dog_app

June 6, 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 `/dogImages`.
- 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 [ ]: # Run this cell to download and unzip images if not already on local drive
        !wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip
        !wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip
        !unzip dogImages.zip
        !unzip lfw.zip
```

```
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

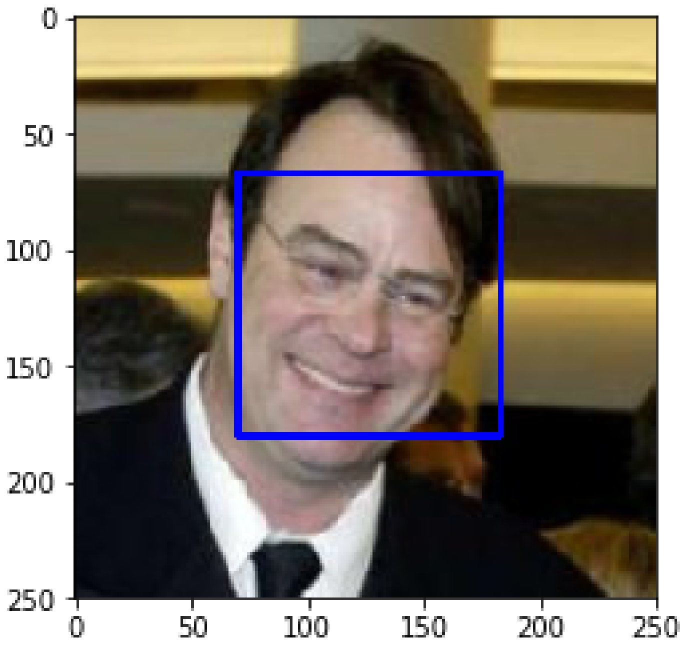
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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: (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.

        # given an array of image filepaths (img_files) and a detector function,
        # returns number of images in img_files containing detected object
        def count_detected_files(img_files, detector_fn):
            num_detected = 0
            for image in img_files:
                num_detected += detector_fn(image)
            return num_detected

        human_files_detected = count_detected_files(human_files_short, face_detector)
        dog_files_detected = count_detected_files(dog_files_short, face_detector)
        print(f'% detected human faces in human_files_short: {human_files_detected}')
        print(f'% detected human faces in dog_files_short: {dog_files_detected}')
```

```
% detected human faces in human_files_short: 98
% detected human faces in dog_files_short: 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 [0]: ### (Optional)
        ### TODO: Test performance of another face detection algorithm.
        ### Feel free to use as many code cells as needed.

        # Note: my code and commentary can be found below in the section
        # titled "Testing Alternative Face Detectors"
```

1.1.3 Testing Alternative Face Detectors

Here, we'll test a few alternative face detectors on the first 100 images from `human_files` and `dog_files`. Let's see if we can find one that outperforms the OpenCV detector.

Face Detector from face_recognition/dlib We'll try using the face_recognition face detector from dlib. Note: this requires installation of the dlib and face_recognition libraries into your local environment. We create a new face detector function `face_detector_dlib` which performs the same function as our original `face_detector` above, using dlib's pre-trained algorithm instead of OpenCV's.

```
In [5]: !pip install face_recognition
```

```
Collecting face_recognition
  Downloading https://files.pythonhosted.org/packages/1e/95/f6c9330f54ab07bfa032bf3715c12455a381
Collecting face-recognition-models>=0.3.0 (from face_recognition)
  Downloading https://files.pythonhosted.org/packages/cf/3b/4fd8c534f6c0d1b80ce0973d01331525538
    100% || 100.2MB 451kB/s eta 0:00:01
Requirement already satisfied: Click>=6.0 in /opt/conda/lib/python3.6/site-packages (from face_r
Requirement already satisfied: numpy in /opt/conda/lib/python3.6/site-packages (from face_recogn
Collecting dlib>=19.7 (from face_recognition)
  Downloading https://files.pythonhosted.org/packages/63/92/05c3b98636661cb80d190a5a777dd94effcc
    100% || 3.2MB 10.5MB/s ta 0:00:01
Requirement already satisfied: Pillow in /opt/conda/lib/python3.6/site-packages (from face_recog
Building wheels for collected packages: face-recognition-models, dlib
  Running setup.py bdist_wheel for face-recognition-models ... done
  Stored in directory: /root/.cache/pip/wheels/d2/99/18/59c6c8f01e39810415c0e63f5bede7d83dfb0ffc
  Running setup.py bdist_wheel for dlib ... done
  Stored in directory: /root/.cache/pip/wheels/96/ac/11/8aadec62cb4fb5b264a9b1b042caf415de9a75f5
```

```
Successfully built face-recognition-models dlib
Installing collected packages: face-recognition-models, dlib, face-recognition
Successfully installed dlib-19.19.0 face-recognition-1.3.0 face-recognition-models-0.3.0
```

```
In [6]: import face_recognition

        # returns "True" if face is detected in image stored at img_path
        # uses face_recognition library from dlib
        def face_detector_dlib(img_path):
            img = face_recognition.load_image_file(img_path)
            faces = face_recognition.face_locations(img)
            return len(faces) > 0

        # test performance of face_detector_dlib function on human_files_short
        # and dog_files_short
        human_files_detected = count_detected_files(human_files_short, face_detector_dlib)
        dog_files_detected = count_detected_files(dog_files_short, face_detector_dlib)
        print(f'% detected human faces in human_files_short: {human_files_detected}')
        print(f'% detected human faces in dog_files_short: {dog_files_detected}')
```

```
% detected human faces in human_files_short: 100
% detected human faces in dog_files_short: 8
```

Compared to the OpenCV algorithm, we can see that this algorithm detects more human faces in `human_files_short`, and fewer human faces in `dog_files_short`. This is an improvement!

face_recognition defaults to a non deep learning based model. However, by adding the parameter `model='cnn'` we can access a more accurate deep learning based face detection model. Note that this only works if GPU acceleration is enabled. Let's test that next.

```
In [7]: # returns "True" if face is detected in image stored at img_path
        # uses face_recognition library from dlib, with CNN's activated
        def face_detector_dlib_cnn(img_path):
            img = face_recognition.load_image_file(img_path)
            faces = face_recognition.face_locations(img, model='cnn')
            return len(faces) > 0

        # test performance of face_detector_dlib_cnn
        human_files_detected = count_detected_files(human_files_short, face_detector_dlib_cnn)
        dog_files_detected = count_detected_files(dog_files_short, face_detector_dlib_cnn)
        print(f'% detected human faces in human_files_short: {human_files_detected}')
        print(f'% detected human faces in dog_files_short: {dog_files_detected}')
```

```
% detected human faces in human_files_short: 100
% detected human faces in dog_files_short: 6
```

Yet another improvement! The algorithm detected all the faces in `human_files_short` and reduced the number of human faces detected in `dog_files_short`.

MTCNN Face Detector from facenet-pytorch Next, let's try using the face detector from facenet-pytorch, which is an implementation of a MTCNN (multi-task cascaded CNN). Note: this requires installation of the facenet-pytorch library into your local environment. We create a new face detector function `face_detector_mtcnn` which utilizes this MTCNN detector

```
In [63]: !pip install facenet_pytorch
```

```
Collecting facenet_pytorch
  Downloading https://files.pythonhosted.org/packages/58/26/9dbb553500bff164cdcd491785cfe55dcbb3
     || 1.9MB 8.8MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from facenet_pyt
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from facenet_
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (fro
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requ
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from
Installing collected packages: facenet-pytorch
Successfully installed facenet-pytorch-2.2.9
```

```
In [66]: import torch
         from facenet_pytorch import MTCNN

         # returns "True" if face is detected in image stored at img_path
         # uses MTCNN face detector from facenet-pytorch
         def face_detector_mtcnn(img_path):
             # initialize face detector
             if torch.cuda.is_available():
                 mtcnn = MTCNN(select_largest='FALSE', device='cuda')
             else:
                 mtcnn = MTCNN(select_largest='FALSE')

             img = cv2.imread(img_path)
             img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
             faces = mtcnn(img)
             return faces is not None

         # test performance of face_detector_mtcnn
         human_files_detected = count_detected_files(human_files_short, face_detector_mtcnn)
         dog_files_detected = count_detected_files(dog_files_short, face_detector_mtcnn)
         print(f'% detected human faces in human_files_short: {human_files_detected}')
         print(f'% detected human faces in dog_files_short: {dog_files_detected}')
```

```
% detected human faces in human_files_short: 100
% detected human faces in dog_files_short: 24
```

This MTCNN detector picks up more human faces in `dog_files_short` than the face_recognition algorithms do. Of the face detector algorithms we've tested, face_recognition with cnn/deep-learning performs best 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.

1.1.4 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 [8]: 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, 102164106.16it/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.

1.1.5 (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 [9]: from PIL import Image
        import torchvision.transforms as transforms

        # 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
    img = Image.open(img_path).convert('RGB')

    # images must be 224x224 and normalized to specific values for VGG-16
    transform = transforms.Compose([transforms.Resize(256),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    transforms.Normalize((0.485, 0.456, 0.406),
                                                         (0.229, 0.224, 0.225))])

    # discard alpha channel if applicable and add dimension for batchsize of 1
    img = transform(img)[:3,:,:].unsqueeze(0)

    # move img to GPU if CUDA is available
    if use_cuda:
        img = img.cuda()

    ## Return the *index* of the predicted class for that image
    logits = VGG16(img)
    _, class_index = torch.max(logits, dim=1)
    return class_index.item()
```

1.1.6 (IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary, you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from `'Chihuahua'` to `'Mexican hairless'`. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

Use these ideas to complete the `dog_detector` function below, which returns `True` if a dog is detected in an image (and `False` if not).

```
In [10]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             ## TODO: Complete the function.
             class_index = VGG16_predict(img_path)
```

```
            return class_index >= 151 and class_index <= 268
```

1.1.7 (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 [11]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         # test performance of dog_detector
         human_files_detected = count_detected_files(human_files_short, dog_detector)
         dog_files_detected = count_detected_files(dog_files_short, dog_detector)
         print(f'% detected dogs in human_files_short: {human_files_detected}')
         print(f'% detected dogs in dog_files_short: {dog_files_detected}')
```

```
% detected dogs in human_files_short: 0
% detected dogs in dog_files_short: 100
```

We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as Inception-v3, ResNet-50, etc). Please use the code cell below to test other pre-trained PyTorch models. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [0]: ### (Optional)
        ### TODO: Report the performance of another pre-trained network.
        ### Feel free to use as many code cells as needed.
```

1.1.8 Testing Other Pre-trained Models as Dog Detectors

Let's test the performance of another pre-trained PyTorch model. To start, we should generalize the `VGG16_predict` function above to work with any pre-trained PyTorch model.

```
In [12]: def ImageNet_predict(img_path, model):
             '''
             Use pre-trained model to obtain index corresponding to
             predicted ImageNet class for image at specified path

             Args:
                 img_path: path to an image
                 model: pre-trained PyTorch model (e.g. vgg16, resnet50, etc.)

             Returns:
                 Index corresponding to model's prediction
             '''
```

```
        # Load image from the given img_path
        img = Image.open(img_path).convert('RGB')

        # images must be 224x224 and normalized to specific values for PyTorch's
        # pre-trained models
        transform = transforms.Compose([transforms.Resize(256),
                                        transforms.CenterCrop(224),
                                        transforms.ToTensor(),
                                        transforms.Normalize((0.485, 0.456, 0.406),
                                                             (0.229, 0.224, 0.225))])

        # discard alpha channel if applicable and add dimension for batchsize of 1
        img = transform(img)[:3,:,:].unsqueeze(0)

        # move img to GPU if CUDA is available
        if use_cuda:
            img = img.cuda()

        # Return the *index* of the predicted class for that image
        logits = model(img)
        _, class_index = torch.max(logits, dim=1)
        return class_index.item()
```

Testing AlexNet

```
In [13]: # load pre-trained model, move to GPU if cuda is available
         Alexnet = models.alexnet(pretrained=True)
         if use_cuda:
             Alexnet = Alexnet.cuda()

         # returns "True" if a dog is detected in the image stored at img_path
         # uses AlexNet
         def dog_detector_alexnet(img_path):
             class_index = ImageNet_predict(img_path, Alexnet)
             return class_index >= 151 and class_index <= 268

         # test performance of dog_detector_alexnet
         human_files_detected = count_detected_files(human_files_short, dog_detector_alexnet)
         dog_files_detected = count_detected_files(dog_files_short, dog_detector_alexnet)
         print(f'% detected dogs in human_files_short: {human_files_detected}')
         print(f'% detected dogs in dog_files_short: {dog_files_detected}')
```

```
Downloading: "https://download.pytorch.org/models/alexnet-owt-4df8aa71.pth" to /root/.torch/mode
100%|| 244418560/244418560 [00:02<00:00, 81645515.05it/s]


% detected dogs in human_files_short: 2
% detected dogs in dog_files_short: 99
```

AlexNet performs quite well, but it looks like VGG-16 slightly outperforms. #### **Testing SqueezeNet**

```
In [14]: # load pre-trained model, move to GPU if cuda is available
         Squeezenet = models.squeezenet1_0(pretrained=True)
         if use_cuda:
             Squeezenet = Squeezenet.cuda()

         # returns "True" if a dog is detected in the image stored at img_path
         # uses SqueezeNet
         def dog_detector_squeezenet(img_path):
             class_index = ImageNet_predict(img_path, Squeezenet)
             return class_index >= 151 and class_index <= 268

         # test performance of dog_detector_squeezenet
         human_files_detected = count_detected_files(human_files_short, dog_detector_squeezenet)
         dog_files_detected = count_detected_files(dog_files_short, dog_detector_squeezenet)
         print(f'% detected dogs in human_files_short: {human_files_detected}')
         print(f'% detected dogs in dog_files_short: {dog_files_detected}')
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/models/squeezenet
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/models/squeezenet
Downloading: "https://download.pytorch.org/models/squeezenet1_0-a815701f.pth" to /root/.torch/mo
100%|| 5017600/5017600 [00:00<00:00, 23803579.53it/s]


% detected dogs in human_files_short: 3
% detected dogs in dog_files_short: 99
```

SqueezeNet seems to detect more dog faces in `human_files_short` compared to AlexNet and VGG16. VGG16 has the best performance of the three models we tested

---

## 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!

1.1.9 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

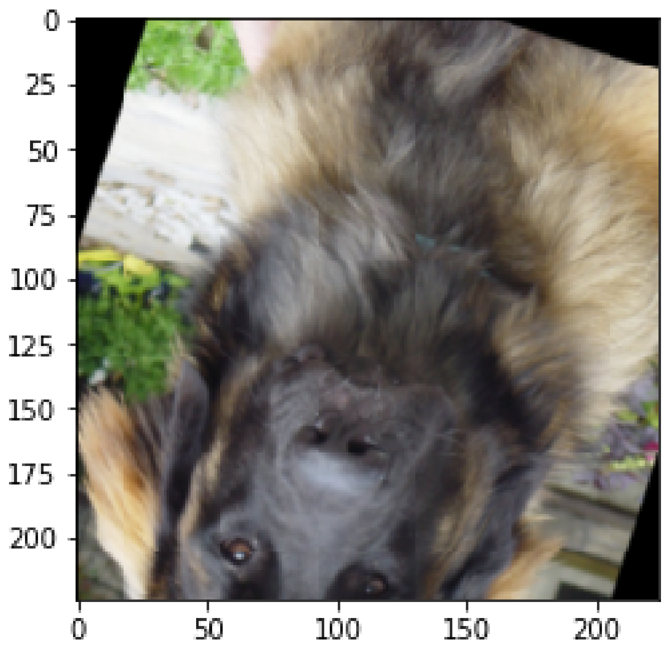
Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dog_images/train`, `dog_images/valid`, and `dog_images/test`, respectively). You may find this documentation on custom datasets to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms!

```
In [15]: import os
         from torchvision import datasets

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         # image size (for square image) to be input into model
         input_size = 224

         # transforms for training dataset, with data augmentation
         train_transforms = transforms.Compose([transforms.RandomHorizontalFlip(),
                                                transforms.RandomVerticalFlip(),
                                                transforms.RandomRotation(20),
                                                transforms.Resize(300),
                                                transforms.RandomResizedCrop(input_size),
                                                transforms.ToTensor(),
                                                transforms.Normalize((0.485, 0.456, 0.406),
                                                                     (0.229, 0.224, 0.225))])

         # transforms for test and validation datasets, no data augmentation
```

```
        test_transforms = transforms.Compose([transforms.Resize(input_size + 32),
                                              transforms.CenterCrop(input_size),
                                              transforms.ToTensor(),
                                              transforms.Normalize((0.485, 0.456, 0.406),
                                                                   (0.229, 0.224, 0.225))])

        # create training, validation, and test datasets with ImageFolder
        root = '/data/dog_images'
        train_data = datasets.ImageFolder(root + '/train', transform=train_transforms)
        valid_data = datasets.ImageFolder(root + '/valid', transform=test_transforms)
        test_data = datasets.ImageFolder(root + '/test', transform=test_transforms)

        # create dataloaders for training, validation, and test sets
        batch_size = 20
        train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, shuffle=T
        valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size)
        test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)

        # create dictionary of dataloaders
        loaders_scratch = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

```
In [16]: # helper function
        def show_img(img_tensor):
            '''takes in an image in tensor form and transforms it so that it can be
            displayed
            '''

            # convert to numpy, rearrange dimensions for matplotlib
            img = img_tensor.numpy().transpose((1, 2, 0))
            # un-normalize
            mean = np.array([0.485, 0.456, 0.406])
            std = np.array([0.229, 0.224, 0.225])
            img = img * std + mean
            img = np.clip(img, 0, 1)

            plt.imshow(img)
            plt.show()
```

```
In [27]: # visualize sample image from train_data
        images, labels = iter(train_loader).next()
        show_img(images[0])
```



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 chose an input tensor with image dimensions 224x224, as this is the standard input size for PyTorch's pre-trained models. 224 is divisible by a high multiple of 2 (32), allowing for a good number of maxpooling dimension reduction layers. To avoid stretching the image, I resized the image to a size slightly larger than the target input size, then cropped a 224x224 square region.

This algorithm is meant to work on real world user supplied images, which could be flipped, not centered, slightly angled, etc. To train a robust model which can handle these real world variations, I thought it best to augment the training dataset with horizontal and vertical flips, rotations, and modest RandomResizedCrop (resizing the image to be closer to target size before cropping). I chose the data augmentation transforms based on variations most likely to occur in user supplied images.

1.1.10 (IMPLEMENTATION) Model Architecture

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

```
In [28]: 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().__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 32, 3, padding=1)
        self.conv2 = nn.Conv2d(32, 64, 3, padding=1)
        self.conv3 = nn.Conv2d(64, 128, 3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)

        self.dropout = nn.Dropout(p=0.25)

        # input nodes to fc1 are calculated based on flattening the output of the
        # convolutional feature detector
        self.fc1 = nn.Linear(128*28*28, 256)
        # there are 133 breeds in the dataset, so we need 133 output nodes
        self.output = nn.Linear(256, 133)

    def forward(self, x):
        ## Define forward behavior
        # convolutional feature detector
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x = self.dropout(x)
        x = F.relu(self.conv2(x))
        x = self.pool(x)
        x = self.dropout(x)
        x = F.relu(self.conv3(x))
        x = self.pool(x)
        x = self.dropout(x)

        # flatten output of feature detector for fully connected layers
        x = x.view(x.shape[0], -1)

        # fully connected classifier
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = F.log_softmax(self.output(x), dim=1)

        return x

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

# instantiate the CNN
model_scratch = Net()

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

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

Answer:

In general, I followed the principle of increasing the depth of the feature maps by powers of 2 as we progress through the model. I drew inspiration from VGG and other models which stack multiple convolutional layers together before a pooling layer. I initially stacked two convolutional layers before every maxpool layer, similar to the earlier stacks in the VGG model, increasing the depth by a power of 2 in each stack.

I started out with a relatively simple structure for the sake of an initial test run. The feature detector consisted of 3 stacks, each containing 2 convolutional layers and one maxpooling layer. I chose to use 3x3 kernels with stride and padding of 1, to avoid reducing the size of the feature maps during convolution. This was followed by two fully connected layers making up the classifier. Following industry standard, I used ReLu as the activation function after each convolutional layer as well as the hidden fully connected layers. I chose to use a log_softmax activation function on the output layer, as opposed to raw logits, so that I could easily obtain predicted class probabilities if needed. I omitted Dropout from my initial structure to test baseline performance.

After training with this initial structure, I added Dropout (p=0.25) after each maxpool layer and after the hidden fully connected layer. This resulted in a boost in accuracy.

Noticing the model took a while to train, I tested a simpler structure to see if we could still attain comparable accuracy with fewer convolutional layers. I adjusted the model to contain only one convolutional layer per stack. There did not seem to be a noticeable decrease in accuracy.

Thus, my final model architecture consists of three stacks, each containing one convolutional layer, ReLu activation, maxpool, then Dropout (p=0.25). The first convolutional layer has depth of 32, and each subsequent layer increases depth by a factor of 2. I kept the same two fully connected linear layers from my initial run, 256 hidden units followed by 133 output units, one for each dog breed class.

1.1.11 (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 [29]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.05)
```

1.1.12 (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 [30]: # the following import is required for training to be robust to truncated images
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True
```

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

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

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            # clear gradients before each forward pass
            optimizer.zero_grad()

            output = model(data)
            loss = criterion(output, target)
            loss.backward()
            optimizer.step()

            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

        ######################
        # validate the model #
        ######################
        with torch.no_grad():
            model.eval()
            for batch_idx, (data, target) in enumerate(loaders['valid']):
                # move to GPU
                if use_cuda:
                    data, target = data.cuda(), target.cuda()
                ## update the average validation loss
                output = model(data)
                loss = criterion(output, target)
                valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_l

        # 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, saving model')
                    torch.save(model.state_dict(), save_path)
                    valid_loss_min = valid_loss
            # return trained model
            return model


        # train the model
        model_scratch = train(40, loaders_scratch, model_scratch, optimizer_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: 4.876665         Validation Loss: 4.841347
validation loss decreased, saving model
Epoch: 2         Training Loss: 4.780977         Validation Loss: 4.664385
validation loss decreased, saving model
Epoch: 3         Training Loss: 4.686862         Validation Loss: 4.602587
validation loss decreased, saving model
Epoch: 4         Training Loss: 4.628593         Validation Loss: 4.548619
validation loss decreased, saving model
Epoch: 5         Training Loss: 4.591722         Validation Loss: 4.540628
validation loss decreased, saving model
Epoch: 6         Training Loss: 4.552777         Validation Loss: 4.528020
validation loss decreased, saving model
Epoch: 7         Training Loss: 4.541504         Validation Loss: 4.480077
validation loss decreased, saving model
Epoch: 8         Training Loss: 4.501096         Validation Loss: 4.407411
validation loss decreased, saving model
Epoch: 9         Training Loss: 4.483840         Validation Loss: 4.365331
validation loss decreased, saving model
Epoch: 10         Training Loss: 4.455938         Validation Loss: 4.307927
validation loss decreased, saving model
Epoch: 11         Training Loss: 4.427498         Validation Loss: 4.286345
validation loss decreased, saving model
Epoch: 12         Training Loss: 4.412623         Validation Loss: 4.297550
Epoch: 13         Training Loss: 4.374321         Validation Loss: 4.217707
validation loss decreased, saving model
Epoch: 14         Training Loss: 4.368522         Validation Loss: 4.262305
Epoch: 15         Training Loss: 4.334863         Validation Loss: 4.248466
Epoch: 16         Training Loss: 4.316039         Validation Loss: 4.146372
```

```
validation loss decreased, saving model
Epoch: 17 	Training Loss: 4.289383 	Validation Loss: 4.180146
Epoch: 18 	Training Loss: 4.255912 	Validation Loss: 4.067364
validation loss decreased, saving model
Epoch: 19 	Training Loss: 4.239897 	Validation Loss: 4.150175
Epoch: 20 	Training Loss: 4.204972 	Validation Loss: 4.124947
Epoch: 21 	Training Loss: 4.194845 	Validation Loss: 3.980459
validation loss decreased, saving model
Epoch: 22 	Training Loss: 4.173296 	Validation Loss: 4.012298
Epoch: 23 	Training Loss: 4.155138 	Validation Loss: 3.969384
validation loss decreased, saving model
Epoch: 24 	Training Loss: 4.129570 	Validation Loss: 3.937038
validation loss decreased, saving model
Epoch: 25 	Training Loss: 4.100697 	Validation Loss: 3.811843
validation loss decreased, saving model
Epoch: 26 	Training Loss: 4.075002 	Validation Loss: 3.827032
Epoch: 27 	Training Loss: 4.051238 	Validation Loss: 3.763293
validation loss decreased, saving model
Epoch: 28 	Training Loss: 4.041080 	Validation Loss: 3.765187
Epoch: 29 	Training Loss: 4.018876 	Validation Loss: 3.796709
Epoch: 30 	Training Loss: 3.996703 	Validation Loss: 3.773710
Epoch: 31 	Training Loss: 3.982344 	Validation Loss: 3.797697
Epoch: 32 	Training Loss: 3.977714 	Validation Loss: 3.737696
validation loss decreased, saving model
Epoch: 33 	Training Loss: 3.935431 	Validation Loss: 3.677693
validation loss decreased, saving model
Epoch: 34 	Training Loss: 3.912823 	Validation Loss: 3.672096
validation loss decreased, saving model
Epoch: 35 	Training Loss: 3.887585 	Validation Loss: 3.739074
Epoch: 36 	Training Loss: 3.869572 	Validation Loss: 3.681379
Epoch: 37 	Training Loss: 3.854571 	Validation Loss: 3.848791
Epoch: 38 	Training Loss: 3.843275 	Validation Loss: 3.616405
validation loss decreased, saving model
Epoch: 39 	Training Loss: 3.832577 	Validation Loss: 3.607732
validation loss decreased, saving model
Epoch: 40 	Training Loss: 3.802985 	Validation Loss: 3.624436
```

1.1.13 (IMPLEMENTATION) Test the Model

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

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

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

```
            total = 0.

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

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

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

        # call test function
        test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.589590


Test Accuracy: 13% (109/836)
```

## 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.

1.1.14 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

```
In [32]: ## TODO: Specify data loaders
         # use same data loaders from previous step, where we built a CNN from scratch
```

```
        loaders_transfer = loaders_scratch

        # create dictionary of datasets
        data_transfer = {'train': train_data, 'valid': valid_data, 'test': test_data}
```

1.1.15 (IMPLEMENTATION) Model Architecture

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

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

         ## TODO: Specify model architecture

         # use pre-trained VGG16 network
         model_transfer = models.vgg16(pretrained=True)

         # freeze parameters of pre-trained feature detector
         for param in model_transfer.features.parameters():
             param.requires_grad = False

         # replace last layer of pre-trained classifier with new layer built for dog
         # breed task
         model_transfer.classifier[6] = nn.Linear(4096, 133)

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

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

```
Out[34]: 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:
In the dog detector section, we saw that VGG16 outperformed AlexNet and SqueezeNet as a dog detector, correctly detecting dogs in all 100 images in `dog_files_short` while showing very few or no false positives in `human_files_short`. Given its strong performance on the dog detection task, I started with VGG16 as the pre-trained model used in this transfer learning exercise.

We have a relatively small dataset (8,000+ images in dogImages/train) which is similar in nature to the training dataset for the pre-trained model. Additionally, the classes in our classification problem (dog breeds) are a subset of the classes in the training dataset (ImageNet categories). Thus we should not need to make many changes to the pre-trained model's architecture, other than changing the number of output units to reflect the task at hand.

We will keep the pre-trained feature detector as is. We set `requires_grad` to false for feature detector parameters so that they will not change during training. For the fully connected classifier, we keep the existing architecture except for the final layer, which is replaced so that the number of output units corresponds to the number of dog breeds in our classification task. We then train the entire classifier.

1.1.16 (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 [35]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr=0.01)
```

1.1.17 (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 [36]: # train the model
         model_transfer = train(30, loaders_transfer, model_transfer,
                                optimizer_transfer, criterion_transfer, use_cuda,
                                'model_transfer.pt')

         # load the model that got the best validation accuracy (uncomment the line below)
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1         Training Loss: 2.847144         Validation Loss: 0.824879
validation loss decreased, saving model
Epoch: 2         Training Loss: 1.865077         Validation Loss: 0.615438
validation loss decreased, saving model
Epoch: 3         Training Loss: 1.726238         Validation Loss: 0.558036
validation loss decreased, saving model
Epoch: 4         Training Loss: 1.580538         Validation Loss: 0.528873
validation loss decreased, saving model
Epoch: 5         Training Loss: 1.542303         Validation Loss: 0.531876
Epoch: 6         Training Loss: 1.459208         Validation Loss: 0.493165
validation loss decreased, saving model
Epoch: 7         Training Loss: 1.434144         Validation Loss: 0.495009
Epoch: 8         Training Loss: 1.381690         Validation Loss: 0.464402
validation loss decreased, saving model
Epoch: 9         Training Loss: 1.376541         Validation Loss: 0.465204
Epoch: 10         Training Loss: 1.314982         Validation Loss: 0.469025
Epoch: 11         Training Loss: 1.309317         Validation Loss: 0.472418
Epoch: 12         Training Loss: 1.274370         Validation Loss: 0.453996
validation loss decreased, saving model
Epoch: 13         Training Loss: 1.241897         Validation Loss: 0.442947
validation loss decreased, saving model
Epoch: 14         Training Loss: 1.248555         Validation Loss: 0.441383
validation loss decreased, saving model
Epoch: 15         Training Loss: 1.211466         Validation Loss: 0.468707
Epoch: 16         Training Loss: 1.192546         Validation Loss: 0.464402
Epoch: 17         Training Loss: 1.194302         Validation Loss: 0.460622
Epoch: 18         Training Loss: 1.127345         Validation Loss: 0.459916
Epoch: 19         Training Loss: 1.141814         Validation Loss: 0.479774
```

```
Epoch: 20        Training Loss: 1.133612        Validation Loss: 0.457309
Epoch: 21        Training Loss: 1.099650        Validation Loss: 0.458303
Epoch: 22        Training Loss: 1.086701        Validation Loss: 0.443447
Epoch: 23        Training Loss: 1.094854        Validation Loss: 0.466277
Epoch: 24        Training Loss: 1.072732        Validation Loss: 0.458698
Epoch: 25        Training Loss: 1.065859        Validation Loss: 0.460159
Epoch: 26        Training Loss: 1.086091        Validation Loss: 0.450899
Epoch: 27        Training Loss: 1.065508        Validation Loss: 0.430130
validation loss decreased, saving model
Epoch: 28        Training Loss: 1.011201        Validation Loss: 0.436124
Epoch: 29        Training Loss: 1.008382        Validation Loss: 0.462479
Epoch: 30        Training Loss: 0.995061        Validation Loss: 0.442096
```

1.1.18 (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 [37]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.480440


Test Accuracy: 86% (720/836)
```

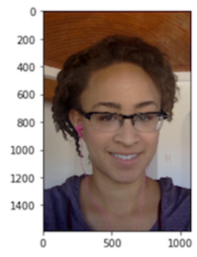
1.1.19 (IMPLEMENTATION) Predict Dog Breed with the Model

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 [38]: # helper function
         def preprocess_img(img_path):
             """Load and pre-process the image located at img_path so that it can be
             passed into model_transfer
             """

             # load image
             img = Image.open(img_path).convert('RGB')
             # transforms to resize, convert to tensor, and normalize
             img = test_transforms(img)
             # discard alpha channel if applicable and add dimension for batchsize of 1
             img = img[:3,:,:].unsqueeze(0)

             return img
```

```
In [39]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.
```

```
hello, human!
```



```
You look like a ...
Chinese_shar-pei
```

Sample Human Output

```python
# 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_transfer['train'].classes]

def predict_breed_transfer(img_path):
    # load the image at img_path and return the predicted dog breed

    # load and pre-process the image to be input into model
    img = preprocess_img(img_path)

    # move image to GPU if CUDA is available
    if use_cuda:
        img = img.cuda()

    # run through model to obtain predicted breed
    output = model_transfer(img)
    _, class_idx = output.max(dim=1)

    return class_names[class_idx.item()]
```

## 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 `dog_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!

1.1.20 (IMPLEMENTATION) Write your Algorithm

```
In [80]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither

             # if human face is detected in image at img_path
             if face_detector_dlib_cnn(img_path):
                 predicted_breed = predict_breed_transfer(img_path)
                 print(f'Hello human! You look like a {predicted_breed}')
                 show_img(preprocess_img(img_path).squeeze())

             # if dog is detected in image at img_path
             elif dog_detector(img_path):
                 predicted_breed = predict_breed_transfer(img_path)
                 print(f'Hello dog! Your predicted breed is {predicted_breed}')
                 show_img(preprocess_img(img_path).squeeze())

             # if neither human face nor dog detected in image at img_path, throw error
             else:
                 print("Error: this app is only designed for images of humans and dogs")
                 show_img(preprocess_img(img_path).squeeze())
```

## 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?

1.1.21 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

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

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

Answer: (Three possible points for improvement)

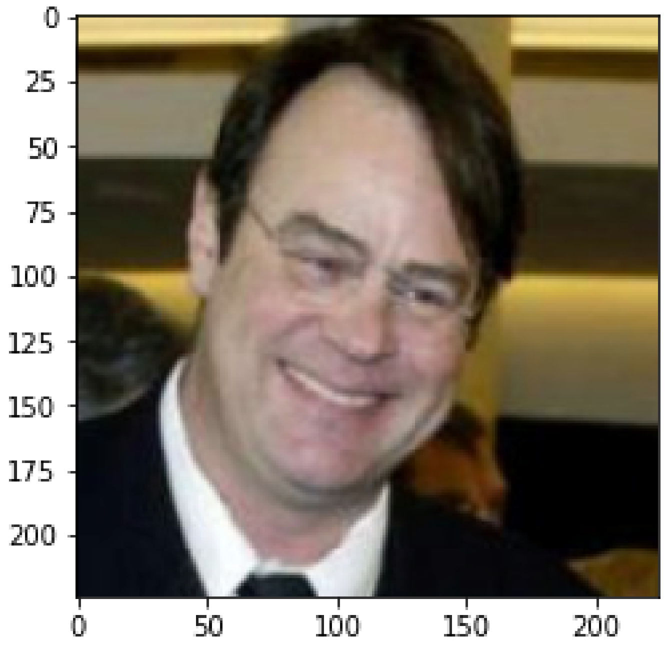
- The algorithm is designed to return the most likely breed (selecting the class with the highest score). One improvement would be to take into account the possibility of mixed breeds. For example, if probability for a given breed is less than a certain amount, or if two or more top classes have scores within a certain range of each other, return the top few breeds instead.
- The dog breed classifier model obtained a test accuracy of 86% after training for 30 epochs. While this produced high enough accuracy to pass the 60% requirement for this project, we could continue to train for additional epochs or adjust learning rate to see whether validation loss truly has reached its minimum.

- While our face_recognition_dlib_cnn face detector achieved improved results compared to the OpenCV face detector, it still picked up some false positives in `dog_files_short`. We could potentially improve the algorithm by finding a face detector with a lower false positive rate.
- We only tested our face and dog detection functions on images of humans and dogs. However, we did not test on images of other animals such as cats. It's possible our functions could mistakenly pick up false positives for humans or dogs in images of other animals. Expanding the testing dataset and choosing the detector function with the best performance across a wider dataset could yield improved results.

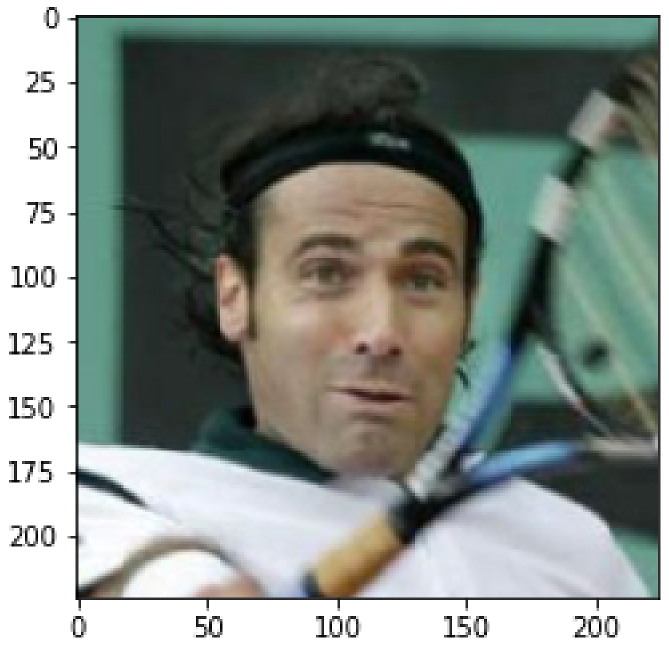
After testing on a few "real world" images, we can make the following observations: * The algorithm successfully classifies pictures of cats as neither dog nor human and throws the error message * The algorithm performed well on the beagle and pomeranian pictures, which were taken from the internet based on a Google search for "beagle" and "pomeranian" respectively. These pictures are not representative of "real world" pictures and are likely highly representative of their breed given the search results * The algorithm did not perform as well on the "real world" images of dogs, guessing 3 different breeds on 3 different pictures of the same dog. The dog in question is a mixed breed, which makes the problem harder, however, neither of its mixes were predicted by the algorithm. One possible improvement would be to tweak data augmentation so that the training dataset better represents "real world" images

```
In [81]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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

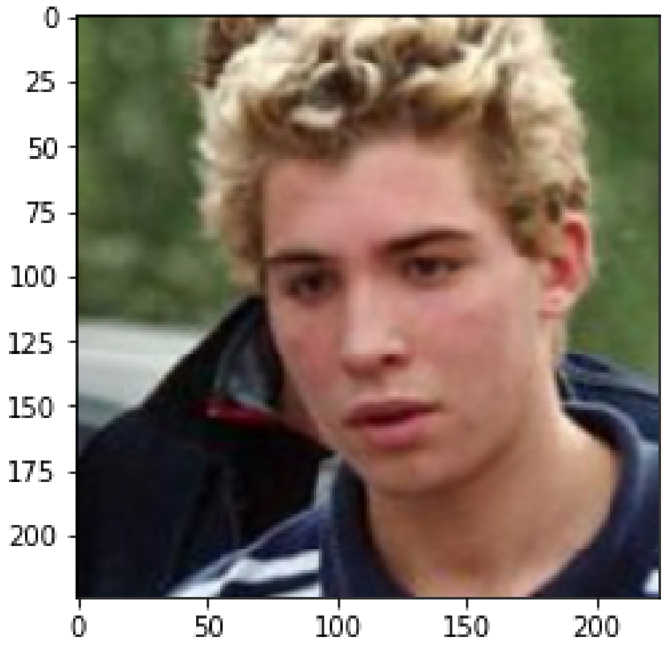
```
Hello human! You look like a Chihuahua
```



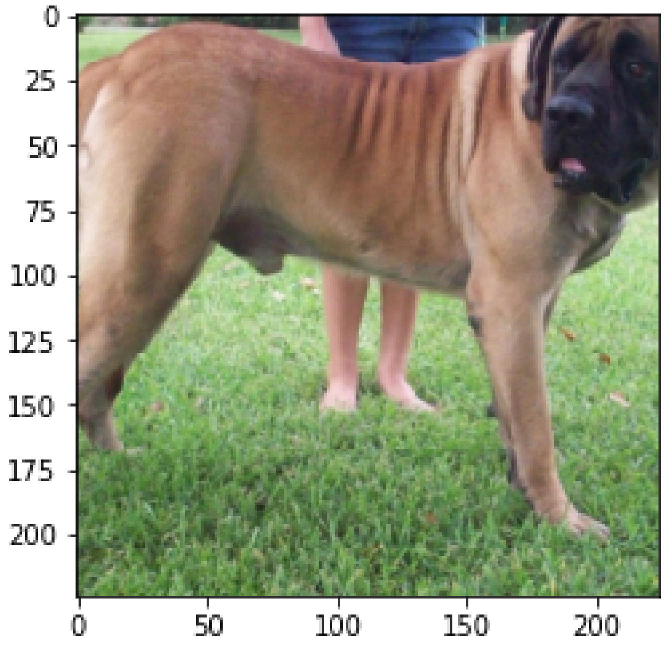
```
Hello human! You look like a Lowchen
```



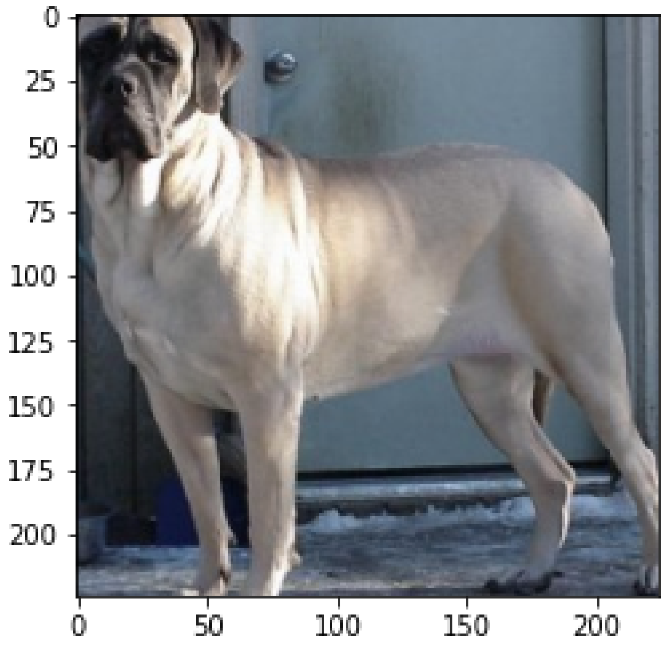
```
Hello human! You look like a Cocker spaniel
```



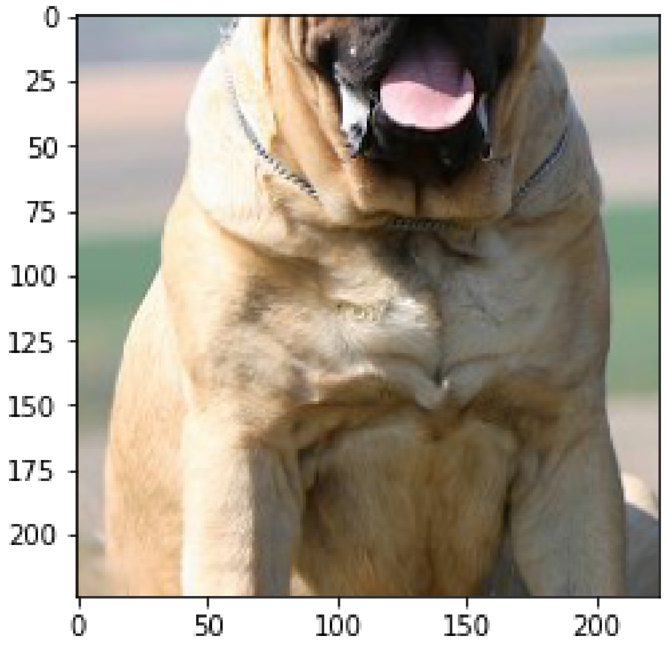
```
Hello dog! Your predicted breed is Mastiff
```



```
Hello dog! Your predicted breed is Mastiff
```

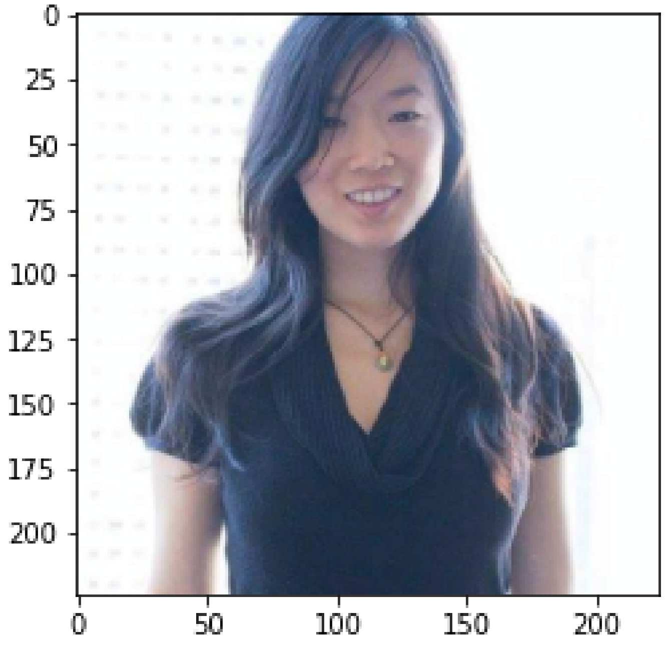


```
Hello dog! Your predicted breed is Mastiff
```

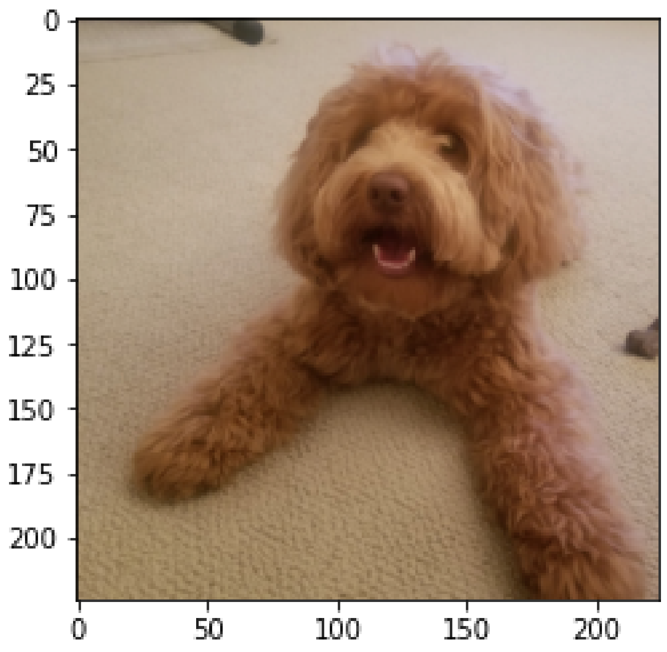


```
In [82]: # test algorithm on images from local computer
         root = '/home/workspace/dog_project/test_images'
         test_files = np.array(glob(root + '/*'))

         for file in np.hstack(test_files):
             run_app(file)
```

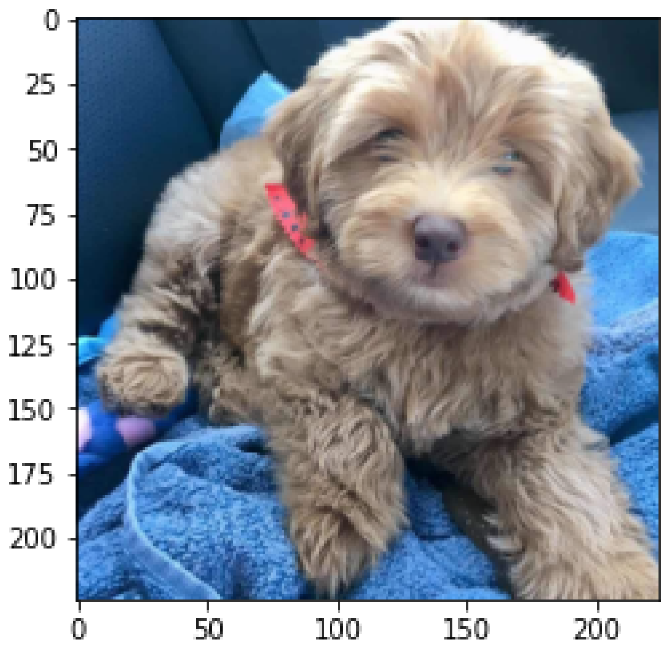
```
Hello human! You look like a Bearded collie
```



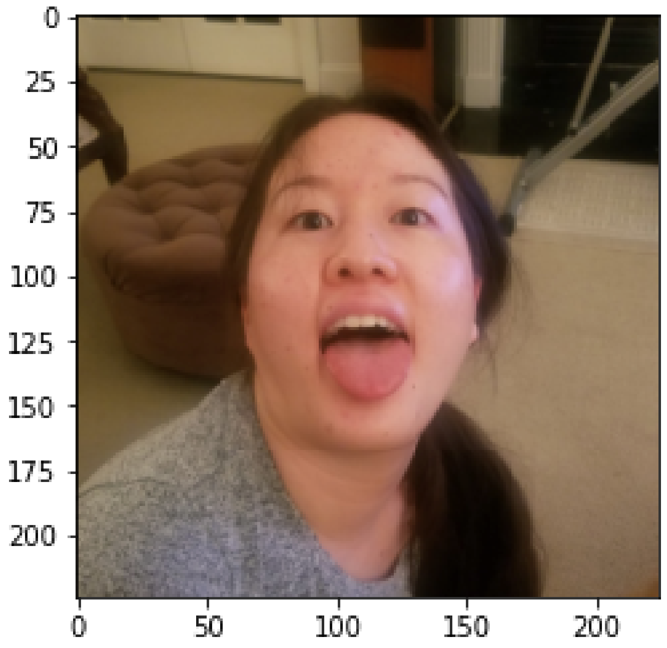
```
Hello dog! Your predicted breed is Portuguese water dog
```



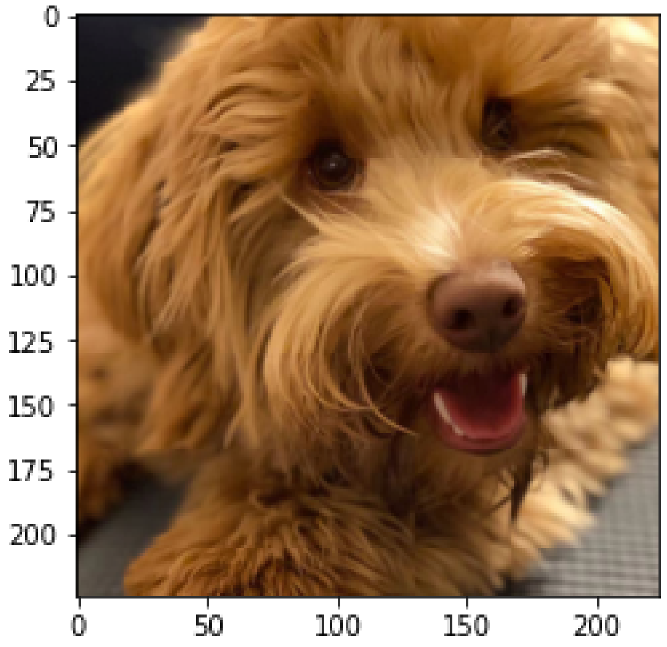
```
Hello dog! Your predicted breed is Cocker spaniel
```



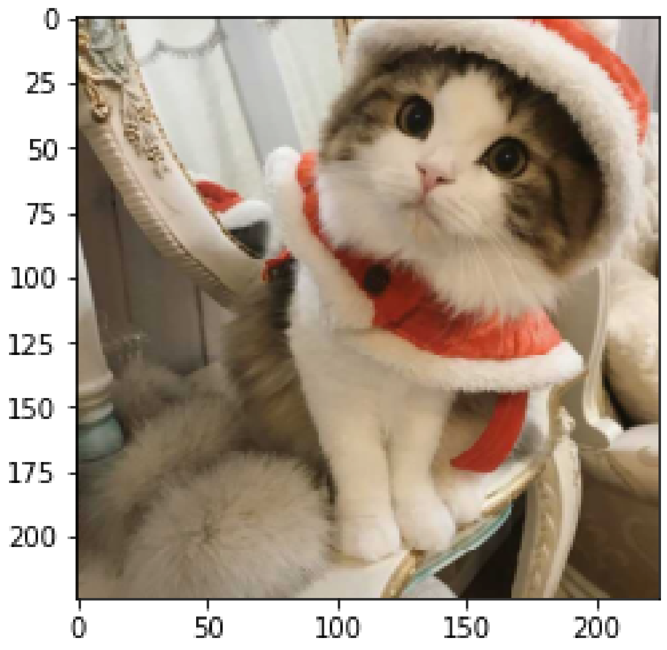
```
Hello human! You look like a Poodle
```



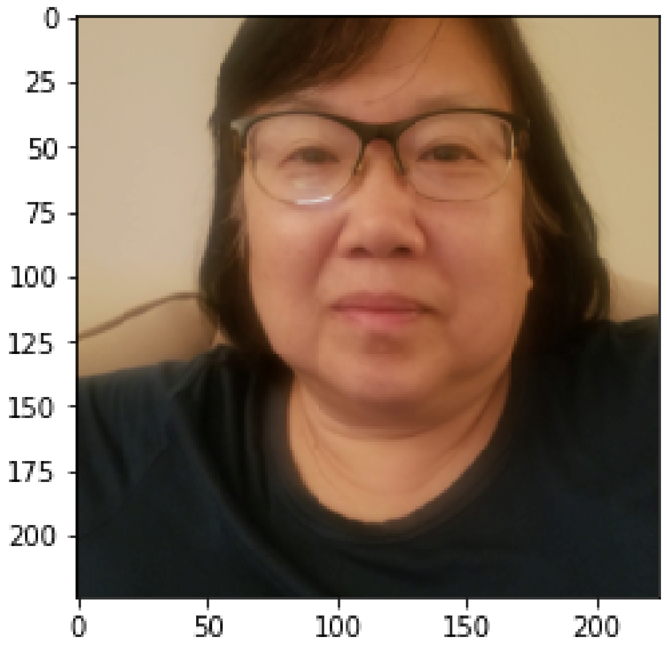
```
Hello dog! Your predicted breed is Havanese
```



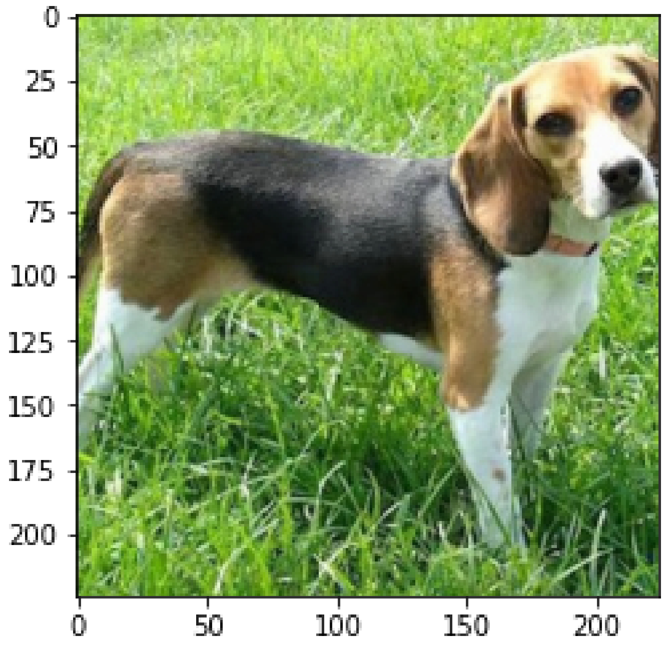
```
Error: this app is only designed for images of humans and dogs
```



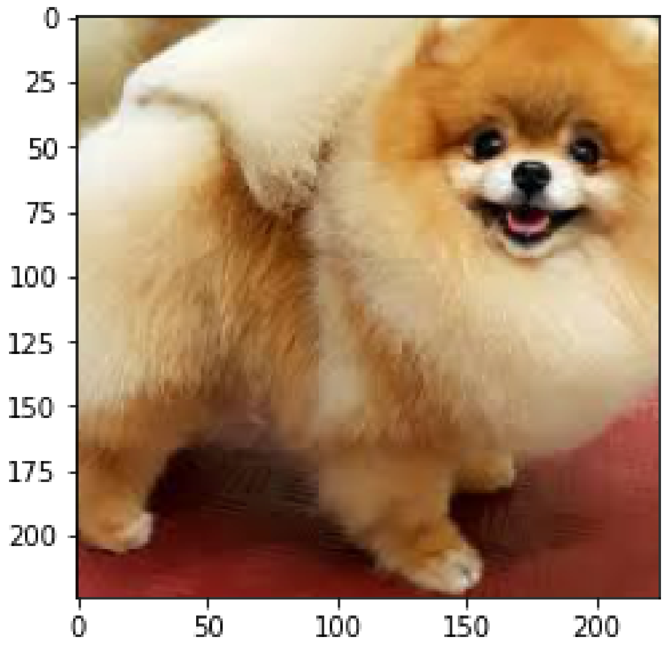
```
Hello human! You look like a Maltese
```



```
Hello dog! Your predicted breed is Beagle
```



```
Hello dog! Your predicted breed is Pomeranian
```



```
Error: this app is only designed for images of humans and dogs
```