dog_app

June 2, 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 [57]: import numpy as np
         from glob import glob

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

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

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

Step 1: Detect Humans

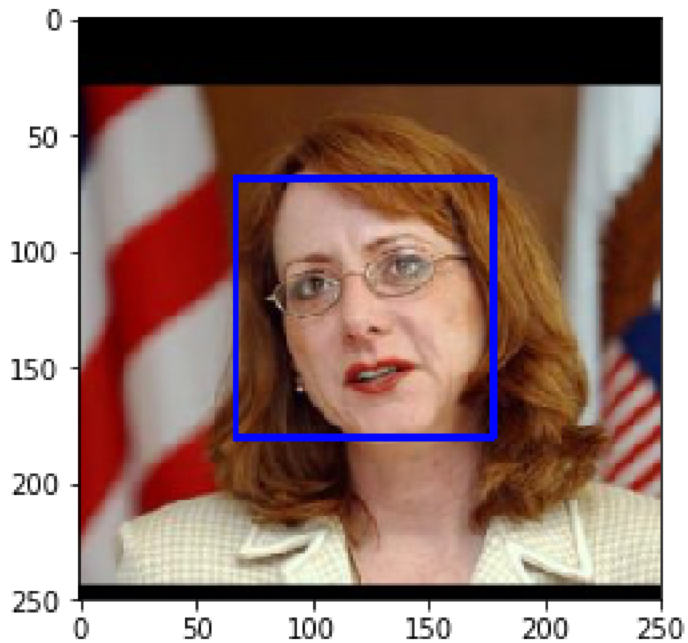
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

        # load color (BGR) image
        img = cv2.imread(human_files[15])
        # convert BGR image to grayscale
        gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

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

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

```python
# get bounding box for each detected face
for (x,y,w,h) in faces:
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(255,5,2),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 [43]: # returns "True" if face is detected in image stored at img_path
         def face_detector(img_path):
             img = cv2.imread(img_path)
             gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
             faces = face_cascade.detectMultiScale(gray)
             return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

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

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

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        true_classification_human=0
        false_classification_dog=0
        for i in range(100):
            true_classification_human +=face_detector(human_files_short[i])
            false_classification_dog +=face_detector(dog_files_short[i])
        print("human_percentage : " + str(true_classification_human))
        print("dog_percentage : " + str(false_classification_dog))
```

```
human_percentage : 98
dog_percentage : 17
```

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

```
In [5]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
        #from matplotlib import pyplot
        #from mtcnn.mtcnn import MTCNN
        #face detection using multi task cascade convoltuional neural network
        #detector = MTCNN()
        def face_detector2(img_path):
            img = pyplot.imgread(img_path)
            faces = detector.detect_faces(img)
            return len(faces) > 0

        #test performance
        #true_classification_human=0
        #false_classification_dog=0
        #for i in range(100):
         #   true_classification_human +=face_detector2(human_files_short[i])
          #  false_classification_dog +=face_detector2(dog_files_short[i])
        #print("human_percentage : " + str(true_classification_human))
        #print("dog_percentage : " + str(false_classification_dog))
```

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 [7]: import torch
        import torchvision.models as models

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 104507868.66it/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 [6]: from PIL import Image
        import torchvision.transforms as transforms
        from torch.autograd import Variable
        # Set PIL to be tolerant of image files that are truncated.
        from PIL import ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True

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

            Args:
                img_path: path to an image

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

            ## TODO: Complete the function.
            ## Load and pre-process an image from the given img_path
            ## Return the *index* of the predicted class for that image
            transforms_in = transforms.Compose([
                transforms.Resize(size=(224,224)),
                transforms.ToTensor(),
                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])

            ])
            img= Image.open(img_path)#.convert('RGB')
            img=transforms_in(img)
            # PyTorch pretrained models expect the Tensor dims to be (num input imgs, num color
            # Currently however, we have (num color channels, height, width); let's fix this by
            # Insert the new axis at index 0 i.e. in front of the other axes/dims.
            img = img.unsqueeze(0)
            # Now that we have preprocessed our img, we need to convert it into a
```

```
    # Variable; PyTorch models expect inputs to be Variables. A PyTorch Variable is a
    # wrapper around a PyTorch Tensor.
    img = Variable(img)
    img = img.cuda()
    # Returns a Tensor of shape (batch, num class labels)
    prediction = VGG16(img)
    prediction = prediction.cpu().data.numpy().argmax()

    ## Return the *index* of the predicted class for that image
    return prediction # 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 [8]: ### 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 >= 151 and pred <= 268:
                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:

```
In [12]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         def test_model_preformance(model,num):
             true_classification_dog = 0
             false_classification_human = 0
             for i in range(100):
                 true_classification_dog += dog_detector(dog_files_short[i])
                 false_classification_human += dog_detector(human_files_short[i])
             print("detected dog precentage in dog_files_short : " + str(true_classification_dog
             print("detected dog precentage in human_files_short : " + str(false_classification_
         test_model_preformance(VGG16,244)
```

```
detected dog precentage in dog_files_short : 100
detected dog precentage in human_files_short : 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 [13]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
         RESNET50 = models.resnet50(pretrained=True)
         test_model_preformance(RESNET50,224)
```

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:02<00:00, 50910088.29it/s]


detected dog precentage in dog_files_short : 100
detected dog precentage in human_files_short : 1
```

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!

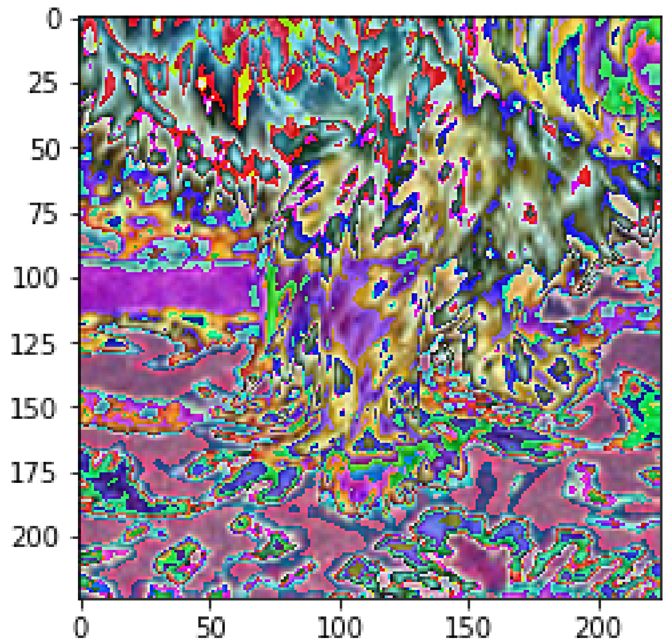
```
In [8]: import torchvision.transforms as transforms
        from torchvision import datasets
        from torchvision import utils
        import os
        # Declare the transforms for train, valid and test sets.
        # Imitate the VGG-16 model.
        # Resize images because the input size of VGG-16 is 224x224
        # Convert to Tensor
        # Normalize images because the values of images should be loaded between [0 - 1]
        transform = {

            # Use RandomHorizontalFlip() to augement data in the train transformation
            'train' : transforms.Compose([transforms.Resize(256),
                                          transforms.RandomResizedCrop(224),
                                          transforms.RandomHorizontalFlip(),
                                          transforms.ToTensor(),
                                          transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                               std=[0.229, 0.224, 0.225])]),

            'valid' : transforms.Compose([transforms.Resize(256),
                                           transforms.CenterCrop(224),
                                          transforms.ToTensor(),
                                          transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                               std=[0.229, 0.224, 0.225])]),

            'test' : transforms.Compose([transforms.Resize(256),
                                          transforms.CenterCrop(224),
                                          transforms.ToTensor(),
                                          transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                               std=[0.229, 0.224, 0.225])])
```

```
    }
    ## Specify appropriate transforms, and batch_sizes


    # Number of subprocesses, if it's 0, it uses the main process.
    num_workers = 0
    # How many samples will be loaded for one batch?
    batch_size = 20

    # Create image datasets (train, valid, test)
    image_datasets = {x: datasets.ImageFolder(os.path.join('/data/dog_images/', x), transfor
                      for x in ['train', 'valid', 'test']}

    # Create data loaders (train, valid, test)
    data_loaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=batch_size,
                                                    shuffle=True, num_workers=num_workers)
                    for x in ['train', 'valid', 'test']}

    # Decrease batch size because of the out of memory in the GPU Instance
    test_loader = torch.utils.data.DataLoader(image_datasets['test'], shuffle=True,
                                              batch_size=15)
```

In [9]:
```
class_names = image_datasets['train'].classes
n_classes = len(class_names)
print('Number of classes: {}'.format(n_classes))
```

```
Number of classes: 133
```

In [25]:
```
# display image
to_pil = transforms.ToPILImage()
image , target = data_loaders['train'].dataset[6679]
img = to_pil(image)
plt.imshow(img)
plt.show()
```



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: - resize the image by rescaling - size for the input tensor [256,256] because that's the average size for the most of images in training data - yes , through flips

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [23]:
```
import torch.nn as nn
import torch.nn.functional as F

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 16, 3)
        self.conv2 = nn.Conv2d(16, 32, 3)
        self.conv3 = nn.Conv2d(32, 64, 3)
        self.conv4 = nn.Conv2d(64, 128, 3)
        self.conv5 = nn.Conv2d(128, 256, 3)

        self.fc1 = nn.Linear(256 * 6 * 6, 133)
```

```
        self.max_pool = nn.MaxPool2d(2, 2,ceil_mode=True)

        self.dropout = nn.Dropout(0.20)

        self.conv_bn1 = nn.BatchNorm2d(224,3)
        self.conv_bn2 = nn.BatchNorm2d(16)
        self.conv_bn3 = nn.BatchNorm2d(32)
        self.conv_bn4 = nn.BatchNorm2d(64)
        self.conv_bn5 = nn.BatchNorm2d(128)
        self.conv_bn6 = nn.BatchNorm2d(256)

    def forward(self, x):
        ## Define forward behavior
        x = F.relu(self.conv1(x))
        x = self.max_pool(x)
        x = self.conv_bn2(x)

        x = F.relu(self.conv2(x))
        x = self.max_pool(x)
        x = self.conv_bn3(x)

        x = F.relu(self.conv3(x))
        x = self.max_pool(x)
        x = self.conv_bn4(x)

        x = F.relu(self.conv4(x))
        x = self.max_pool(x)
        x = self.conv_bn5(x)

        x = F.relu(self.conv5(x))
        x = self.max_pool(x)
        x = self.conv_bn6(x)

        x = x.view(-1, 256 * 6 * 6)

        x = self.dropout(x)
        x = self.fc1(x)
        return x

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

# instantiate the CNN
model_scratch = Net()
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))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=9216, out_features=133, bias=True)
  (max_pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=True)
  (dropout): Dropout(p=0.2)
  (conv_bn1): BatchNorm2d(224, eps=3, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
```

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

Answer:

network structure : - 5 convolutionsl layers : feature extraction - after each convolutional layer thers is a max pooling layer to reduce the dimensionality - 3 fully connected linear layers to classify images - dropout technique to reduce overfitting - Relu activation function for all layers and sigmoid function for last layer to get the probablity - batch normalization

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 [24]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(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 [25]: from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         def train(n_epochs, train_loader, valid_loader, model, optimizer, criterion, use_cuda,
             """returns trained model"""
```

```
# initialize tracker for minimum validation loss
valid_loss_min = np.Inf

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

    ###################
    # train the model #
    ###################
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        ## find the loss and update the model parameters accordingly
        ## record the average training loss, using something like
        ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
        # clear the gradients of all optimized variables
        optimizer.zero_grad()
        # forward pass
        output = model(data)
        # calculate batch loss
        loss = criterion(output, target)
        # backward pass
        loss.backward()
        # parameter update
        optimizer.step()
        # update training loss
        train_loss += loss.item() * data.size(0)

    ######################
    # validate the model #
    ######################
    model.eval()
    for batch_idx, (data, target) in enumerate(valid_loader):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        ## update the average validation loss
        ## update the average validation loss

        # forward pass
        output = model(data)
        # batch loss
        loss = criterion(output, target)
        # update validation loss
```

```
                valid_loss += loss.item() * data.size(0)

            # calculate average losses
            train_loss = train_loss / len(train_loader.dataset)
            valid_loss = valid_loss / len(valid_loader.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
            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(), save_path)
                valid_loss_min = valid_loss

        # return trained model
        return model
```

In [27]:
```
# train the model
model_scratch = train(10, data_loaders['train'], data_loaders['valid'], model_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

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

```
Epoch: 1 	Training Loss: 4.826013 	Validation Loss: 4.628939
Validation loss decreased (inf --> 4.628939).   Saving model...
Epoch: 2 	Training Loss: 4.612916 	Validation Loss: 4.455565
Validation loss decreased (4.628939 --> 4.455565).   Saving model...
Epoch: 3 	Training Loss: 4.497184 	Validation Loss: 4.364533
Validation loss decreased (4.455565 --> 4.364533).   Saving model...
Epoch: 4 	Training Loss: 4.431536 	Validation Loss: 4.293670
Validation loss decreased (4.364533 --> 4.293670).   Saving model...
Epoch: 5 	Training Loss: 4.348284 	Validation Loss: 4.213801
Validation loss decreased (4.293670 --> 4.213801).   Saving model...
Epoch: 6 	Training Loss: 4.305940 	Validation Loss: 4.194487
Validation loss decreased (4.213801 --> 4.194487).   Saving model...
Epoch: 7 	Training Loss: 4.257858 	Validation Loss: 4.136398
Validation loss decreased (4.194487 --> 4.136398).   Saving model...
Epoch: 8 	Training Loss: 4.209033 	Validation Loss: 4.068348
Validation loss decreased (4.136398 --> 4.068348).   Saving model...
Epoch: 9 	Training Loss: 4.165435 	Validation Loss: 4.044844
Validation loss decreased (4.068348 --> 4.044844).   Saving model...
```

```
Epoch: 10 	Training Loss: 4.135056 	Validation Loss: 4.000339
Validation loss decreased (4.044844 --> 4.000339).  Saving model...
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [31]: def test(loaders_test, model, criterion, use_cuda):

             # monitor test loss and accuracy
             test_loss = 0.
             correct = 0.
             total = 0.

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

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

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

         # call test function
         test(data_loaders['test'], model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.964201


Test Accuracy: 11% (96/836)
```

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 [ ]: ## TODO: Specify data loaders
        loaders_transfer = loaders_scratch.copy()
```

1.1.13 (IMPLEMENTATION) Model Architecture

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

```
In [32]: # Load VGG-16 model
         model_transfer = models.vgg16(pretrained=True)

         # Freeze the pre-trained weights
         for param in model_transfer.features.parameters():
             param.required_grad = False

         # Get the input of the last layer of VGG-16
         n_inputs = model_transfer.classifier[6].in_features

         # Create a new layer(n_inputs -> 133)
         # The new layer's requires_grad will be automatically True.
         last_layer = nn.Linear(n_inputs, 133)

         # Change the last layer to the new layer.
         model_transfer.classifier[6] = last_layer

         # Print the model.
         print(model_transfer)

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

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_size=(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_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(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), padding=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(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), padding=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(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), padding=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(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=25088, 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 use ResNet50 as a pretrained model to extract features - there is two options for transfer learning i choose useful layers so i only change the last layer with a new layer consists of number of classes - model features parameters was frozen i only train the linear layers

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 [33]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr=0.001)
```

```
In [ ]:
```

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 [35]: n_epochs = 5
         model_transfer = train(n_epochs, data_loaders['train'], data_loaders['valid'], model_tr
                                 optimizer_transfer, criterion_transfer, use_cuda, 'model_transfer.
```

```
Epoch: 1         Training Loss: 4.237799         Validation Loss: 2.818531
Validation loss decreased (inf --> 2.818531).    Saving model...
Epoch: 2         Training Loss: 2.667137         Validation Loss: 1.243700
Validation loss decreased (2.818531 --> 1.243700).    Saving model...
Epoch: 3         Training Loss: 1.807303         Validation Loss: 0.754109
Validation loss decreased (1.243700 --> 0.754109).    Saving model...
Epoch: 4         Training Loss: 1.461667         Validation Loss: 0.583182
Validation loss decreased (0.754109 --> 0.583182).    Saving model...
Epoch: 5         Training Loss: 1.283027         Validation Loss: 0.514557
Validation loss decreased (0.583182 --> 0.514557).    Saving model...



        ---------------------------------------------------------------------------

        RuntimeError                              Traceback (most recent call last)

        <ipython-input-35-52b546857aff> in <module>()
          9
         10 # load the model that got the best validation accuracy
    ---> 11 model_transfer.load_state_dict(torch.load('model_scratch.pt'))


        /opt/conda/lib/python3.6/site-packages/torch/nn/modules/module.py in load_state_dict(sel
        719         if len(error_msgs) > 0:
        720             raise RuntimeError('Error(s) in loading state_dict for {}:\n\t{}'.format
    --> 721                                self.__class__.__name__, "\n\t".join(error_msgs)))
        722
        723     def parameters(self):
```

```
RuntimeError: Error(s) in loading state_dict for VGG:
    Missing key(s) in state_dict: "features.0.weight", "features.0.bias", "features.2.we
    Unexpected key(s) in state_dict: "conv1.weight", "conv1.bias", "conv2.weight", "conv
```

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]:
```
# Load the trained model 'model_transfer.pt'
model_transfer.load_state_dict(torch.load('model_transfer.pt', map_location='cpu'))
test(data_loaders['test'], model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.550470


Test Accuracy: 83% (699/836)
```

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.

### and returns the dog breed that is predicted by the model.
import torchvision.transforms as transforms
device = torch.device("cuda:0" if use_cuda else "cpu")


# 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 data_loaders['train'].dataset.cla

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    image = Image.open(img_path).convert('RGB')
    prediction_transform =  transforms.Compose([transforms.Resize(256),
                                       transforms.CenterCrop(224),
                                       transforms.ToTensor(),
                                       transforms.Normalize(mean=[0.485, 0.456, 0.4
                                                            std=[0.229, 0.224, 0.2

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

```
        model_transfer.eval()
        idx = torch.argmax(model_transfer(image))
        return class_names[idx]


    # Display input image
    def display_image(img_path):
        # Display image
        img = Image.open(img_path)
        _, ax = plt.subplots()
        ax.imshow(img)
        plt.axis('off')
        plt.show()

    # Display dog breed images
    def display_breeds(labels):
        fig = plt.figure(figsize=(16,4))
        for i, label in enumerate(labels):
            subdir = ''.join(['/data/dog_images/valid/', label + '/'])
            file = random.choice(os.listdir(subdir))
            path = ''.join([subdir, file])
            img = Image.open(path)
            ax = fig.add_subplot(1,3,i+1)
            ax.imshow(img, cmap="gray", interpolation='nearest')
            plt.title(label.split('.')[1])
            plt.axis('off')
        plt.show()
```

Step 5: Write your Algorithm

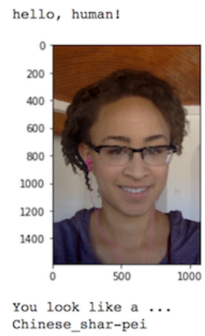
Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is 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 [59]:
```
def run_app(img_path):
    ## handle cases for a human face, dog, and neither
```



Sample Human Output

```
img = Image.open(img_path)
plt.imshow(img)
plt.show()
if(face_detector(img_path)):
    print("Human Detected")
elif(dog_detector(img_path)):
    print("Dog detected")
    prediction = predict_breed_transfer(img_path)
    print("Dog Breed: {0}".format(prediction))
else:
    print("Neither dog not human 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?

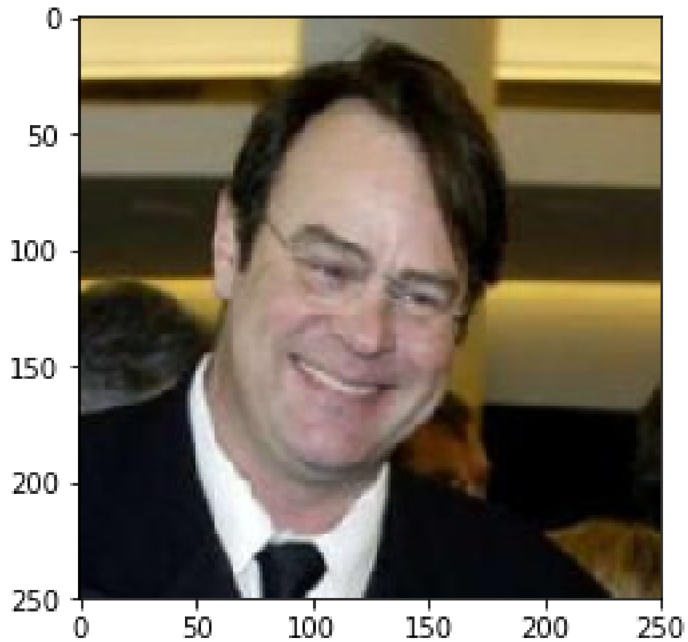
1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

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.

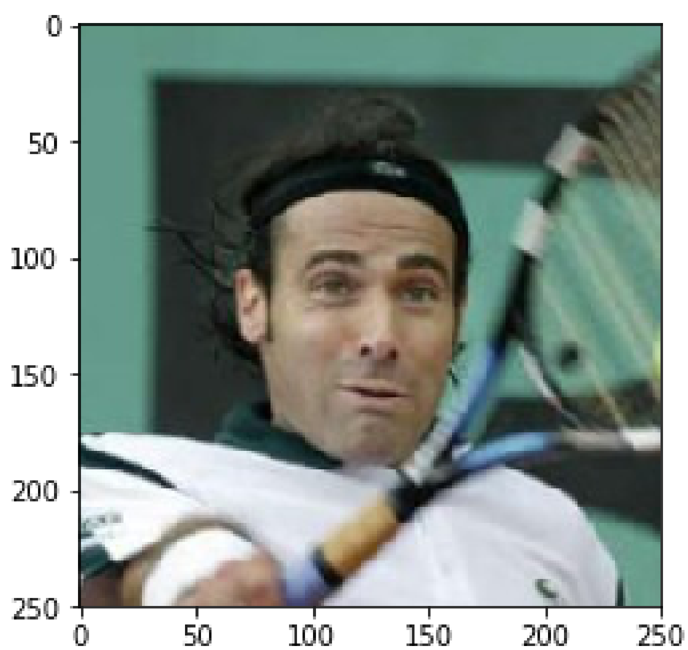
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: Hyper-parameter tuning and training will improve Large datasets (big data) will improve the performance of the model Random transformations: More rotating, flipping, cropping and then training with these transformations will improve

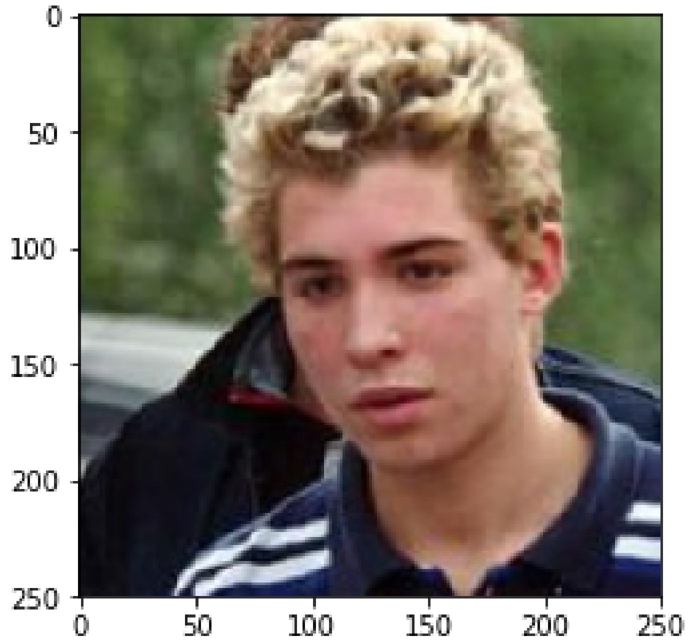
```
In [62]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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



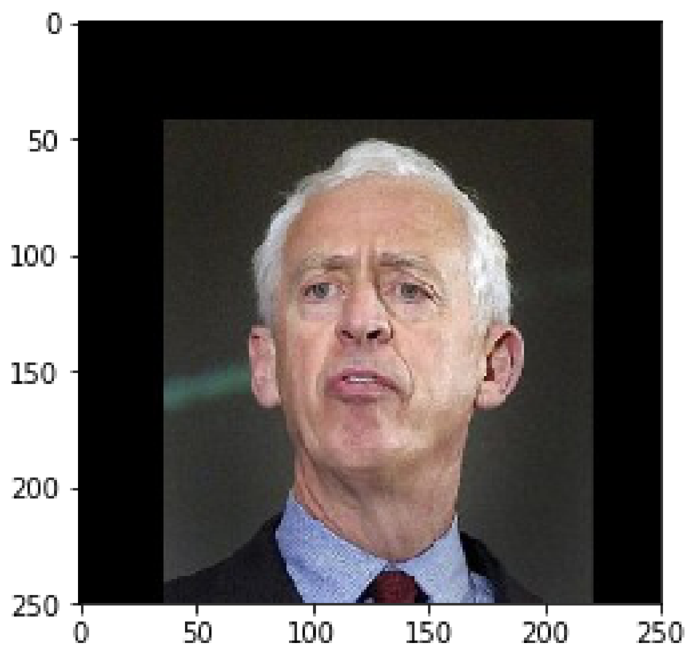
Human Detected



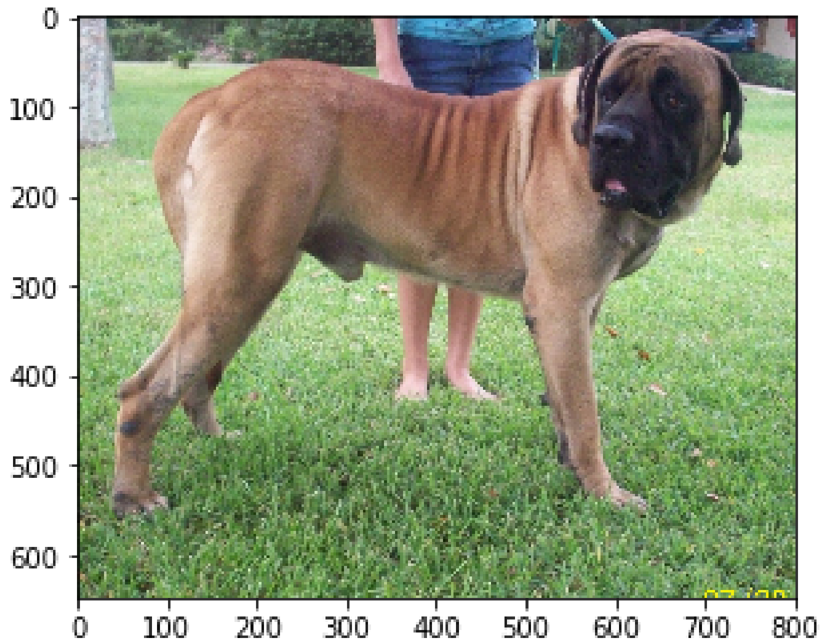
Human Detected



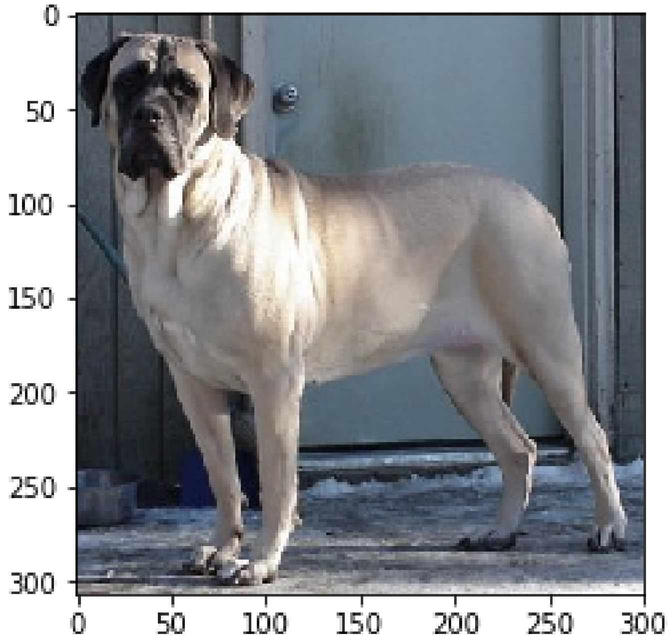
Human Detected



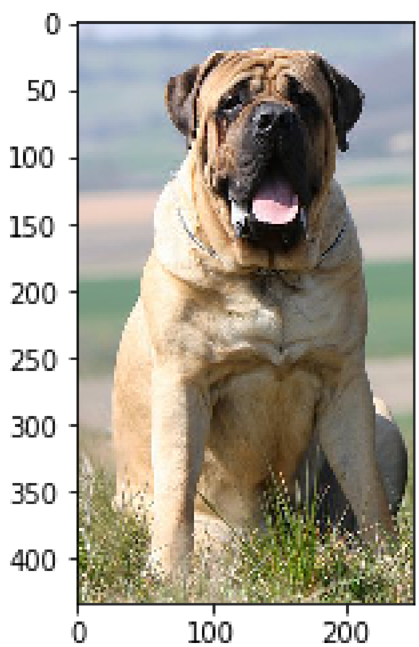
Human Detected



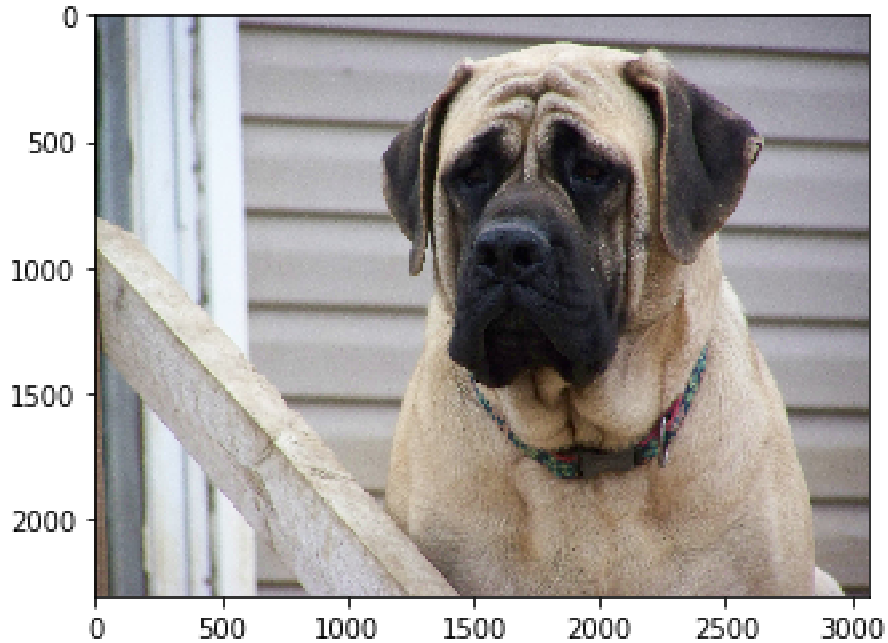
Dog detected
Dog Breed: Bullmastiff




```
Dog detected
Dog Breed: Mastiff
```



```
Dog detected
Dog Breed: Bullmastiff
```




```
Dog detected
Dog Breed: Mastiff
```