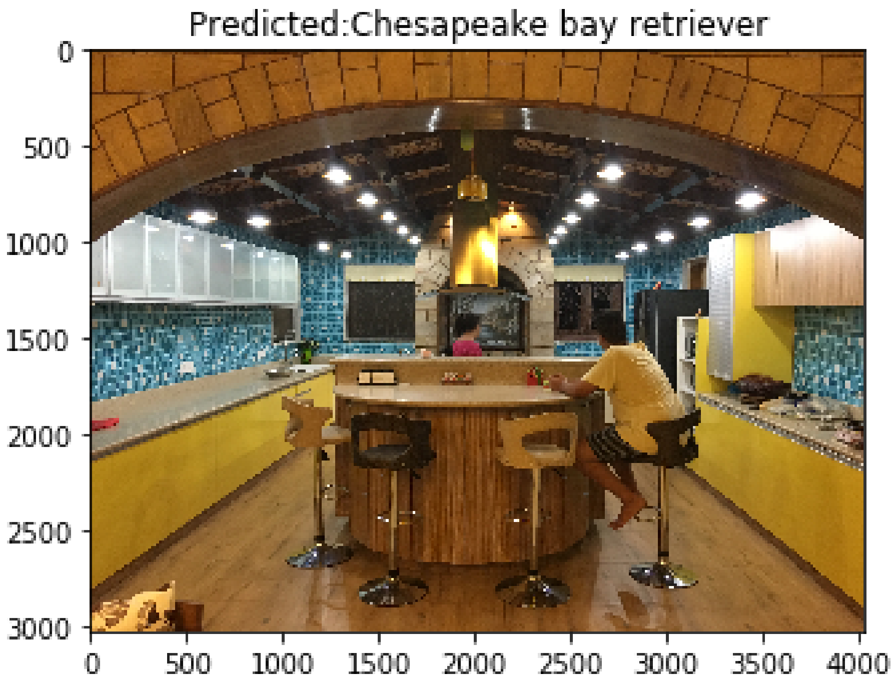
```
Hello Human!
```



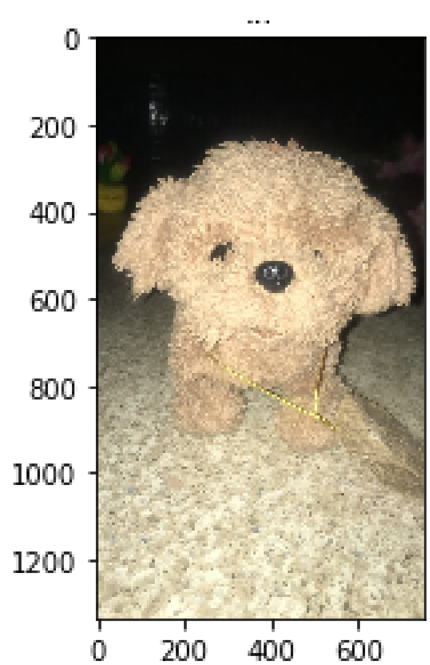

Hello Human!



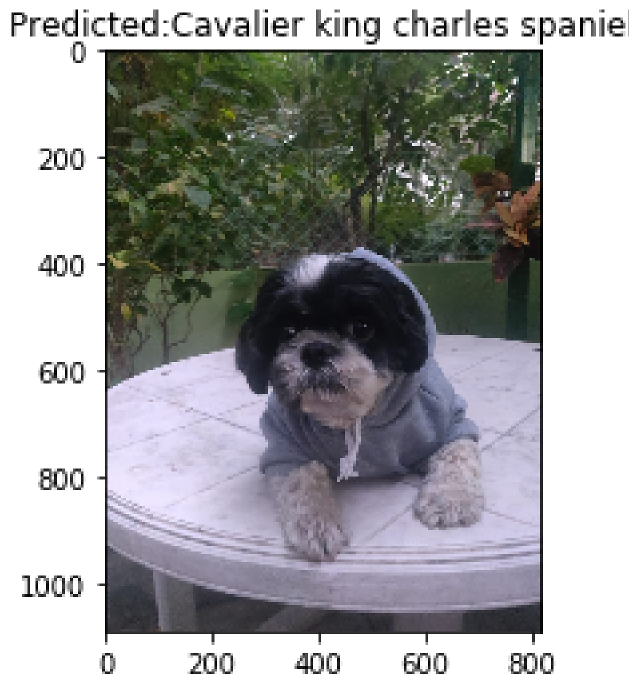

Hello Human!



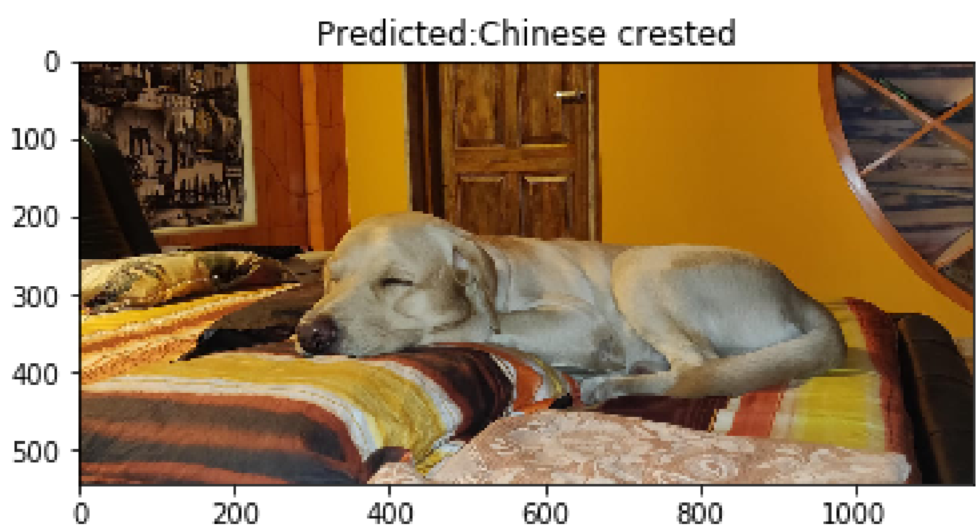

```
Oh, we're sorry! We couldn't detect any dog or human face in the image.
```



```
Try another!
Hello Doggie!
```

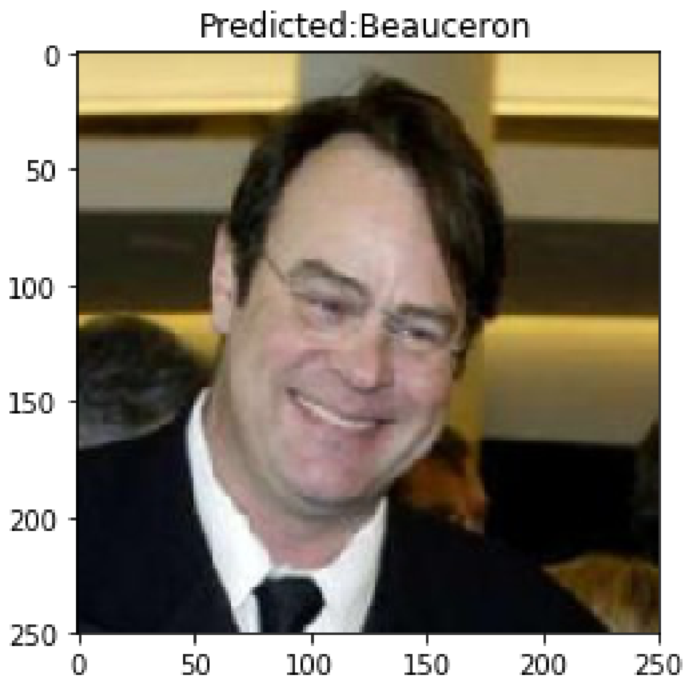



```
Hello Doggie!
```

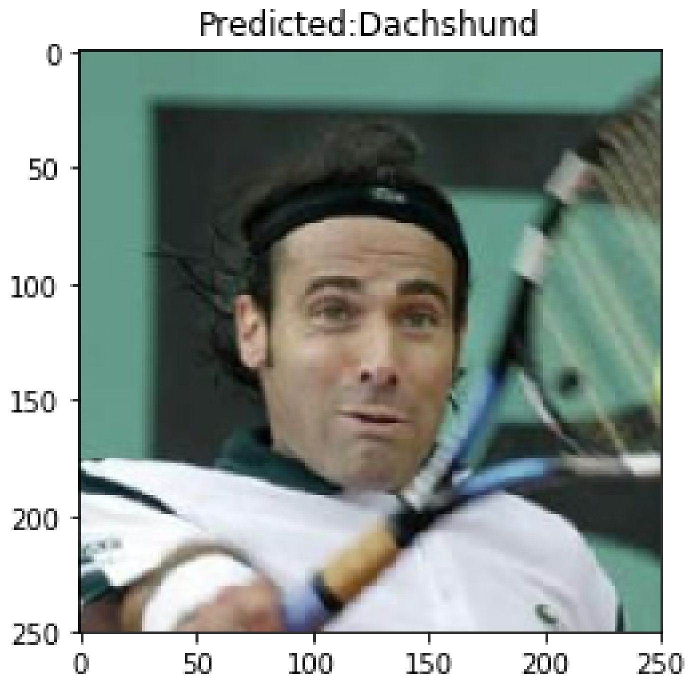


In [77]:
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.

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

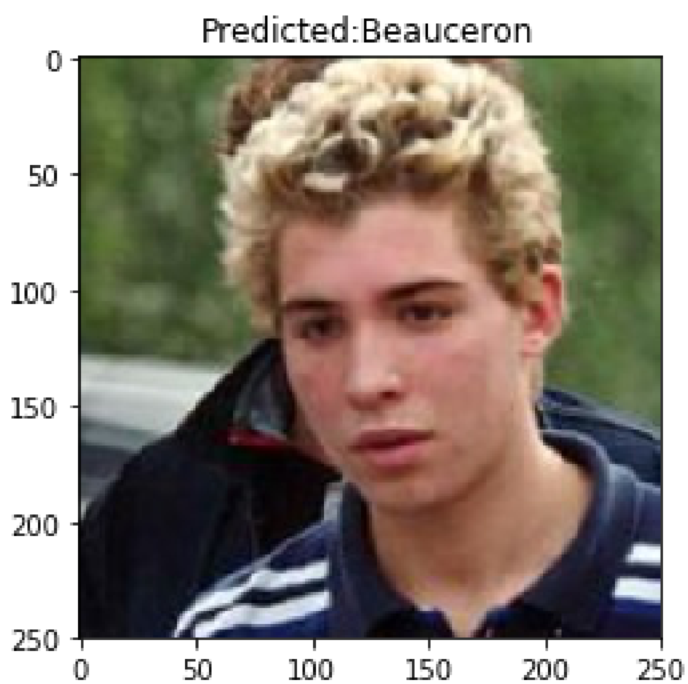
```
Hello Human!
```



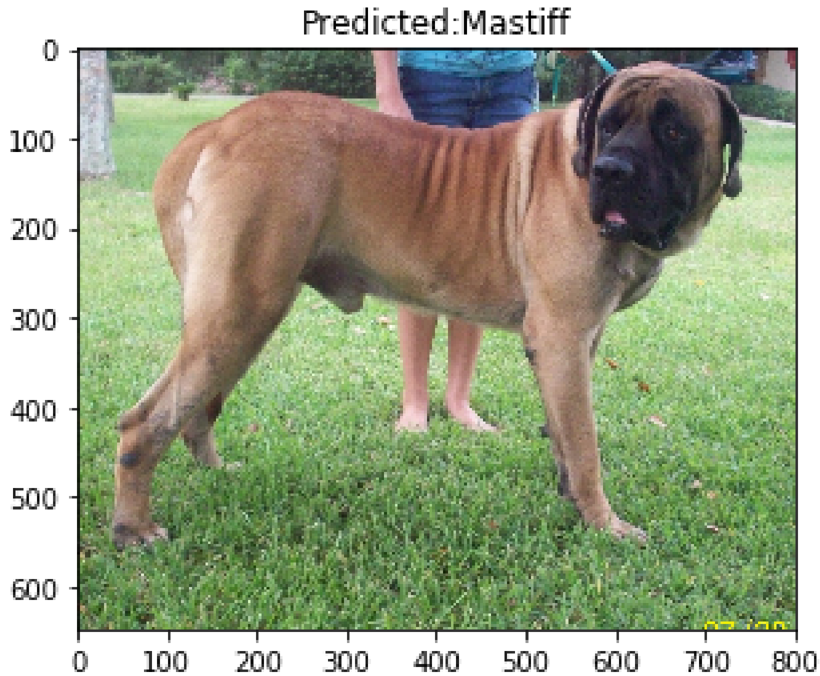

```
Hello Human!
```


Predicted:Dachshund
0
50
100
150
200
250
0
50
100
150
200
250

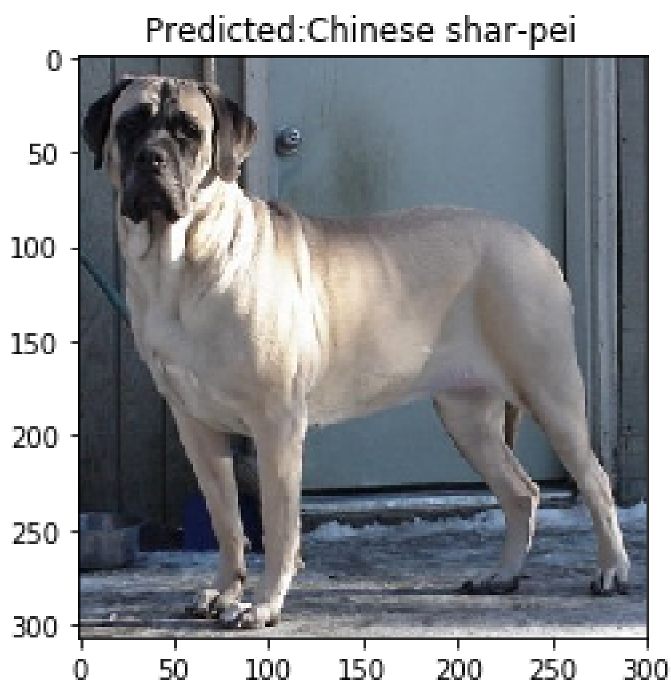
Hello Human!


Predicted:Beauceron
0
50
100
150
200
250
0
50
100
150
200
250

Hello Doggie!




Hello Doggie!



```
Hello Doggie!
```