dog_app

December 23, 2019

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.

Step 0: Import Datasets

Make sure that you've downloaded the required human and dog datasets:

Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

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

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

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

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

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

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

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

Step 1: Detect Humans

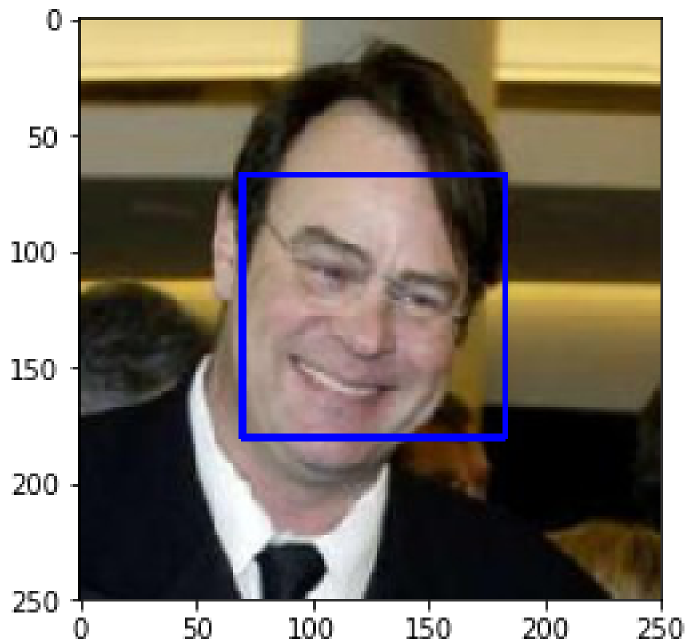
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer:

Haar Face Detection

The percentage of the detected face - Humans:98%

The percentage of the detected face - Dogs:17%

```
In [5]: from tqdm import tqdm

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        count_humans = 0
        count_dogs = 0

        num_filesh = len(human_files_short)
        num_filesd = len(dog_files_short)

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

        for file in dog_files_short:
            if face_detector(file) == True:
                count_dogs += 1
```

```
print('Haar Face Detection')
print('The percentage of the detected face - Humans:{0:.0%}'.format(count_humans / num_f
print('The percentage of the detected face - Dogs:{0:.0%}'.format(count_dogs / num_files
```

```
Haar Face Detection
The percentage of the detected face - Humans:98%
The percentage of the detected face - Dogs:17%
```

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

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

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

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

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

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

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

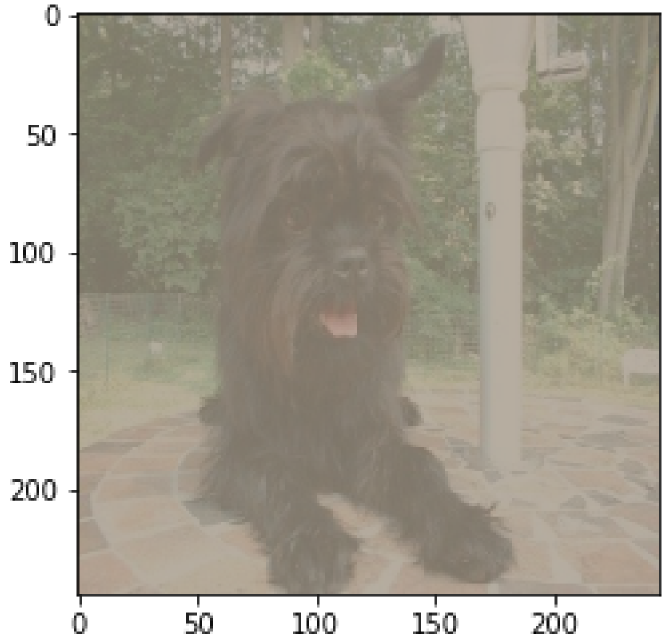
Before writing the function, make sure that you take the time to learn how to appropriately pre-process tensors for pre-trained models in the PyTorch documentation.

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

        def load_convert_image_to_tensor(img_path):
            image = Image.open(img_path).convert('RGB')
            # resize to (244, 244) because VGG16 accept this shape
            in_transform = transforms.Compose([
                                transforms.Resize(size=(244, 244)),
                                transforms.ToTensor()]) # normalization .

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

```
In [8]: # helper function for un-normalizing an image  - from STYLE TRANSFER exercise
        # and converting it from a Tensor image to a NumPy image for display
        def image_convert(tensor):
            """ Display a tensor as an image. """

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

            return image
```

```
In [9]: dog_image = Image.open('/data/dog_images/train/001.Affenpinscher/Affenpinscher_00001.jpg
        plt.imshow(dog_image)
        plt.show()
```

```
In [10]: test_tensor = load_convert_image_to_tensor('/data/dog_images/train/001.Affenpinscher/Af
         # print(test_tensor)
         print(test_tensor.shape)
         plt.imshow(image_convert(test_tensor))

torch.Size([1, 3, 244, 244])


Out[10]: <matplotlib.image.AxesImage at 0x7f2d402fb358>
```




```
In [11]: from PIL import Image
         import torchvision.transforms as transforms

         def VGG16_predict(img_path):
             image_tensor = load_convert_image_to_tensor(img_path)

             # move model inputs to cuda, if GPU available
             if use_cuda:
                 image_tensor = image_tensor.cuda()

             # get sample outputs
             output = VGG16(image_tensor)
             # convert output probabilities to predicted class
             _, preds_tensor = torch.max(output, 1)
             pred = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso

             return int(pred) # predicted class index



             '''
             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
```

In [12]:
```
import ast
import requests


LABELS_MAP_URL = "https://gist.githubusercontent.com/yrevar/942d3a0ac09ec9e5eb3a/raw/c2

def get_human_readable_label_for_class_id(class_id):
    labels = ast.literal_eval(requests.get(LABELS_MAP_URL).text)
    print(f"Label:{labels[class_id]}")
    return labels[class_id]


test_prediction = VGG16_predict('/data/dog_images/train/001.Affenpinscher/Affenpinscher
pred_class = int(test_prediction)

print(f"Predicted class id: {pred_class}")
class_description = get_human_readable_label_for_class_id(pred_class)
print(f"Predicted class for image is *** {class_description.upper()} ***")
```

```
Predicted class id: 252
Label:affenpinscher, monkey pinscher, monkey dog
Predicted class for image is *** AFFENPINSCHER, MONKEY PINSCHER, MONKEY DOG ***
```

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 [131]:
```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
```

```
            prediction = VGG16_predict(img_path)
            return ((prediction >= 151) & (prediction <=268)) # true/false
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

Answer: Percentage of the human images that have a detected dog: 0%
Percentage of the dog images that have a detected dog: 98%

```
In [14]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         detected_dogs_in_humans = 0
         detected_dogs_in_dogs = 0

         for ii in range(100):
             if dog_detector(human_files_short[ii]):
                 detected_dogs_in_humans += 1
                 print(f"This human ({ii}) looks like a dog")
                 human_dog_image = Image.open(human_files_short[ii])
                 plt.imshow(human_dog_image)
                 plt.show()
             if dog_detector(dog_files_short[ii]):
                 detected_dogs_in_dogs +=1

         print (f"Percentage of human images that have a detected dog: {detected_dogs_in_humans}
         print (f"Percentage of dog images that have a detected dog: {detected_dogs_in_dogs}%")
```

```
Percentage of human images that have a detected dog: 0%
Percentage of dog images that have a detected dog: 98%
```

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 [ ]:
```

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 [32]: import os
         import random
         import requests
         import time
         import ast
         import numpy as np
         from glob import glob
         import cv2
         from tqdm import tqdm
         from PIL import Image, ImageFile

         import torch
```

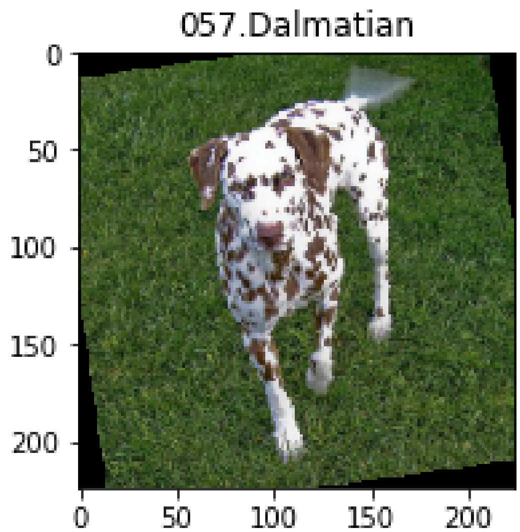
```
import torchvision
from torchvision import datasets
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision.models as models

import matplotlib.pyplot as plt
%matplotlib inline

ImageFile.LOAD_TRUNCATED_IMAGES = True

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

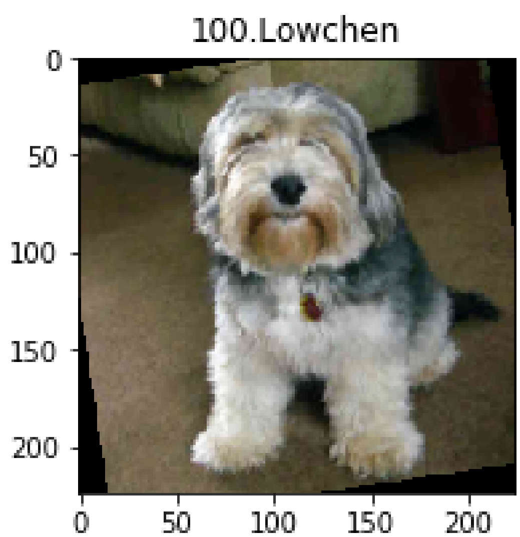
```
True
```

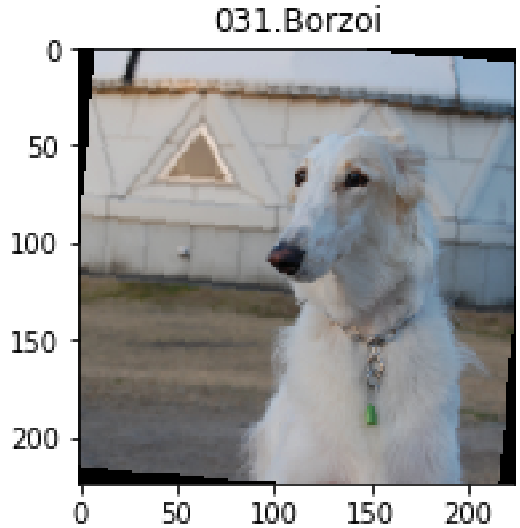
```
In [33]: #not running this one right now


         # how many samples per batch to load
         batch_size = 16

         # number of subprocesses to use for data loading
         num_workers = 2

         # convert data to a normalized torch.FloatTensor
         transform = transforms.Compose([transforms.Resize(size=224),
                                         transforms.CenterCrop((224,224)),
                                         transforms.RandomHorizontalFlip(), # randomly flip and
                                         transforms.RandomRotation(10),
                                         transforms.ToTensor(),
                                         transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0

         # define training, test and validation data directories
         data_dir = '/data/dog_images/'

         image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x), transform)
                           for x in ['train', 'valid', 'test']}
         loaders_scratch = {
             x: torch.utils.data.DataLoader(image_datasets[x], shuffle=True, batch_size=batch_si
             for x in ['train', 'valid', 'test']}
```

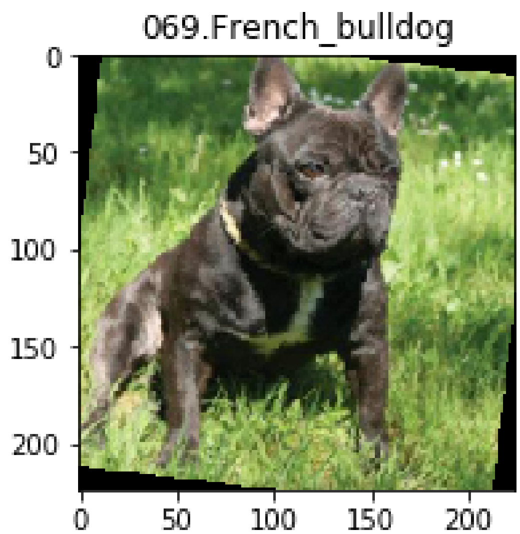
```
In [34]: # Get a batch of training data
         inputs, classes = next(iter(loaders_scratch['train']))
```

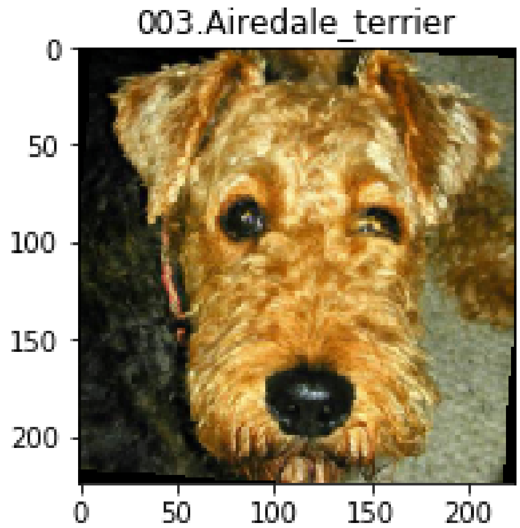
```python
for image, label in zip(inputs, classes):
    image = image.to("cpu").clone().detach()
    image = image.numpy().squeeze()
    image = image.transpose(1,2,0)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = image.clip(0, 1)

    fig = plt.figure(figsize=(12,3))
    plt.imshow(image)
    plt.title(class_names[label])
```

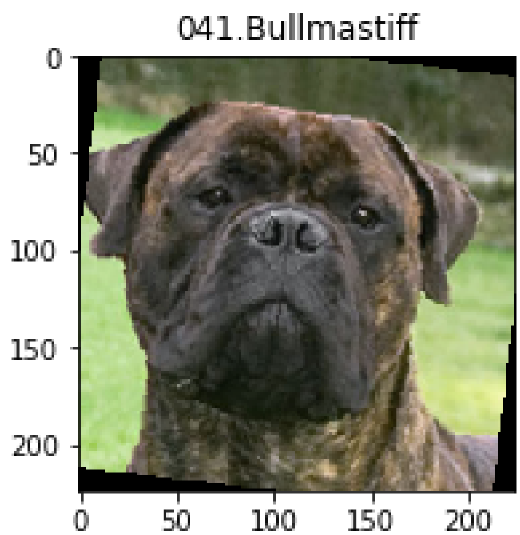




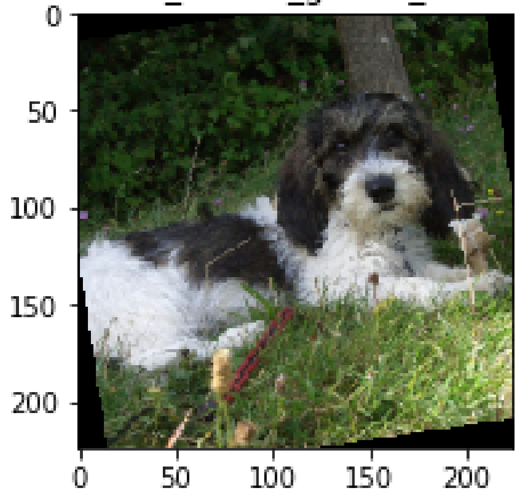

031.Borzoi
0
50
100
150
200
0
50
100
150
200


069.French_bulldog
0
50
100
150
200
0
50
100
150
200

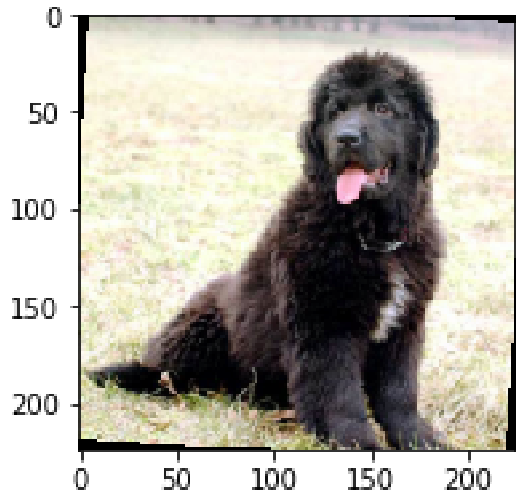

003.Airedale_terrier
0
50
100
150
200
0 50 100 150 200

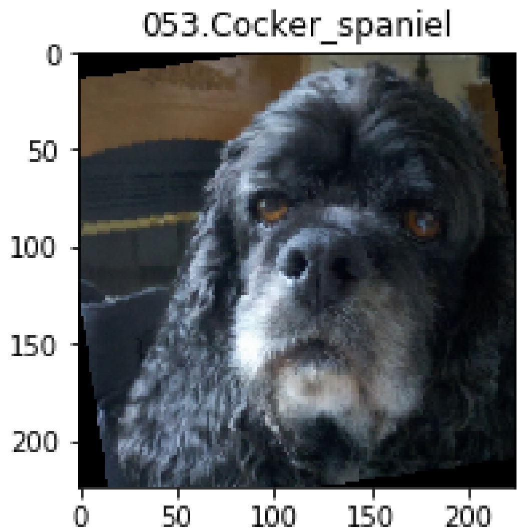

041.Bullmastiff
0
50
100
150
200
0 50 100 150 200

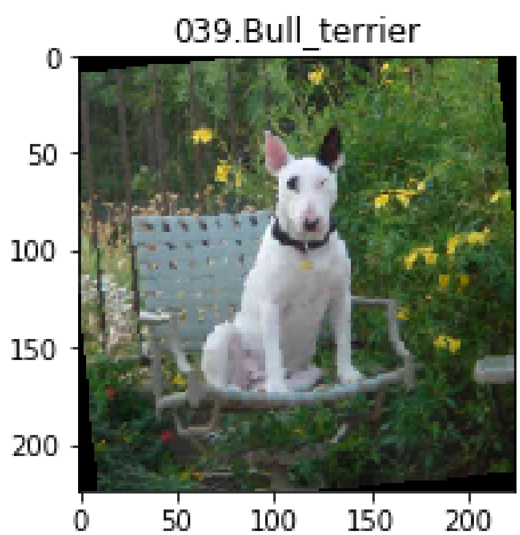
119.Petit_basset_griffon_vendeen

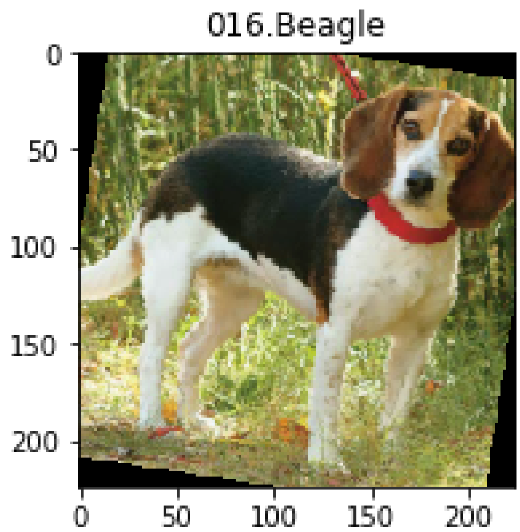


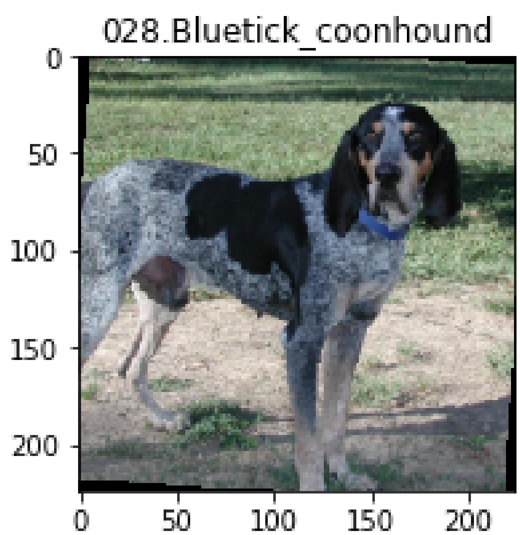
106.Newfoundland

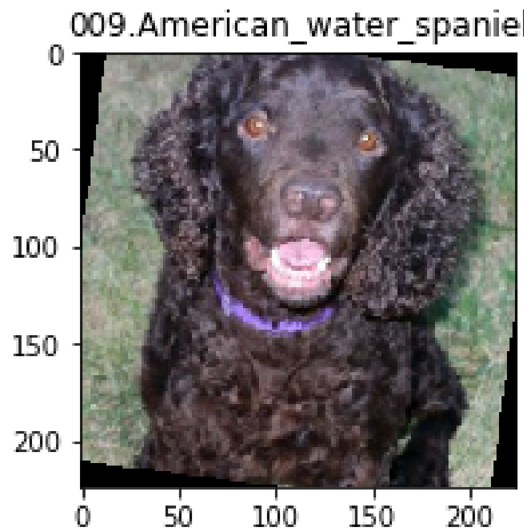


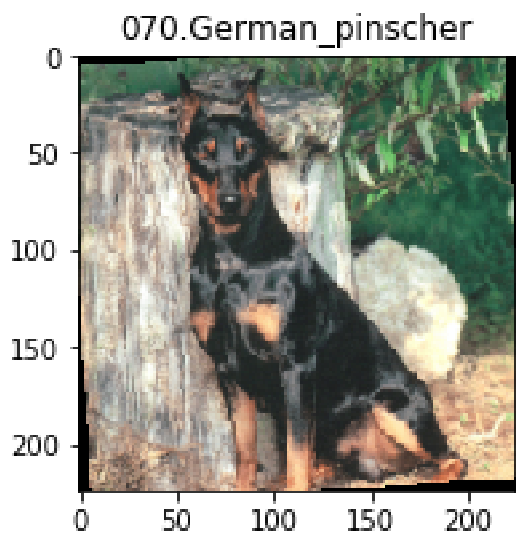

053.Cocker_spaniel
0
50
100
150
200
0
50
100
150
200

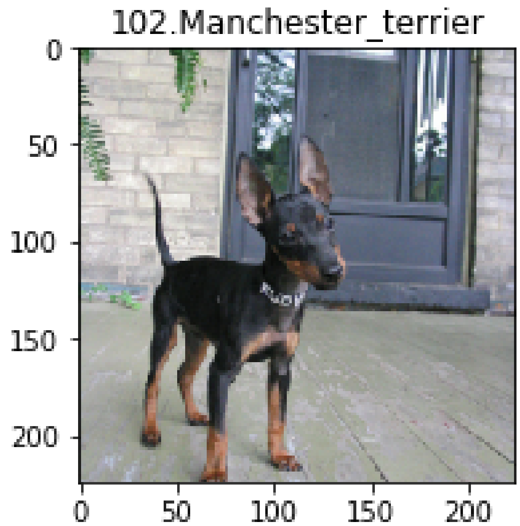

039.Bull_terrier
0
50
100
150
200
0
50
100
150
200

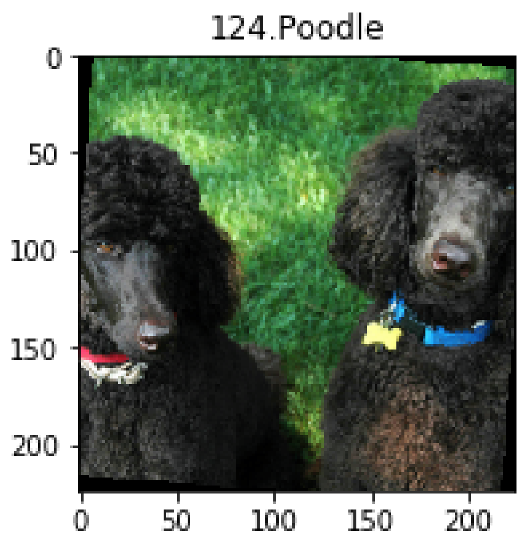

016.Beagle
0
50
100
150
200


028.Bluetick_coonhound
0
50
100
150
200


009.American_water_spaniel
0
50
100
150
200
0
50
100
150
200


070.German_pinscher
0
50
100
150
200
0
50
100
150
200





In [ ]:

In [ ]:

Creating loaders for each dataset

In [ ]:

In [35]:
```
# Check the dataset sizes
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'valid', 'test']}
```

```
print('Number of records of training dataset: {}'.format(dataset_sizes['train']))
print('Number of records of validation dataset: {}'.format(dataset_sizes['valid']))
print('Number of records of test dataset: {}'.format(dataset_sizes['test']))
```

```
Number of records of training dataset: 6680
Number of records of validation dataset: 835
Number of records of test dataset: 836
```

In [36]:
```
class_names = image_datasets['train'].classes
nb_classes = len(class_names)

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

```
Number of classes: 133

Class names:

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

In [37]:
```
# The image should be normalized, the label is a integer value between 0 - 132
data_loaders['train'].dataset[1000]
```

Out[37]:
```
(tensor([[[-0.9192, -0.9192, -0.9020,  ..., -0.7308, -0.7308, -0.9020],
          [-0.9020, -0.9192, -0.9020,  ..., -0.8164, -0.7137, -0.7993],
          [-0.9020, -0.9020, -0.9020,  ..., -0.7993, -0.7479, -0.8164],
          ...,
          [-1.2274, -1.1589, -1.1247,  ...,  0.7933,  0.7591,  0.6563],
          [-1.0904, -1.0219, -1.0390,  ...,  0.6221,  0.6392,  0.6392],
          [-1.1075, -1.0390, -1.0219,  ...,  0.5707,  0.4851,  0.5536]],

         [[-0.6527, -0.6527, -0.6527,  ..., -0.4251, -0.3901, -0.5301],
          [-0.5826, -0.6176, -0.6352,  ..., -0.4601, -0.3200, -0.3901],
          [-0.5476, -0.5651, -0.6001,  ..., -0.4951, -0.4076, -0.4601],
          ...,
          [-1.0903, -1.0203, -0.9678,  ...,  0.6429,  0.5378,  0.3452],
          [-0.9328, -0.8627, -0.8627,  ...,  0.5728,  0.4678,  0.3978],
          [-0.9678, -0.8978, -0.8803,  ...,  0.5728,  0.3978,  0.4328]],

         [[-0.8110, -0.7761, -0.7064,  ...,  0.1128,  0.1128, -0.0441],
          [-0.7587, -0.7238, -0.6890,  ...,  0.0953,  0.1999,  0.0953],
          [-0.7238, -0.7064, -0.7064,  ...,  0.0431,  0.0953,  0.0256],
          ...,
          [-0.5495, -0.4798, -0.4973,  ...,  0.8099,  0.6879,  0.5311],
          [-0.4275, -0.3578, -0.4275,  ...,  0.7402,  0.6182,  0.5659],
          [-0.4624, -0.3927, -0.3927,  ...,  0.7402,  0.5659,  0.6008]]]), 16)
```

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: I loaded in the training, test and validation data, then created DataLoaders for each of these sets of data.

I resized all image to 224, center cropped and added some simple data augmentation by randomly flipping and rotating the given image data.

I approached the problem iteratively, starting with the examples from the previous labs, especially Cifar and MMNIST examples.

We are working with (224, 224, 3) images in this project so the inputs are significantly bigger than the labs (28, 28, 1) for Mnist and (32x32x3) for CIFAR.

Most of the pretrained models require the input to be 224x224 images. Also, we'll need to match the normalization used when the models were trained. Each color channel was normalized separately, the means are [0.485, 0.456, 0.406] and the standard deviations are [0.229, 0.224, 0.225].

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [38]:
```python
# 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.Sequential(
#             nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1),
#             nn.BatchNorm2d(16),
#             nn.ReLU())
#         self.conv2 = nn.Sequential(
#             nn.Conv2d(16, 32, kernel_size=3, stride=1, padding=1),
#             nn.BatchNorm2d(32),
#             nn.ReLU())
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        # convolutional layer (sees 16x16x16 tensor)
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)

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

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

```
            # dropout layer (p=0.25)
            self.dropout = nn.Dropout(0.25)
            self.batch_norm = nn.BatchNorm1d(num_features=500)

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

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

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

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

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

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

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

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

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

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

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

    # instantiate the CNN
    model_scratch = Net()
    print(model_scratch)

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=50176, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=133, bias=True)
  (dropout): Dropout(p=0.25)
  (batch_norm): BatchNorm1d(500, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
```

In [ ]:

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

Answer:

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

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

MaxPooling2D seems to be a common choice to downsample in these type of classification problems and that is why I chose it.

The more convolutional layers we include, the more complex patterns in color and shape a model can detect.

The first layer in my CNN is a convolutional layer that takes (224, 224, 3) inpute shap.

I'd like my new layer to have 16 filters, each with a height and width of 3. When performing the convolution, I'd like the filter to jump 1 pixel at a time.

_nn.Conv2d(in_channels, out_channels, kernelsize, stride=1, padding=0)

I want this layer to have the same width and height as the input layer, so I will pad accordingly; Then, to construct this convolutional layer, I would use the following line of code: self.conv2 = nn.Conv2d(3, 32, 3, padding=1)

I am adding a pool layer that takes in a kernel_size and a stride after every convolution layer. This will down-sample the input's x-y dimensions, by a factor of 2:

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

I am adding a fully connected Linear Layer to produce a 133-dim output. As well as a Dropout layer to avoid overfitting.

Forward pass would give:

torch.Size([16, 3, 224, 224]) torch.Size([16, 16, 112, 112]) torch.Size([16, 32, 56, 56]) torch.Size([16, 64, 28, 28]) torch.Size([16, 50176]) torch.Size([16, 500]) torch.Size([16, 133])

1.1.9 (IMPLEMENTATION) Specify Loss Function and Optimizer

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

In [39]:
```
import torch.optim as optim

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

```
    ### TODO: select optimizer
    optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.01, momentum=0.9)
```

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 [ ]:

```
In [49]: def train(n_epochs, train_loader, valid_loader,
                   model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

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

                 ###################
                 # train the model #
                 ###################
                 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 #
            ######################
            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

                # 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}\t Validation 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 [50]: print(use_cuda)
         #model_scratch = train(20, loaders_scratch, model_scratch, optimizer_scratch,
         #                      criterion_scratch, use_cuda, 'model_scratch.pt')



         n_epochs = 20
         # train the model
         model_scratch = train(n_epochs, data_loaders['train'], data_loaders['valid'], model_scr
                               optimizer_scratch, criterion_scratch, use_cuda, 'model_scratch.pt'
```

```
True
Epoch: 1        Training Loss: 4.189605         Validation Loss: 4.138966
Validation loss decreased (inf --> 4.138966).    Saving model...
```

```
Epoch: 2        Training Loss: 3.861674         Validation Loss: 3.937385
Validation loss decreased (4.138966 --> 3.937385).    Saving model...
Epoch: 3        Training Loss: 3.730970         Validation Loss: 3.976724
Epoch: 4        Training Loss: 3.654463         Validation Loss: 3.859546
Validation loss decreased (3.937385 --> 3.859546).    Saving model...
Epoch: 5        Training Loss: 3.618310         Validation Loss: 3.838076
Validation loss decreased (3.859546 --> 3.838076).    Saving model...
Epoch: 6        Training Loss: 3.575762         Validation Loss: 3.826848
Validation loss decreased (3.838076 --> 3.826848).    Saving model...
Epoch: 7        Training Loss: 3.569950         Validation Loss: 3.809786
Validation loss decreased (3.826848 --> 3.809786).    Saving model...
Epoch: 8        Training Loss: 3.522715         Validation Loss: 3.821274
Epoch: 9        Training Loss: 3.513622         Validation Loss: 3.730057
Validation loss decreased (3.809786 --> 3.730057).    Saving model...
Epoch: 10        Training Loss: 3.456461         Validation Loss: 3.814577
Epoch: 11        Training Loss: 3.426236         Validation Loss: 3.769355
Epoch: 12        Training Loss: 3.403027         Validation Loss: 3.700939
Validation loss decreased (3.730057 --> 3.700939).    Saving model...
Epoch: 13        Training Loss: 3.430585         Validation Loss: 3.738554
Epoch: 14        Training Loss: 3.376506         Validation Loss: 3.745205
Epoch: 15        Training Loss: 3.331763         Validation Loss: 3.743664
Epoch: 16        Training Loss: 3.336293         Validation Loss: 3.732765
Epoch: 17        Training Loss: 3.296951         Validation Loss: 3.673484
Validation loss decreased (3.700939 --> 3.673484).    Saving model...
Epoch: 18        Training Loss: 3.303752         Validation Loss: 3.734811
Epoch: 19        Training Loss: 3.267675         Validation Loss: 3.750989
Epoch: 20        Training Loss: 3.263788         Validation Loss: 3.691528
```

```
In [51]: model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [52]: def test(loaders, model, criterion, use_cuda):

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

             model.eval()
             for batch_idx, (data, target) in enumerate(loaders['test']):
                 # move to GPU
                 if use_cuda:
                     data, target = data.cuda(), target.cuda()
```

```
                # forward pass: compute predicted outputs by passing inputs to the model
                output = model(data)
                # calculate the loss
                loss = criterion(output, target)

                # update average test loss
                test_loss += loss.item()*data.size(0)
                # convert output probabilities to predicted class
                pred = output.data.max(1, keepdim=True)[1]
                # compare predictions to true label
                correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
                total += data.size(0)
                # print testing statistics

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

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

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

In [53]:
```
# call test function
test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Testing Loss Average: 3.696285

Test Accuracy: 16% (135/836)
```

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 [54]:
```
## TODO: Specify data loaders
loaders_transfer = loaders_scratch
print(loaders_transfer)
```

```
{'train': <torch.utils.data.dataloader.DataLoader object at 0x7f2d3e3893c8>, 'valid': <torch.uti
```

1.1.13 (IMPLEMENTATION) Model Architecture

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

In [55]:
```
# 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:

It is very efficient to use pre-trained networks to solve challenging problems in computer vision.

Once trained, these models work very well as feature detectors for images they weren't trained on. Here we'll use transfer learning to train a network that can classify our dog photos.

I chose the VGG16 model.

i thought the VGG16 is sutable for the current problem. Because it already trained large dataset.and it performed really well (came 2nd in imagenet classification competition)

The fully connected layer was trained on the ImageNet dataset, so it won't work for the dog classification specific problem.

That means we need to replace the classifier (133 classes), but the features will work perfectly on their own. So I initialized randomly the weights in the new fully connected layer, and the rest of the weights using the pre-trained weights. And overfitting is not as much of a concern when training on a large data set. And the model classifies like my problem needs.

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

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [61]: n_epochs = 1
         model_transfer = train(n_epochs, data_loaders['train'], data_loaders['valid'], model_tr
                                optimizer_transfer, criterion_transfer, use_cuda, 'model_transfer.

         # 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: 1.051800         Validation Loss: 0.632024
Validation loss decreased (inf --> 0.632024).    Saving model...
```

1.1.16 (IMPLEMENTATION) Test the Model

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

```
In [62]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Testing Loss Average: 0.637072

Test Accuracy: 81% (678/836)
```

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 [ ]:
```

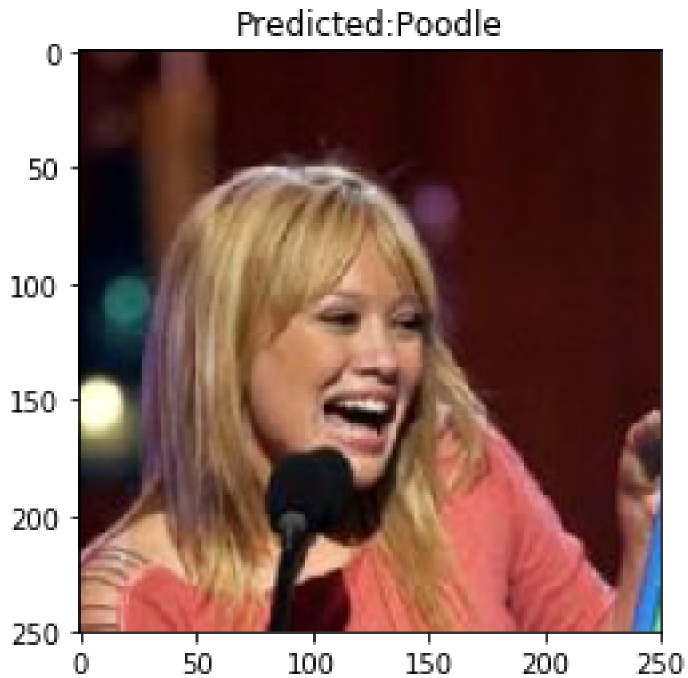
```
In [117]: def image_to_tensor(img_path):
              '''
              As per Pytorch documentations: All pre-trained models expect input images normaliz
              i.e. mini-batches of 3-channel RGB images
              of shape (3 x H x W), where H and W are expected to be at least 224.
              The images have to be loaded in to a range of [0, 1] and
              then normalized using mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225]
              You can use the following transform to normalize:
              '''
              img = Image.open(img_path).convert('RGB')
              transformations = transforms.Compose([transforms.Resize(size=224),
                                                     transforms.CenterCrop((224,224)),
                                                    transforms.ToTensor(),
                                                    transforms.Normalize(mean=[0.485, 0.456, 0.40
                                                                         std=[0.229, 0.224, 0.225
```

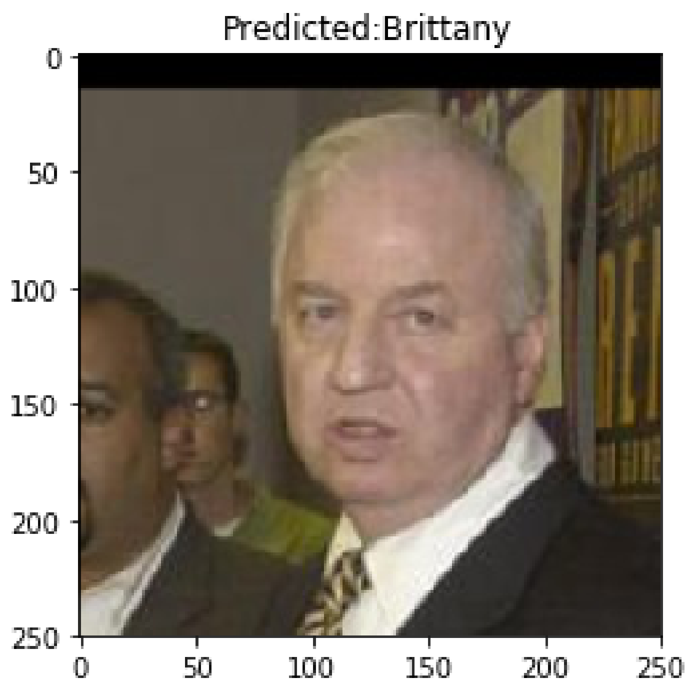
```
        image_tensor = transformations(img)[:3,:,:].unsqueeze(0)
        return image_tensor
```

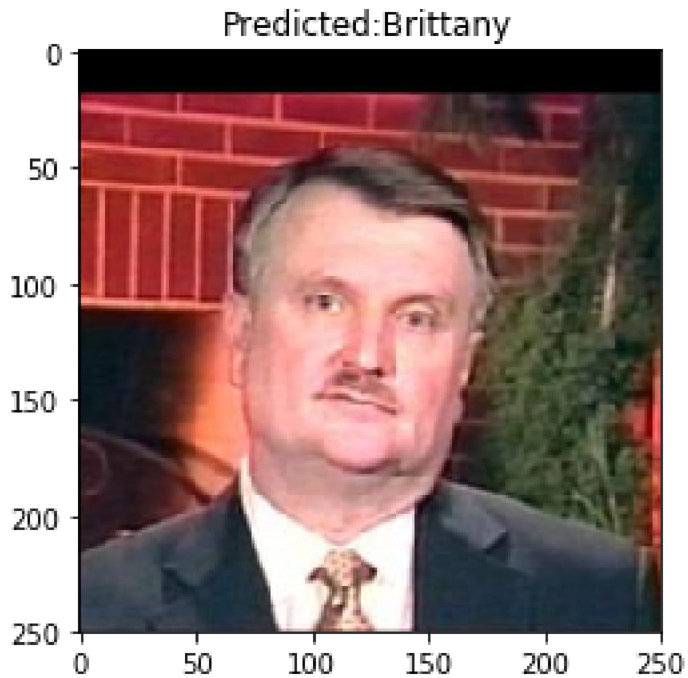
In [118]:
```
### TODO: Write a function that takes a path to an image as input
### and returns the dog breed that is predicted by the model.

# list of class names by index, i.e. a name can be accessed like class_names[0]
#class_names = [item[4:].replace("_", " ") for item in  image_datasets['train'].classe

import torchvision.transforms as transforms

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

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    image_tensor = image_to_tensor(img_path)

    # move model inputs to cuda, if GPU available
    if use_cuda:
        image_tensor = image_tensor.cuda()

    # get sample outputs
    output = model_transfer(image_tensor)
    # convert output probabilities to predicted class
    _, preds_tensor = torch.max(output, 1)
    pred = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tens

    return class_names[pred]
```

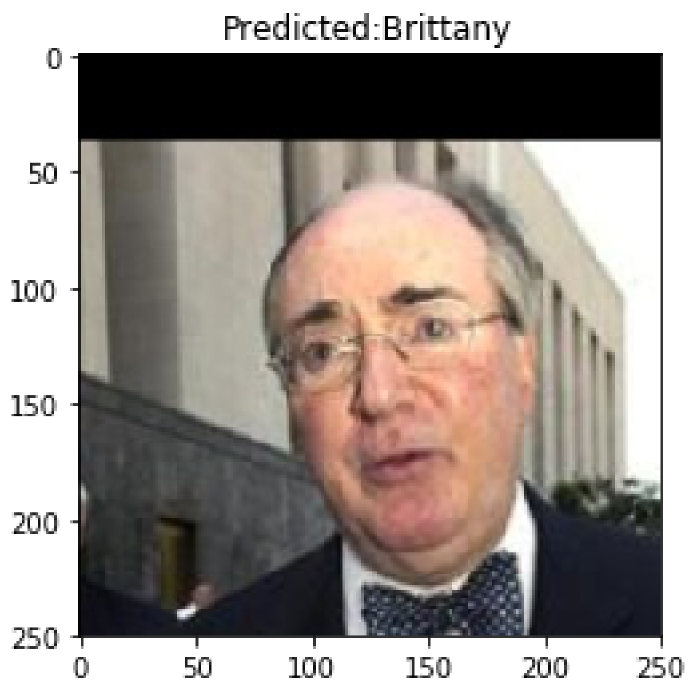
In [119]:
```
def display_image(img_path, title="Title"):
    image = Image.open(img_path)
    plt.title(title)
    plt.imshow(image)
    plt.show()
```

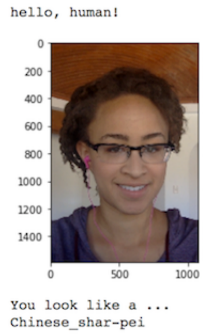
In [120]:
```
import random

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


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


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


Predicted:Brittany
0
50
100
150
200
250


Predicted:Brittany
0
50
100
150
200
250



Sample Human Output

Step 5: Write your Algorithm
Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is detected in the image, provide output that indicates an error.

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

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

1.1.18 (IMPLEMENTATION) Write your Algorithm

```
In [133]: def run_app(img_path):
              # check if image has human faces:

              # check if image has dogs:
              if dog_detector(img_path):
                  print("Hello Doggie!")
                  predicted_breed = predict_breed_transfer(img_path)
                  display_image(img_path, title=f"Predicted:{predicted_breed}")

                  print("Your breed is most likley ...")
                  print(predicted_breed.upper())


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

                  print("You look like a ...")
                  print(predicted_breed.upper())
              else:
                  print("Oh, we're sorry! We couldn't detect any dog or human face in the image.
```

```
                display_image(img_path, title="...")
                print("Try another!")
            print("\n")
```

In [ ]:

In [ ]:

In [ ]:

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: (Three possible points for improvement)

Fine tune the model to give a better accuracy

Return the top N predicted classes and their probabilities, not just one class

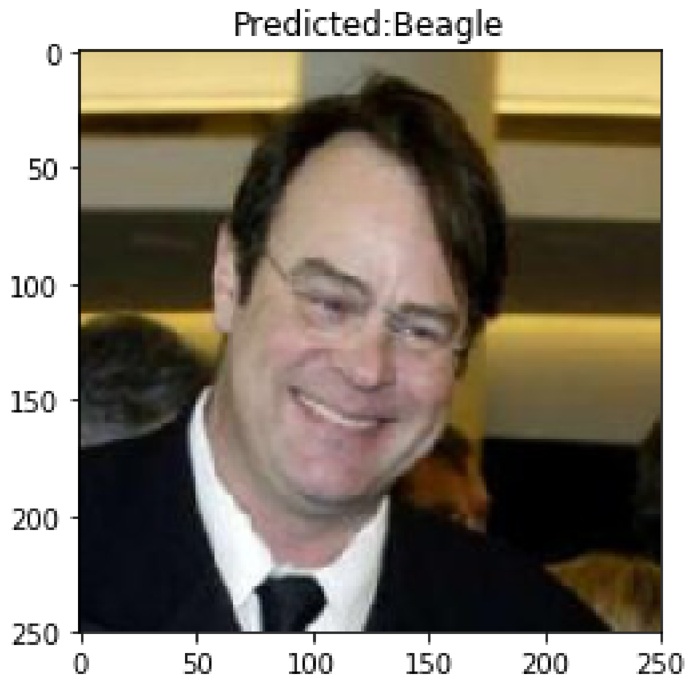
Serve this function as an API (Flask, AWS, etc.)

Handle better the case when there are multiple dogs/humans or dogs and humans in an image

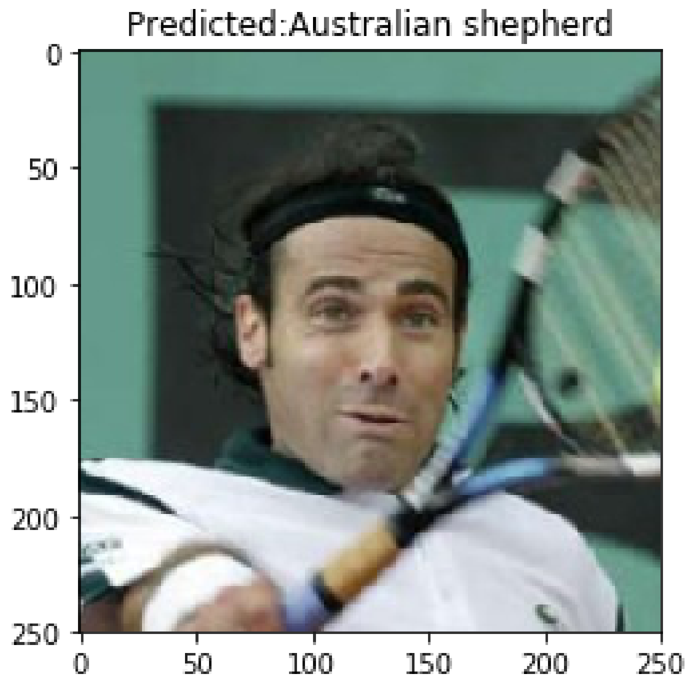
Benckmark different models, optimizers and loss functions, as well as different input image sizes.

In [137]:
```
## 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

# Tes!
for file in np.hstack((human_files_short[:5], dog_files_short[:5])):
    run_app(file)
```

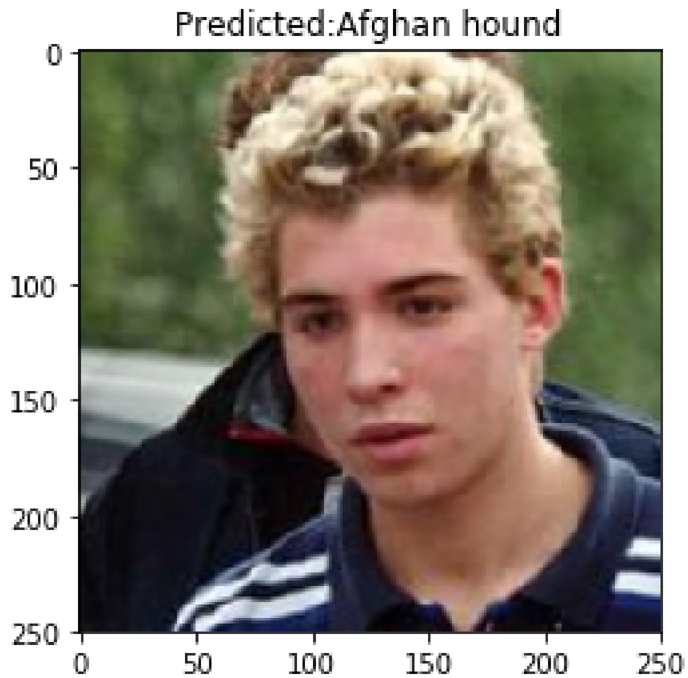
```
Hello Human!
```



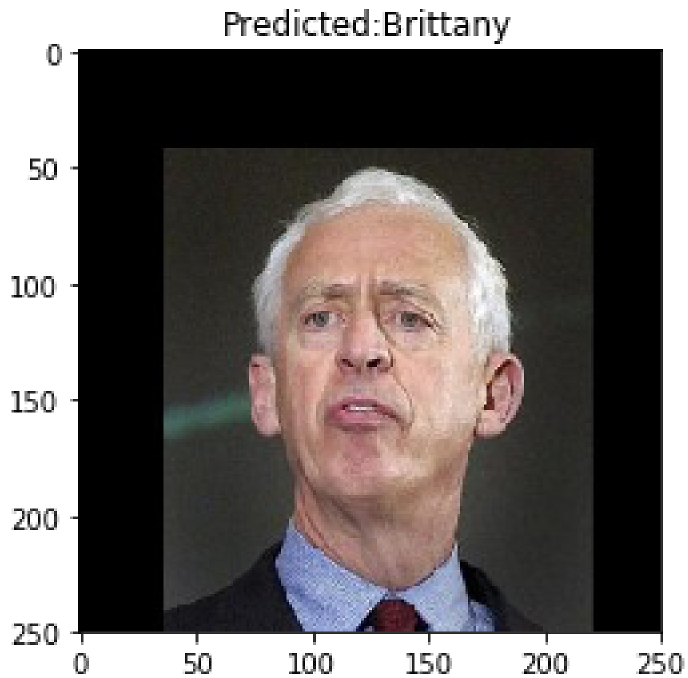

```
You look like a ...
BEAGLE


Hello Human!
```



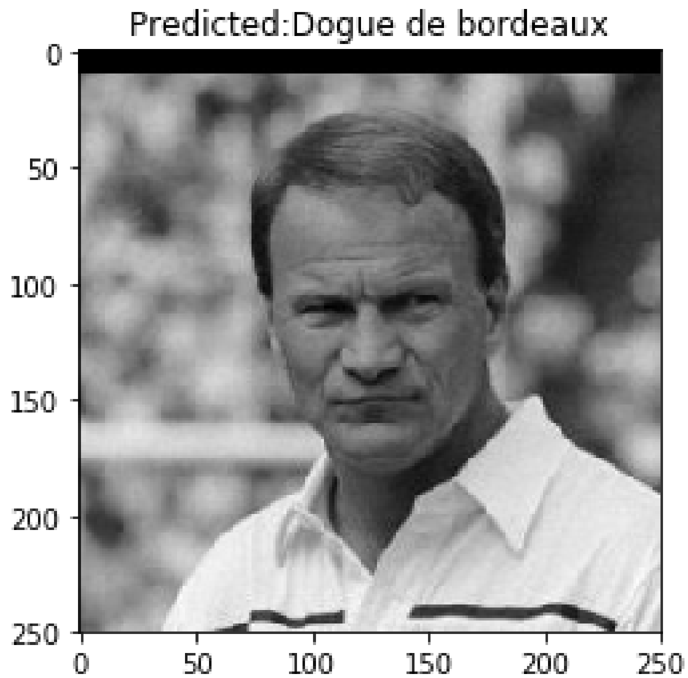

```
You look like a ...
AUSTRALIAN SHEPHERD


Hello Human!
```



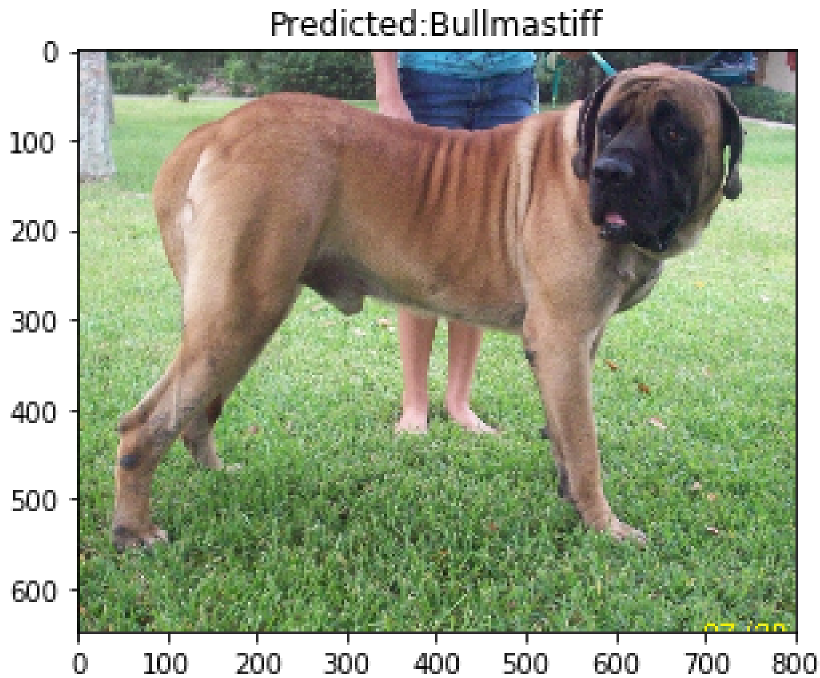

```
You look like a ...
AFGHAN HOUND


Hello Human!
```



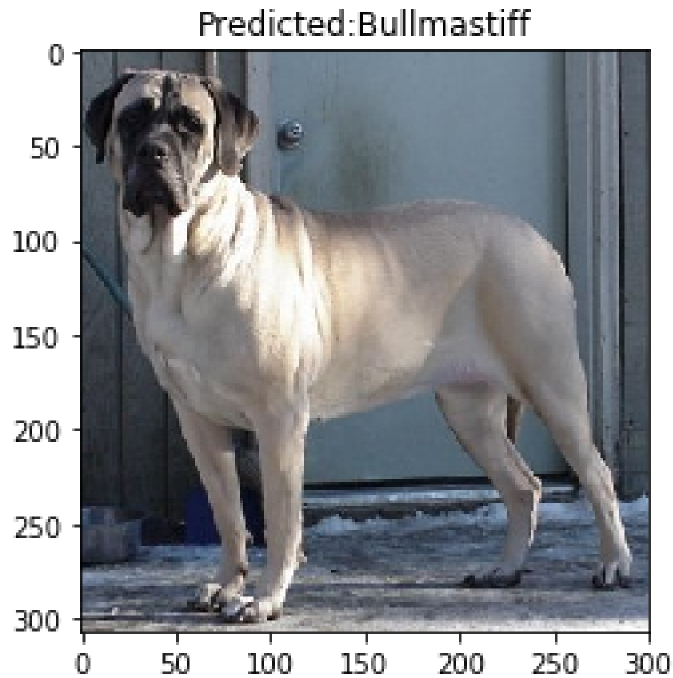

```
You look like a ...
BRITTANY


Hello Human!
```



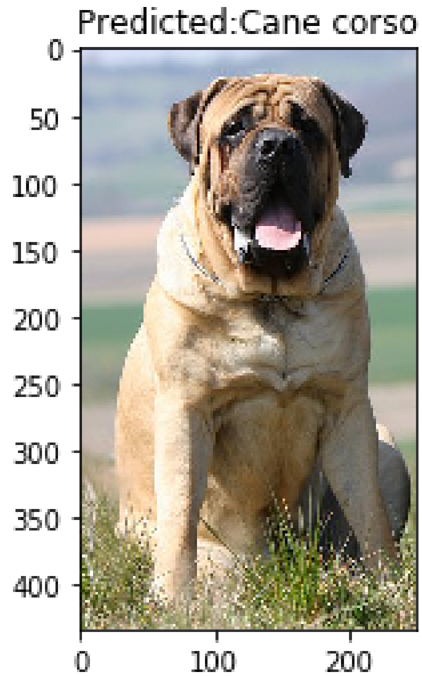

```
You look like a ...
DOGUE DE BORDEAUX


Hello Doggie!
```



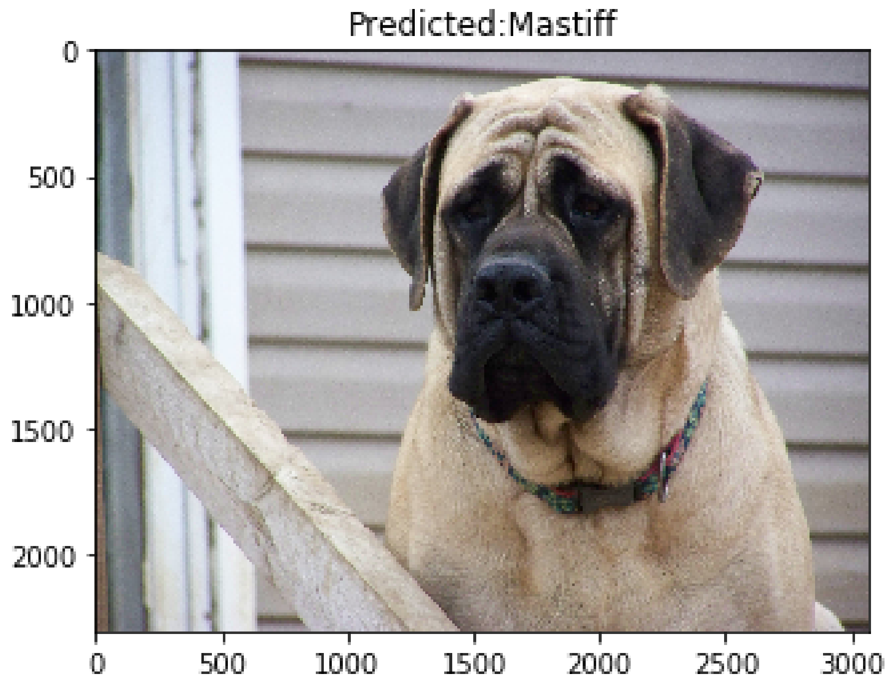

```
Your breed is most likley ...
BULLMASTIFF


Hello Doggie!
```



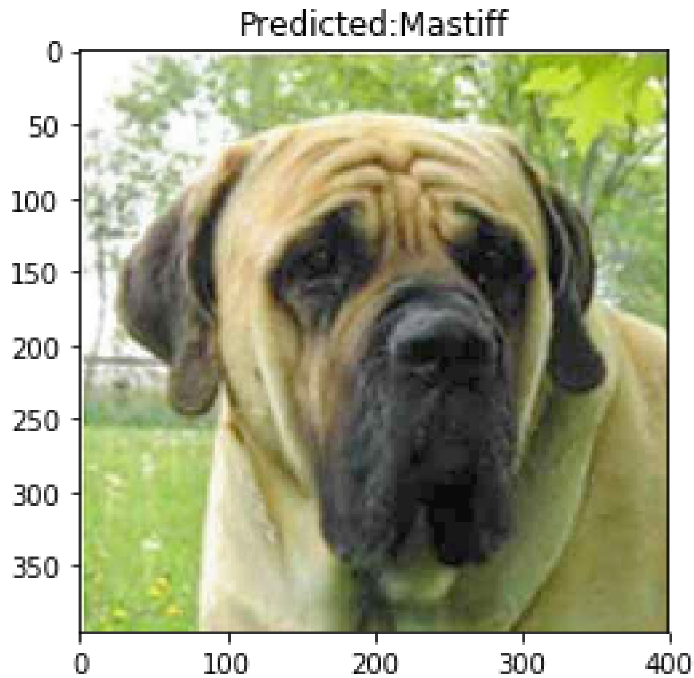

```
Your breed is most likley ...
BULLMASTIFF


Hello Doggie!
```




```
Your breed is most likley ...
CANE CORSO


Hello Doggie!
```




```
Your breed is most likley ...
MASTIFF


Hello Doggie!
```




```
Your breed is most likley ...
MASTIFF
```

In [ ]:

In [ ]: