Convolutional Neural Networks

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.

Why We're Here

In this notebook, you will make the first steps towards developing an algorithm that could be used as part of a mobile or web app. At the end of this project, your code will accept any user-supplied image as input. If a dog is detected in the image, it will provide an estimate of the dog's breed. If a human is detected, it will provide an estimate of the dog breed that is most resembling. The image below displays potential sample output of your finished project (... but we expect that each student's algorithm will behave differently!).

Sample Dog Output

In this real-world setting, you will need to piece together a series of models to perform different tasks; for instance, the algorithm that detects humans in an image will be different from the CNN that infers dog breed. There are many points of possible failure, and no perfect algorithm exists. Your imperfect solution will nonetheless create a fun user experience!

The Road Ahead

We break the notebook into separate steps. Feel free to use the links below to navigate the 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 (https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip). Unzip the folder and place it in this project's home directory, at the location `/dog_images`.
- Download the [human dataset (https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip). 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 (http://www.7-zip.org/)](http://www.7-zip.org/) 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

In [6]:

```
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(d
og_files))
```

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

Step 1: Detect Humans

In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers (http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detec to detect human faces in images.

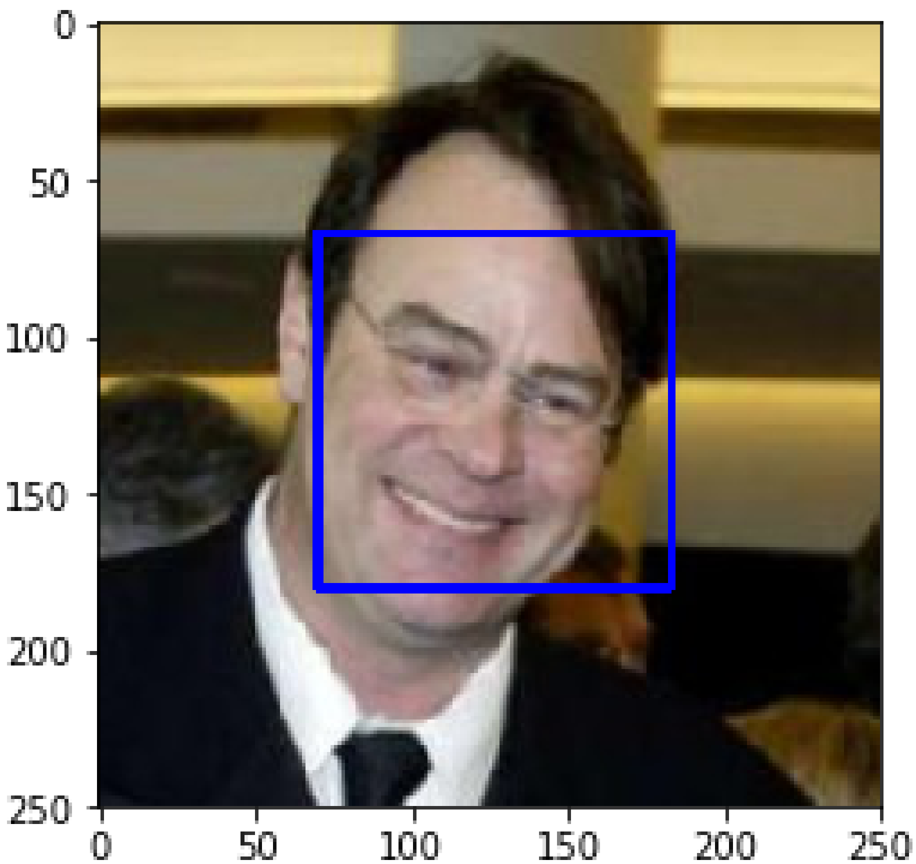
OpenCV provides many pre-trained face detectors, stored as XML files on github (https://github.com/opencv/opencv/tree/master/data/haarcas We have downloaded one of these detectors and stored it in the `haarcascades` directory. In the next code cell, we demonstrate how to use this detector to find human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

In [7]:

```
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.

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 [8]:

```
# 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_BGR2GRA
Y)
    faces = face_cascade.detectMultiScale(gray
)
    return len(faces) > 0
```

(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 [9]:

```
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_dete
ctor algorithm
## on the images in human_files_short and dog_
files_short.
human_files_true, human_files_false = 0, 0
dog_files_true, dog_files_false = 0, 0

for i in range(100):
    if face_detector(human_files_short[i]):
        human_files_true += 1
    else:
        human_files_false += 1

    if face_detector(dog_files_short[i]):
        dog_files_true += 1
    else:
        dog_files_false += 1

print("Percentage of human faces in 100 human
 image files is {} ".format(human_files_true))
```

```
print("Percentage of human faces in 100 dog im
age files is {} ".format(dog_files_true))
```

```
Percentage of human faces in 100
human image files is 98
Percentage of human faces in 100
dog image files is 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 [10]:

```
### (Optional)
### TODO: Test performance of anotherface dete
ction algorithm.
### Feel free to use as many code cells as nee
ded.
```

Step 2: Detect Dogs

In this section, we use a pre-trained model (http://pytorch.org/docs/master/torchvision/models.html) to detect dogs in images.

Obtain Pre-trained VGG-16 Model

The code cell below downloads the VGG-16 model, along with weights that have been trained on ImageNet (http://www.image-net.org/), 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 (https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a).

In [11]:

```
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.py
torch.org/models/vgg16-397923af.p
th" to /root/.torch/models/vgg16-
397923af.pth
100%|██████████| 553433881/553433
881 [00:07<00:00, 77689657.80it/
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.

(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/Affenpinsche`
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 (http://pytorch.org/docs/stable/torchvision/models.html).

In [12]:

```
from PIL import Image
import torchvision.transforms as transforms

def load_image(img_path):
    ''' Load in and transform an image'''
    image = Image.open(img_path).convert('RGB'
)



    # VGG-16 Takes 224x224 images as input, so
we resize all of them and convert data to a no
rmalized torch.FloatTensor
    in_transform = transforms.Compose([
                        transforms.Resize(224
),
                        transforms.CenterCrop(
224),
                        transforms.ToTensor(),
                        transforms.Normalize((
0.5, 0.5, 0.5),
                                             (
0.25, 0.25, 0.25))])

    # discard the transparent, alpha channel
 (that's the :3) and add the batch dimension
    image = in_transform(image)[:3,:,:].unsque
eze(0)
```

```
    return image


def VGG16_predict(img_path):
    '''
    Use pre-trained VGG-16 model to obtain ind
ex corresponding to
    predicted ImageNet class for image at spec
ified 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 cla
ss for that image

    image = load_image(img_path)
    if use_cuda:
        image = image.cuda()
    predict = VGG16(image)
    #predict_index = predict.data.argmax()
    predict_index = torch.max(predict, 1)[1].i
tem()
```

```
    return predict_index # predicted class ind
ex
```

In [13]:

```
VGG16_predict(dog_files_short[1])
```

Out[13]:

```
243
```

(IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary (https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a), 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 [14]:

```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    index = VGG16_predict(img_path)
    if (index>=151 and index<=268):
        return True # return true for the above condition
    else:
        return False
```

In [15]:

```
dog_detector(dog_files_short[50])
```

Out[15]:

```
True
```

In [16]:

```
dog_detector(human_files_short[50])
```

Out[16]:

```
False
```

(IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.

- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

Answer:

In [17]:

```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
from tqdm import tqdm

dog_predict_true, human_predict_true = 0, 0

for i in tqdm(range(len(human_files_short))):
    if dog_detector(human_files_short[i]):
        human_predict_true += 1
for i in tqdm(range(len(dog_files_short))):
    if dog_detector(dog_files_short[i]):
        dog_predict_true += 1

print("Percentage of human faces predicted through dog detector is {} ".format(human_predict_true))
print("Percentage of dog faces predicted through dog detector is {} ".format(dog_predict_true))
```

```
100%|██████████| 100/100 [00:03<0
0:00, 30.70it/s]
100%|██████████| 100/100 [00:04<0
0:00, 25.57it/s]

Percentage of human faces predict
ed through dog detector is 0
Percentage of dog faces predicted
through dog detector is 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 (http://pytorch.org/docs/master/torchvision/models.html#inc v3)](http://pytorch.org/docs/master/torchvision/models.html#inception-v3), [ResNet-50 (http://pytorch.org/docs/master/torchvision/models.html#id3](http://pytorch.org/docs/master/torchvision/models.html#id3) 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 [18]:

```
### (Optional)
### TODO: Report the performance of another pr
e-trained network.
### Feel free to use as many code cells as nee
ded.
```

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 Wate

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 La

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!

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate [data loaders (http://pytorch.org/docs/stable/data.html#torch.utils.data.Da](http://pytorch.org/docs/stable/data.html#torch.utils.data.Da) 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 (http://pytorch.org/docs/stable/torchvision/datasets.html)](http://pytorch.org/docs/stable/torchvision/datasets.html) to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of [transforms (http://pytorch.org/docs/stable/torchvision/transforms.html?](http://pytorch.org/docs/stable/torchvision/transforms.html?)

In [19]:

```
import os
from torchvision import datasets
import torchvision.transforms as transforms
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes

# no. of subprocesses used for data loading
num_workers = 0
# samples per batch to load
batch_size = 20

# Data Directory
data_dir = '/data/dog_images/'
train_data_dir = os.path.join(data_dir, 'train/')
valid_data_dir = os.path.join(data_dir, 'valid/')
test_data_dir = os.path.join(data_dir, 'test/')

# convert data into a normalised torch.FloatTensor
transform_train = transforms.Compose([
    transforms.Resize(224),
```

```
    transforms.CenterCrop(224),
    transforms.RandomRotation(30),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.2
5, 0.25, 0.25))
    ])

transform_validation = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.2
5, 0.25, 0.25))
    ])

# choose the training, valid and test datasets
train_data = datasets.ImageFolder(train_data_d
ir, transform = transform_train)
valid_data = datasets.ImageFolder(valid_data_d
ir, transform = transform_validation)
test_data = datasets.ImageFolder(test_data_dir
, transform = transform_validation)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(tra
in_data, batch_size = batch_size, num_workers
= num_workers, shuffle = True)
valid_loader = torch.utils.data.DataLoader(val
id_data, batch_size = batch_size, num_workers
= num_workers, shuffle = False)
```

```
test_loader = torch.utils.data.DataLoader(valid_data, batch_size = batch_size, num_workers = num_workers, shuffle = False)

# loading from scratch
loaders_scratch = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

In [20]:

```
print("Total no. of classes in image data directory : {}" .format(len(train_data.classes)))
print("Total no. of training data in image data directory : {}" .format(len(train_data)))
print("Total no. of valid data in image data directory : {}" .format(len(valid_data)))
print("Total no. of test in image data directory : {}" .format(len(test_data)))
```

```
Total no. of classes in image data directory : 133
Total no. of training data in image data directory : 6680
Total no. of valid data in image data directory : 835
Total no. of test in image data directory : 836
```

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:

- For preprocessing the data, firstly i load the data directory, then transform the data for train, valid & test, after then data folder are loaded with transformation and finaly prepared the data loaders.
- I resized the images in 224x224 pixels, because VGG takes the same size specification as its input.
- Augmentation is done via *RandomRotation* of 30 units and *RandomHorizontalFip* and also conversion into Tensors and Normalization the images is been done.

(IMPLEMENTATION) Model Architecture

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

In [21]:

```
import torch.nn as nn
import torch.nn.functional as F

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and comp
lete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN

        # convolutional layer (sees 224*224*3
 image tensor)
        self.conv1 = nn.Conv2d(3, 16, 3, paddi
ng = 1)
        # convolutional layer (sees 112*112*16
image tensor)
        self.conv2 = nn.Conv2d(16, 32, 3, padd
ing = 1)
        # convolutional layer (sees 56*56*32 i
mage tensor)
        self.conv3 = nn.Conv2d(32, 64, 3, padd
ing = 1)
        # convolutional layer (sees 28*28*64 i
mage tensor)

        # maxpooling layer
        self.pool = nn.MaxPool2d(2, 2)
```

```
        # fully connected layers
        self.fc1 = nn.Linear(28*28*64, 500)
        self.fc2 = nn.Linear(500, 133)

        # dropout layer
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        ## Define forward behavior

        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))

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

        # dropout layer1
        x = self.dropout(x)

        # fully connected layer1
        x = F.relu(self.fc1(x))

        # dropout layer2
        x = self.dropout(x)

        # fully connected layer2
        x = self.fc2(x)

        return x
```

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

# instantiate the CNN
model_scratch = Net()

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

In [22]:

```
print(model_scratch)
```

```
Net(
  (conv1): Conv2d(3, 16, kernel_s
ize=(3, 3), stride=(1, 1), paddin
g=(1, 1))
  (conv2): Conv2d(16, 32, kernel_
size=(3, 3), stride=(1, 1), paddi
ng=(1, 1))
  (conv3): Conv2d(32, 64, kernel_
size=(3, 3), stride=(1, 1), paddi
ng=(1, 1))
  (pool): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
  (fc1): Linear(in_features=5017
6, out_features=500, bias=True)
  (fc2): Linear(in_features=500,
out_features=133, bias=True)
  (dropout): Dropout(p=0.2)
)
```

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

Answer:

- The input is RGB image cropped into 224x224 pixel and the depth is 3 (3 colors), we will have our input with the shape 3x224x224.
- The desired no. of output is the same as no. of classes (here we have 133 classes in our images datasets).
- Therefore, I created 3 convolutional layers with relu activation function and one max pooling layer(2,2), the first layer takes (3,224,224) input and converted it into a depth of 16 layers, the filter used was 3x3 with stride of 1 and padding of 1.

1.first convolutional layer (sees 224 *224* 3 image tensor).
2.second convolutional layer (sees 112 *112* 16 tensor).
3.third convolutional layer (sees 56 *56* 32 tensor).

- After the 3rd convolutional layer, the shape of image tensor becomes 28 *28* 64
- one pool layer (2,2) was used in order to reduce the size of the images to half.
- Then flatten image input using view function to reshape the tensor.

- Then, two full connected Linear layers with relu activation function were added, and dropout layers for the hidden layers with a percentage of 25% to avoid the bias:
- first linear layer (64 *4* 4 -> 500).

(IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a [loss function (http://pytorch.org/docs/stable/nn.html#loss-functions)](http://pytorch.org/docs/stable/nn.html#loss-functions) and [optimizer (http://pytorch.org/docs/stable/optim.html)](http://pytorch.org/docs/stable/optim.html). Save the chosen loss function as `criterion_scratch` , and the optimizer as `optimizer_scratch` below.

In [23]:

```
import torch.optim as optim

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

### TODO: select optimizer
optimizer_scratch = optim.SGD(model_scratch.pa
rameters(), lr = 0.01)
```

(IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. [Save the final model parameters (http://pytorch.org/docs/master/notes/serialization.html)](http://pytorch.org/docs/master/notes/serialization.html) at filepath `'model_scratch.pt'` .

In [24]:

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

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

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enume
rate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), ta
rget.cuda()
            ## find the loss and update the mo
del parameters accordingly
            ## record the average training los
s, using something like
            ## train_loss = train_loss + ((1 /
```

```
(batch_idx + 1)) * (loss.data - train_loss))

            # clear the gradients of all optim
ized variables
            optimizer.zero_grad()
            # forward pass: compute predicted
 outputs by passing inputs to the model
            output = model(data)
            # compute batch loss
            loss = criterion(output, target)
            # backpropagation
            loss.backward()
            # perform a single optimizer step
(parameter update)
            optimizer.step()
            # update training loss
            train_loss = train_loss + ((1 / (b
atch_idx + 1)) * (loss.data - train_loss))

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enume
rate(loaders['valid']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), ta
rget.cuda()
            ## update the average validation l
oss
```

```
            # forward pass
            output = model(data)
            # compute batch loss(validation lo
ss)
            loss = criterion(output, target)
            # update validation loss
            valid_loss = valid_loss + ((1 / (b
atch_idx + 1)) * (loss.data - valid_loss))

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

        ## TODO: save the model if validation
 loss has decreased
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased (
{:.6f} --> {:.6f}).  Saving model ...'.format(
            valid_loss_min,
            valid_loss))
            torch.save(model.state_dict(), sav
e_path)
            valid_loss_min = valid_loss
    # return trained model
    return model
```

```
# train the model
model_scratch = train(25, loaders_scratch, mod
el_scratch, optimizer_scratch,
                              criterion_scratch, use_c
uda, 'model_scratch.pt')

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

```
Epoch: 1        Training Loss: 4.
877176  Validation Loss: 4.843791
Validation loss decreased (inf --
> 4.843791).  Saving model ...
Epoch: 2        Training Loss: 4.
768137  Validation Loss: 4.685503
Validation loss decreased (4.8437
91 --> 4.685503).  Saving model
...
Epoch: 3        Training Loss: 4.
606674  Validation Loss: 4.519958
Validation loss decreased (4.6855
03 --> 4.519958).  Saving model
...
Epoch: 4        Training Loss: 4.
432306  Validation Loss: 4.373931
Validation loss decreased (4.5199
58 --> 4.373931).  Saving model
...
Epoch: 5        Training Loss: 4.
313960  Validation Loss: 4.301816
Validation loss decreased (4.3739
31 --> 4.301816).  Saving model
...
Epoch: 6        Training Loss: 4.
212862  Validation Loss: 4.240564
Validation loss decreased (4.3018
16 --> 4.240564).  Saving model
...
Epoch: 7        Training Loss: 4.
```

```
152478  Validation Loss: 4.235842
Validation loss decreased (4.2405
64 --> 4.235842).  Saving model
...
Epoch: 8        Training Loss: 4.
077073  Validation Loss: 4.206270
Validation loss decreased (4.2358
42 --> 4.206270).  Saving model
...
Epoch: 9        Training Loss: 4.
022922  Validation Loss: 4.171990
Validation loss decreased (4.2062
70 --> 4.171990).  Saving model
...
Epoch: 10       Training Loss: 3.
952611  Validation Loss: 4.201785
Epoch: 11       Training Loss: 3.
907908  Validation Loss: 4.142095
Validation loss decreased (4.1719
90 --> 4.142095).  Saving model
...
Epoch: 12       Training Loss: 3.
833783  Validation Loss: 4.192571
Epoch: 13       Training Loss: 3.
776234  Validation Loss: 4.153396
Epoch: 14       Training Loss: 3.
711396  Validation Loss: 4.024396
Validation loss decreased (4.1420
95 --> 4.024396).  Saving model
...
Epoch: 15       Training Loss: 3.
```

```
642509  Validation Loss: 4.064059
Epoch: 16       Training Loss: 3.
574608  Validation Loss: 4.055506
Epoch: 17       Training Loss: 3.
490962  Validation Loss: 4.058595
Epoch: 18       Training Loss: 3.
419300  Validation Loss: 4.057310
Epoch: 19       Training Loss: 3.
353457  Validation Loss: 4.063167
Epoch: 20       Training Loss: 3.
290732  Validation Loss: 4.024445
Epoch: 21       Training Loss: 3.
194374  Validation Loss: 4.075867
Epoch: 22       Training Loss: 3.
116292  Validation Loss: 4.018756
Validation loss decreased (4.0243
96 --> 4.018756).  Saving model
...
Epoch: 23       Training Loss: 3.
026543  Validation Loss: 3.961245
Validation loss decreased (4.0187
56 --> 3.961245).  Saving model
...
Epoch: 24       Training Loss: 2.
937717  Validation Loss: 4.096186
Epoch: 25       Training Loss: 2.
862013  Validation Loss: 4.094659
```

(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 [25]:

```
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 outp
uts 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_i
dx + 1)) * (loss.data - test_loss))
        # convert output probabilities to pred
icted class
        pred = output.data.max(1, keepdim=True
)[1]
        # compare predictions to true label
        correct += np.sum(np.squeeze(pred.eq(t
```

```
arget.data.view_as(pred))).cpu().numpy())
        total += data.size(0)

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

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

# call test function
test(loaders_scratch, model_scratch, criterion
_scratch, use_cuda)
```

```
Test Loss: 3.961245


Test Accuracy: 12% (108/835)
```

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.

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders (http://pytorch.org/docs/master/data.html#torch.utils.data.Da 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

In [35]:

```
## TODO: Specify data loaders
import os
from torchvision import datasets
import torchvision.transforms as transforms
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
### TODO: Write data loaders for training, val
idation, and test sets
## Specify appropriate transforms, and batch_s
izes

# no. of subprocesses used for data loading
num_workers = 0
# samples per batch to load
batch_size = 20
# percentage of training set to use as validat
ion
valid_size = 0.2

# Data Directory
data_dir = '/data/dog_images/'
train_data_dir = os.path.join(data_dir, 'trai
n/')
valid_data_dir = os.path.join(data_dir, 'vali
d/')
test_data_dir = os.path.join(data_dir, 'test/'
)
```

```
# convert data into a normalised torch.FloatTe
nsor
transform_train = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.RandomRotation(30),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.2
5, 0.25, 0.25))
    ])

transform_validation = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.2
5, 0.25, 0.25))
    ])

# choose the training, valid and test datasets
train_data = datasets.ImageFolder(train_data_d
ir, transform = transform_train)
valid_data = datasets.ImageFolder(valid_data_d
ir, transform = transform_validation)
test_data = datasets.ImageFolder(test_data_dir
, transform = transform_validation)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(tra
in_data, batch_size = batch_size, num_workers
```

```
= num_workers, shuffle = True)
valid_loader = torch.utils.data.DataLoader(val
id_data, batch_size = batch_size, num_workers
= num_workers, shuffle = False)
test_loader = torch.utils.data.DataLoader(vali
d_data, batch_size = batch_size, num_workers =
num_workers, shuffle = False)

# Loading from scratch
loaders_transfer = {'train': train_loader, 'va
lid': valid_loader, 'test': test_loader}
```

In [36]:

```
# looking at the specialised convolutional and pooling layers of VGG16
# also its input and output features of fully connected layers
print(VGG16)
print(VGG16.classifier[6].in_features)
print(VGG16.classifier[6].out_features)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_siz
e=(3, 3), stride=(1, 1), padding=
(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_si
ze=(3, 3), stride=(1, 1), padding
=(1, 1))
    (3): ReLU(inplace)
    (4): MaxPool2d(kernel_size=2,
stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_s
ize=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_
size=(3, 3), stride=(1, 1), paddi
ng=(1, 1))
    (8): ReLU(inplace)
    (9): MaxPool2d(kernel_size=2,
stride=2, padding=0, dilation=1,
ceil_mode=False)
    (10): Conv2d(128, 256, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel
_size=(3, 3), stride=(1, 1), padd
```

```
ing=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (15): ReLU(inplace)
    (16): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (22): ReLU(inplace)
    (23): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
```

```
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (29): ReLU(inplace)
    (30): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Linear(in_features=2508
8, out_features=4096, bias=True)
    (1): ReLU(inplace)
    (2): Dropout(p=0.5)
    (3): Linear(in_features=4096,
out_features=4096, bias=True)
    (4): ReLU(inplace)
    (5): Dropout(p=0.5)
    (6): Linear(in_features=4096,
out_features=1000, bias=True)
  )
)
4096
1000
```

(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 [37]:

```
import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
# Loading the VGG16 model from pytorch
model_transfer = models.vgg16(pretrained = Tru
e)

# gradient update stops/Freezing pretrained pa
rameters
for param in model_transfer.features.parameter
s():
    param.requires_grad = False

# producing a new linear layer to introduce ou
r needed outputs
new_fc_layer = nn.Linear(model_transfer.classi
fier[6].in_features, 133)

# updating the last classifier layer
model_transfer.classifier[6] = new_fc_layer

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

In [38]:

```
print(model_transfer)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_siz
e=(3, 3), stride=(1, 1), padding=
(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_si
ze=(3, 3), stride=(1, 1), padding
=(1, 1))
    (3): ReLU(inplace)
    (4): MaxPool2d(kernel_size=2,
stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_s
ize=(3, 3), stride=(1, 1), paddin
g=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_
size=(3, 3), stride=(1, 1), paddi
ng=(1, 1))
    (8): ReLU(inplace)
    (9): MaxPool2d(kernel_size=2,
stride=2, padding=0, dilation=1,
ceil_mode=False)
    (10): Conv2d(128, 256, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel
_size=(3, 3), stride=(1, 1), padd
```

```
ing=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (15): ReLU(inplace)
    (16): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (22): ReLU(inplace)
    (23): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
```

```
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel
_size=(3, 3), stride=(1, 1), padd
ing=(1, 1))
    (29): ReLU(inplace)
    (30): MaxPool2d(kernel_size=
2, stride=2, padding=0, dilation=
1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Linear(in_features=2508
8, out_features=4096, bias=True)
    (1): ReLU(inplace)
    (2): Dropout(p=0.5)
    (3): Linear(in_features=4096,
out_features=4096, bias=True)
    (4): ReLU(inplace)
    (5): Dropout(p=0.5)
    (6): Linear(in_features=4096,
out_features=133, bias=True)
  )
)
```

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

Answer:

- I downloaded the VGG16 model and freezed all its parameters, as for transfer learning, I don't want to train them. They are already well trained.
- I just changed the Final layer of classifier (VGG16.classifier[6]) with my new Linear layer
- As the model has many Conv layers, which are pretrained, they are the ones perfectly suitable for producing feature maps.
- The classifier is also well trained.

Therefore,after training of the last linear layer, the model should have best accuracy.

(IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a [loss function (http://pytorch.org/docs/master/nn.html#loss-functions)](http://pytorch.org/docs/master/nn.html#loss-functions) and [optimizer (http://pytorch.org/docs/master/optim.html)](http://pytorch.org/docs/master/optim.html). Save the chosen loss function as `criterion_transfer` , and the optimizer as `optimizer_transfer` below.

In [39]:

```
criterion_transfer = nn.CrossEntropyLoss()
optimizer_transfer = optim.SGD(model_transfer.
classifier.parameters(), lr = 0.01)
```

(IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. [Save the final model parameters (http://pytorch.org/docs/master/notes/serialization.html)](http://pytorch.org/docs/master/notes/serialization.html) at filepath `'model_transfer.pt'` .

In [40]:

```
# train the model
n_epochs = 20
model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer, criterion_transfer,
                       use_cuda, 'model_transfer.pt')

# 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: 1.
937757  Validation Loss: 0.724736
Validation loss decreased (inf --
> 0.724736).  Saving model ...
Epoch: 2        Training Loss: 0.
951634  Validation Loss: 0.605325
Validation loss decreased (0.7247
36 --> 0.605325).  Saving model
...
Epoch: 3        Training Loss: 0.
758542  Validation Loss: 0.573047
Validation loss decreased (0.6053
25 --> 0.573047).  Saving model
...
Epoch: 4        Training Loss: 0.
658831  Validation Loss: 0.516844
Validation loss decreased (0.5730
47 --> 0.516844).  Saving model
...
Epoch: 5        Training Loss: 0.
556028  Validation Loss: 0.550989
Epoch: 6        Training Loss: 0.
542004  Validation Loss: 0.526290
Epoch: 7        Training Loss: 0.
472010  Validation Loss: 0.521582
Epoch: 8        Training Loss: 0.
432230  Validation Loss: 0.475550
Validation loss decreased (0.5168
44 --> 0.475550).  Saving model
...
```

```
Epoch: 9 	Training Loss: 0.
399862 	Validation Loss: 0.490799
Epoch: 10 	Training Loss: 0.
361041 	Validation Loss: 0.455072
Validation loss decreased (0.4755
50 --> 0.455072).  Saving model
...
Epoch: 11 	Training Loss: 0.
326908 	Validation Loss: 0.493100
Epoch: 12 	Training Loss: 0.
299175 	Validation Loss: 0.468739
Epoch: 13 	Training Loss: 0.
291153 	Validation Loss: 0.452873
Validation loss decreased (0.4550
72 --> 0.452873).  Saving model
...
Epoch: 14 	Training Loss: 0.
249313 	Validation Loss: 0.465284
Epoch: 15 	Training Loss: 0.
246523 	Validation Loss: 0.478785
Epoch: 16 	Training Loss: 0.
233076 	Validation Loss: 0.452092
Validation loss decreased (0.4528
73 --> 0.452092).  Saving model
...
Epoch: 17 	Training Loss: 0.
221275 	Validation Loss: 0.420545
Validation loss decreased (0.4520
92 --> 0.420545).  Saving model
...
Epoch: 18 	Training Loss: 0.
```

```
213242  Validation Loss: 0.495878
Epoch: 19       Training Loss: 0.
196361  Validation Loss: 0.439368
Epoch: 20       Training Loss: 0.
197138  Validation Loss: 0.423334
```

(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 [41]:

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

```
Test Loss: 0.420545


Test Accuracy: 87% (734/835)
```

(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 [43]:

```
### TODO: Write a function that takes a path t
o an image as input
### and returns the dog breed that is predicte
d by the model.

# list of class names by index, i.e. a name ca
n be accessed like class_names[0]
class_names = [item[4:].replace("_", " ") for
item in train_data.classes]

def load_image(img_path):
    ''' Load in and transform an image'''
    image = Image.open(img_path).convert('RGB'
)


    # The model takes 224x224 images as input,
so we resize all of them and convert data to a
normalized torch.FloatTensor
    in_transform = transforms.Compose([
                        transforms.Resize(224
),
                        transforms.CenterCrop(
224),
                        transforms.ToTensor(),
                        transforms.Normalize((
0.5, 0.5, 0.5),
                                             (
```

```
0.25, 0.25, 0.25))])

    # discard the transparent, alpha channel
 (that's the :3) and add the batch dimension
    image = in_transform(image)[:3,:,:].unsque
eze(0)
    return image


def predict_breed_transfer(img_path):
    # load the image and return the predicted
 breed
    image = load_image(img_path)
    if use_cuda:
        image = image.cuda()
    predict = model_transfer(image)
    #predict_index = torch.argmax(predict)
    predict_index = torch.max(predict, 1)[1]

    return class_names[predict_index]
```

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!

Sample Human Output

(IMPLEMENTATION) Write your Algorithm

In [48]:

```
### TODO: Write your algorithm.
### Feel free to use as many code cells as nee
ded.

def run_app(img_path):
    ## handle cases for a human face, dog, and
neither
    image = Image.open(img_path) # Loading the
image

    if dog_detector(img_path):
        plt.imshow(image)
        plt.show()
        prediction = predict_breed_transfer(im
g_path)
        print("Hey!!!There is a doggy.It looks
like {}".format(prediction))

    elif face_detector(img_path):
        plt.imshow(image)
        plt.show()
        prediction = predict_breed_transfer(im
g_path)
        print("Hello Human!!!If you were a dog
gy, you would look like {}".format(prediction
))

    else:
```

```
        plt.imshow(img)
        plt.show()
        print("Oh Sorry!!!Neither human nor do
ggy detected")
```

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?

(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: (Three possible points for improvement)

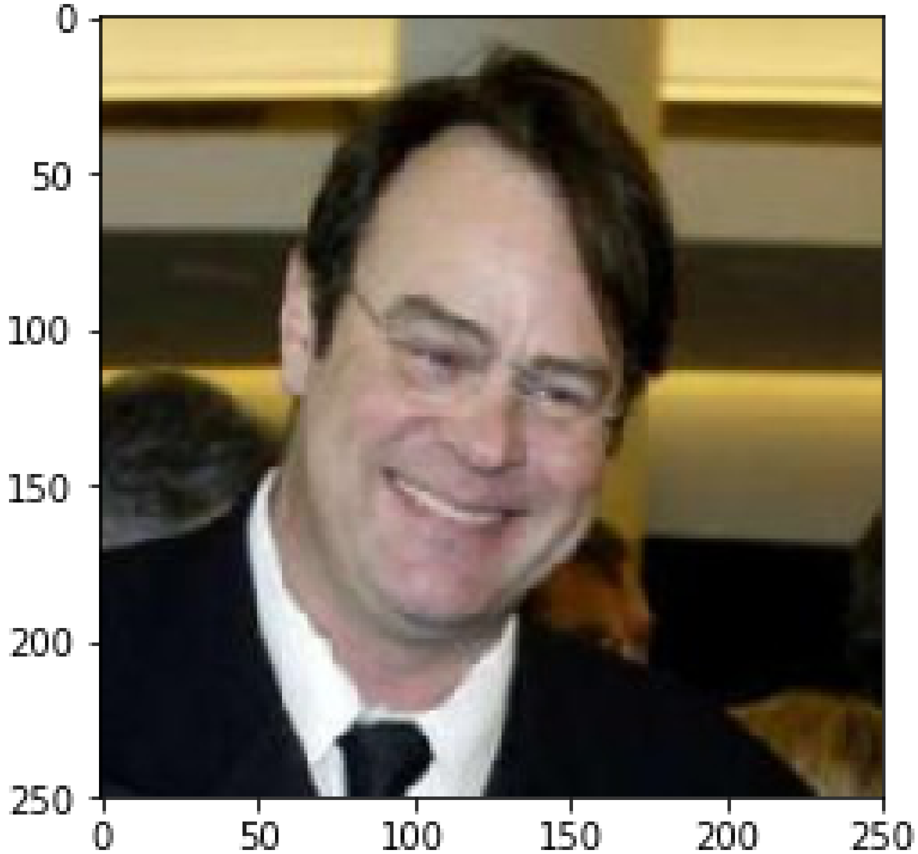
- The scratch model outputs an accuracy of 12%, which is good but needs more improvement.It looks like the model is a bit overfitting the data, so the validation loss increases even in 25 epochs.

I think we can improve the scratch model accuracy by:

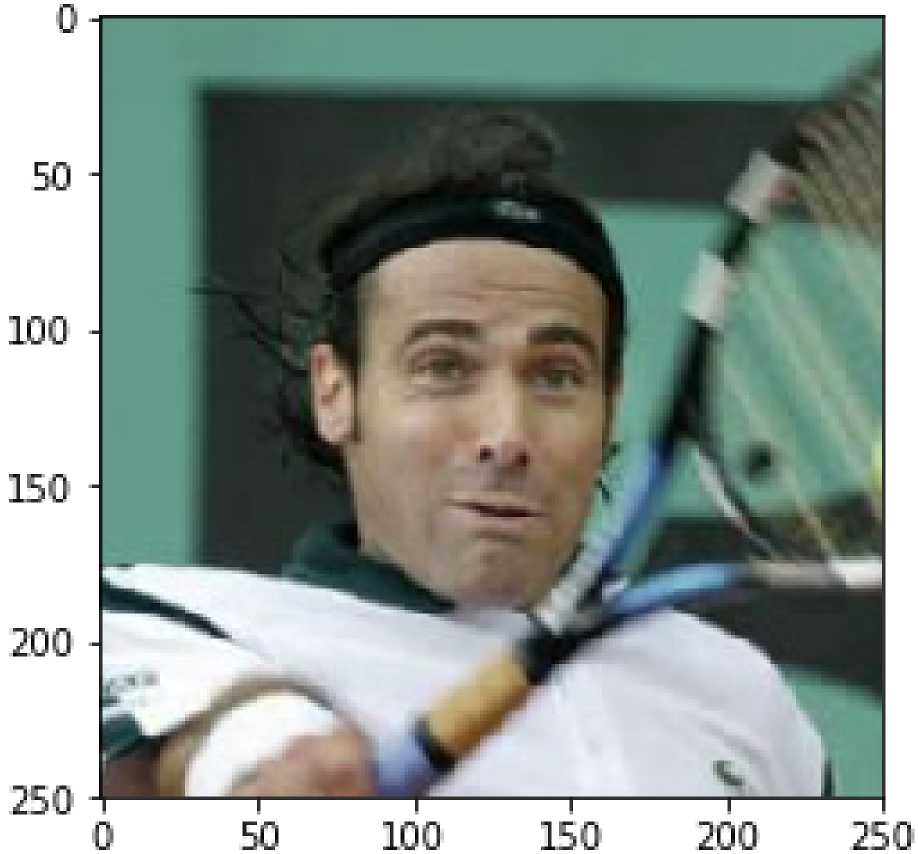
- Increasing the dropout layer by a value of 0.1 as I go by each classification layer.Constant Dropout is likely overfitting the data in the later classification layers.
- I have used 3 convolutional and 2 classification layers.Perhaps increasing them suffices my accuracy.
- We saw that even in 25 epochs, the validation loss increases.Perhaps adding a bit more training data and increasing the no.of epochs may generalise the model better.

In [49]:

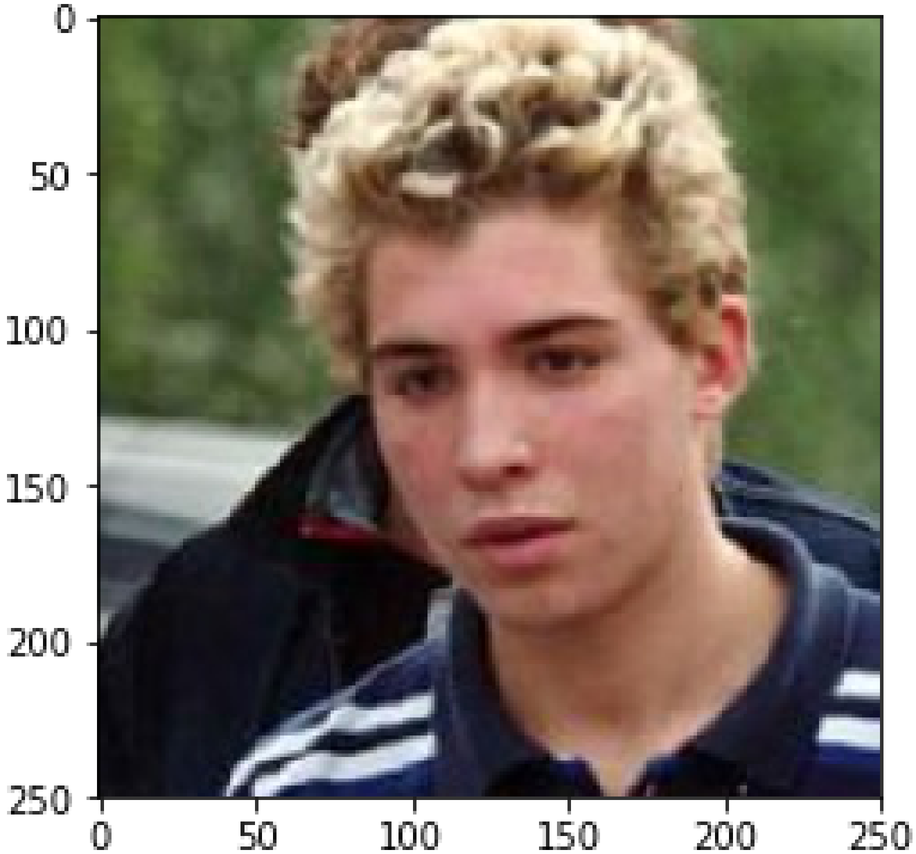
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as need
ed.

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



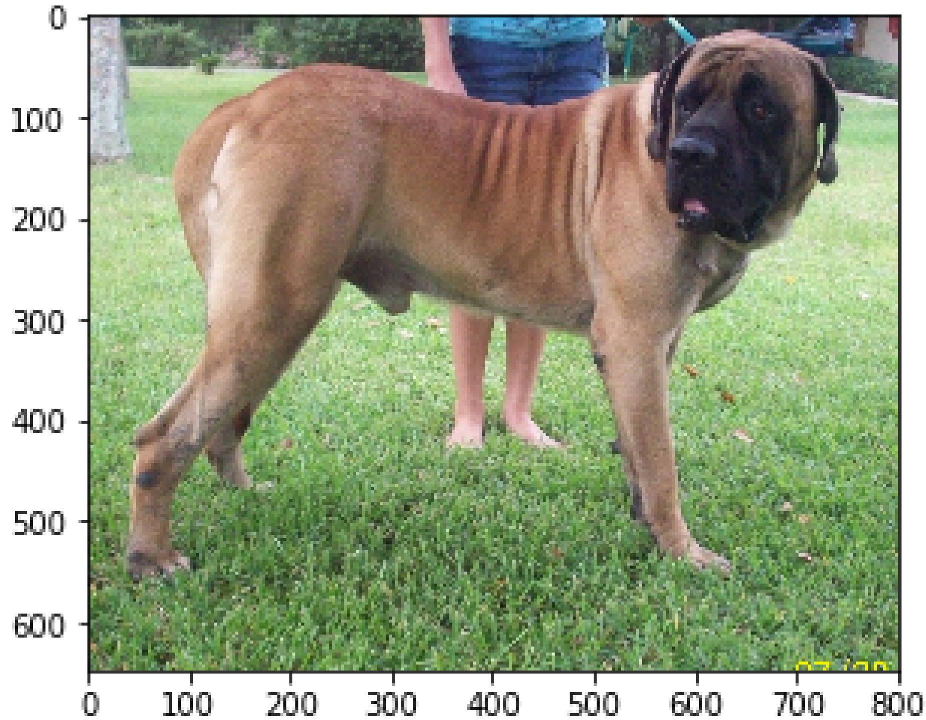

```
Hello Human!!!If you were a dogg
y, you would look like Brittany
```



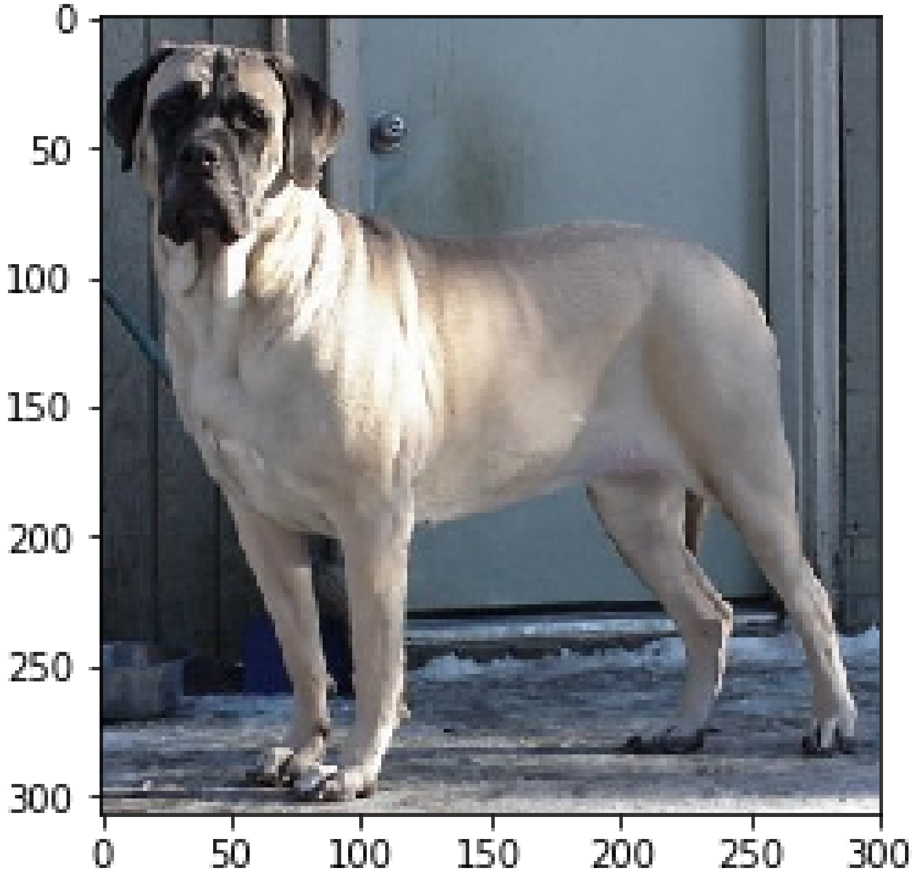
```
Hello Human!!!If you were a dogg
y, you would look like Lowchen
```



```
Hello Human!!!If you were a dogg
y, you would look like Portuguese
water dog
```



Hey!!!There is a doggy.It looks l
ike Mastiff




```
Hey!!!There is a doggy.It looks l
ike Mastiff
```