dog_app

June 7, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

Step 0: Import Datasets

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

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

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

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

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

```
In [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

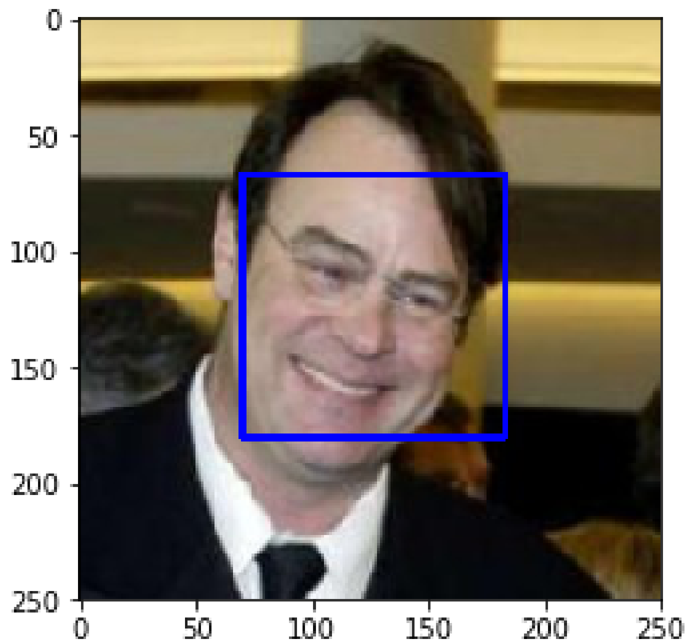
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

        human_face_count = 0
        human_dog_face_count = 0

        for image in tqdm(human_files_short):
            if face_detector(image):
                human_face_count += 1

        for image in tqdm(dog_files_short):
            if face_detector(image):
                human_dog_face_count += 1

        print(f"% of Human Faces detected in first 100 human_files is: {human_face_count}")
        print(f" % of Human Faces detected in first 100 dog_files is: {human_dog_face_count}")
        ## on the images in human_files_short and dog_files_short.
```

```
100%|| 100/100 [00:02<00:00, 34.60it/s]
100%|| 100/100 [00:30<00:00,  3.31it/s]
```

```
% of Human Faces detected in first 100 human_files is: 98
 % of Human Faces detected in first 100 dog_files is: 17
```

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

```
In [5]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
```

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

```
In [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()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 94166086.94it/s]
```

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

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

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

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

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

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

    Args:
        img_path: path to an image

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

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image

    img = Image.open(img_path)

    #transforms and utilize the normalization for pretrained models
    transform = transforms.Compose([
        transforms.Resize(225),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                             std=[0.229, 0.224, 0.225])
    ])

    #apply transforms on the image
    img = transform(img)
    img = torch.unsqueeze(img, 0)
    if use_cuda:
        img = img.cuda()
    #Predictions on the Image
    pred = VGG16(img)

    #index of the pred image
```

```
        idx = torch.argmax(pred)

        # return predicted class index
        return idx.item()
```

1.1.5 (IMPLEMENTATION) Write a Dog Detector

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

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

```
In [8]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.

            idx = VGG16_predict(img_path)

            if idx in range(151, 269):
                return True
            else:
                return False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

Answer:

```
In [9]: ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.

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

        dog_face_in_human_count = 0
        dog_face_in_dog_count = 0

        for image in tqdm(human_files_short):
            if dog_detector(image):
                dog_face_in_human_count += 1

        for image in tqdm(dog_files_short):
            if dog_detector(image):
                dog_face_in_dog_count += 1
```

```
        print( f" % of Dog Faces detected in first 100 human_files is: {dog_face_in_human_count}
        print( f" % of Dog Faces detected in first 100 dog_files is: {dog_face_in_dog_count}")
```

```
100%|| 100/100 [00:03<00:00, 28.69it/s]
100%|| 100/100 [00:04<00:00, 25.02it/s]

 % of Dog Faces detected in first 100 human_files is: 0
 % of Dog Faces detected in first 100 dog_files is: 100
```

We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as Inception-v3, 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 [10]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)

Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

We mention that the task of assigning breed to dogs from images is considered exceptionally challenging. To see why, consider that *even a human* would have trouble distinguishing between a Brittany and a Welsh Springer Spaniel.

Brittany	Welsh Springer Spaniel

It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).

Curly-Coated Retriever	American Water Spaniel

Likewise, recall that labradors come in yellow, chocolate, and black. Your vision-based algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.

Yellow Labrador	Chocolate Labrador

We also mention that random chance presents an exceptionally low bar: setting aside the fact that the classes are slightly imabalanced, a random guess will provide a correct answer roughly 1 in 133 times, which corresponds to an accuracy of less than 1%.

Remember that the practice is far ahead of the theory in deep learning. Experiment with many different architectures, and trust your intuition. And, of course, have fun!

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

In [ ]:

In [11]:
```
import os
from torchvision import datasets
import torchvision.transforms as transforms

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

from PIL import ImageFile
#
ImageFile.LOAD_TRUNCATED_IMAGES = True
data_dir = '/data/dog_images'
batch_size = 20

#data transforms

data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(15),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    'valid': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
```

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

    num_workers = 0
    image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x), data_transforms[x]
                      for x in ['train', 'valid', 'test']}

    loaders_data = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size = batch_si
                                                   shuffle = True, num_workers = num_workers
                      for x in ['train', 'valid', 'test']}

    dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'valid', 'test']}
    class_names = image_datasets['train'].classes
    n_classes = len(class_names)


    #print the numbers of classes, data in test, validation and training
    print(f"No. of images in training: {dataset_sizes['train']}")
    print(f"No. of images in validation: {dataset_sizes['valid']}")
    print(f"No. of images in testing: {dataset_sizes['test']}")
    print(f"No. of Classes (breeds): {n_classes}")
```

```
No. of images in training: 6680
No. of images in validation: 835
No. of images in testing: 836
No. of Classes (breeds): 133
```

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 have resized the images to **224x224** pixels following the Imagenet standards

- Yes, I have decided to augmented them by rotation (**RandomRotation of 15 degrees**) for the training dataset as this would help the model to genralize. Further added a(**RandomHorizontalFlip**) then transformed the images into Tensors. Finally Normalized the image with mean and standard deviation. These tensors will be fed to the cnn network

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [12]: import torch.nn as nn
         import torch.nn.functional as F
         # define the CNN architecture
         class Net(nn.Module):
             ### TODO: choose an architecture, and complete the class
             def __init__(self):
                 super(Net, self).__init__()

                 ## Define layers of a CNN

                 # Input to cnn : 224x224x3 image tensor a RGB image
                 #convolutional layer with 16 filters, each filter having a width and height of
                 #output channel increase by a factor of 2 image size decreases by 2

                 self.conv1 = nn.Conv2d(3, 16, 3, padding = 1 )
                 # cnn layer -->112x112x16 image tensor
                 self.conv2 = nn.Conv2d(16, 32, 3, padding = 1)
                 # cnn layer --> 56x56x32 image tensor
                 self.conv3 = nn.Conv2d(32, 64, 3, padding = 1)
                 # cnn layer -->28x28x64 image tensor
                 self.conv4 = nn.Conv2d(64, 128, 3, padding = 1)
                 # cnn layer -->14x14x128 image tensor
                 self.conv5 = nn.Conv2d(128, 256, 3, padding = 1 )

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

                 #Droput of .20
                 self.dropout = nn.Dropout(0.2)

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

                 # linear layer (256 * 7 * 7 -> 512)
                 self.fc1 = nn.Linear(256 * 7 * 7, 512)
                 # linear layer (256 * 7 * 7 -> n_classes (133))
                 self.fc2 = nn.Linear(512, n_classes)

             def forward(self, x):
                 ## Define forward behavior
                 # add sequence of convolutional and max pooling layers
```

```
            x = self.pool(F.relu(self.conv1(x)))
            x = self.conv_bn2(x)
            x = self.pool(F.relu(self.conv2(x)))
            x = self.conv_bn3(x)
            x = self.pool(F.relu(self.conv3(x)))
            x = self.conv_bn4(x)
            x = self.pool(F.relu(self.conv4(x)))
            x = self.conv_bn5(x)
            x = self.pool(F.relu(self.conv5(x)))
            x = self.conv_bn6(x)

            # flatten image
            x = x.view(-1, 256 * 7 * 7)
            # add dropout layer
            x = self.dropout(x)

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

    # check if CUDA is available
    use_cuda = torch.cuda.is_available()
    # 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))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (dropout): Dropout(p=0.2)
  (conv_bn1): BatchNorm2d(224, eps=3, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
  (fc1): Linear(in_features=12544, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=133, bias=True)
)
```

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

Answer:

- CNN has 5 convolution layers and 2 fully connected layers. The input paramters to the cnn are defined above (Kernel size = 3, stride = 1 and padding = 1)
- Each convolutional layer changes the output of the previous layer to generate a new set of filters. and it generates much more filters in my case 16/32/64/128/256 filters respectively
- The network utilize max pooling layer of 2*2.
- Relu activations are used after each layers excpet in the final one
- Dropout is applied with the probability of 0.20,to overcome the overfitting problem.
- Batch normalization is applied after the max pooling.

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 [13]: import torch.optim as optim

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

         # specify optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.001, 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 [14]: 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
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
            # clear the gradients
            optimizer.zero_grad()
            # forward pass
            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # backward pass
            loss.backward()
            optimizer.step()
            # update training loss
            train_loss = train_loss + (1 / (batch_idx + 1)) * (loss.data - train_loss)

        ######################
        # validate the model #
        ######################
        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
            # calculate the batch loss
            output = model(data)
            loss = criterion(output, target)
            # update average validation loss
            valid_loss = valid_loss + (1 / (batch_idx + 1)) * (loss.data - valid_loss)


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

        ## TODO: save the model if validation loss has decreased
        if valid_loss <= valid_loss_min:
```

```
                print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss


        # return trained model
        return model


    # train the model

    n_epochs = 35
    loaders_scratch = loaders_data
    model_scratch = train(n_epochs, 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: 4.764592 	Validation Loss: 4.557551
Validation loss decreased (inf --> 4.557551).  Saving model ...
Epoch: 2 	Training Loss: 4.517922 	Validation Loss: 4.300688
Validation loss decreased (4.557551 --> 4.300688).  Saving model ...
Epoch: 3 	Training Loss: 4.359538 	Validation Loss: 4.158280
Validation loss decreased (4.300688 --> 4.158280).  Saving model ...
Epoch: 4 	Training Loss: 4.199427 	Validation Loss: 3.950366
Validation loss decreased (4.158280 --> 3.950366).  Saving model ...
Epoch: 5 	Training Loss: 4.105052 	Validation Loss: 3.836745
Validation loss decreased (3.950366 --> 3.836745).  Saving model ...
Epoch: 6 	Training Loss: 4.024915 	Validation Loss: 3.735175
Validation loss decreased (3.836745 --> 3.735175).  Saving model ...
Epoch: 7 	Training Loss: 3.927507 	Validation Loss: 3.728712
Validation loss decreased (3.735175 --> 3.728712).  Saving model ...
Epoch: 8 	Training Loss: 3.851270 	Validation Loss: 3.713184
Validation loss decreased (3.728712 --> 3.713184).  Saving model ...
Epoch: 9 	Training Loss: 3.817995 	Validation Loss: 3.654767
Validation loss decreased (3.713184 --> 3.654767).  Saving model ...
Epoch: 10 	Training Loss: 3.740992 	Validation Loss: 3.508133
Validation loss decreased (3.654767 --> 3.508133).  Saving model ...
Epoch: 11 	Training Loss: 3.679420 	Validation Loss: 3.503793
Validation loss decreased (3.508133 --> 3.503793).  Saving model ...
Epoch: 12 	Training Loss: 3.653083 	Validation Loss: 3.483705
Validation loss decreased (3.503793 --> 3.483705).  Saving model ...
Epoch: 13 	Training Loss: 3.572877 	Validation Loss: 3.404453
Validation loss decreased (3.483705 --> 3.404453).  Saving model ...
Epoch: 14 	Training Loss: 3.535560 	Validation Loss: 3.454973
```

```
Epoch: 15         Training Loss: 3.493177        Validation Loss: 3.352664
Validation loss decreased (3.404453 --> 3.352664).  Saving model ...
Epoch: 16         Training Loss: 3.450382        Validation Loss: 3.324121
Validation loss decreased (3.352664 --> 3.324121).  Saving model ...
Epoch: 17         Training Loss: 3.392452        Validation Loss: 3.316399
Validation loss decreased (3.324121 --> 3.316399).  Saving model ...
Epoch: 18         Training Loss: 3.367084        Validation Loss: 3.365277
Epoch: 19         Training Loss: 3.334580        Validation Loss: 3.255436
Validation loss decreased (3.316399 --> 3.255436).  Saving model ...
Epoch: 20         Training Loss: 3.283276        Validation Loss: 3.206129
Validation loss decreased (3.255436 --> 3.206129).  Saving model ...
Epoch: 21         Training Loss: 3.243421        Validation Loss: 3.154956
Validation loss decreased (3.206129 --> 3.154956).  Saving model ...
Epoch: 22         Training Loss: 3.181235        Validation Loss: 3.099002
Validation loss decreased (3.154956 --> 3.099002).  Saving model ...
Epoch: 23         Training Loss: 3.145403        Validation Loss: 3.165967
Epoch: 24         Training Loss: 3.152083        Validation Loss: 3.205071
Epoch: 25         Training Loss: 3.059414        Validation Loss: 3.029891
Validation loss decreased (3.099002 --> 3.029891).  Saving model ...
Epoch: 26         Training Loss: 3.039874        Validation Loss: 3.064959
Epoch: 27         Training Loss: 3.034859        Validation Loss: 3.078768
Epoch: 28         Training Loss: 2.928015        Validation Loss: 2.973772
Validation loss decreased (3.029891 --> 2.973772).  Saving model ...
Epoch: 29         Training Loss: 2.929127        Validation Loss: 2.878753
Validation loss decreased (2.973772 --> 2.878753).  Saving model ...
Epoch: 30         Training Loss: 2.901170        Validation Loss: 2.895752
Epoch: 31         Training Loss: 2.826754        Validation Loss: 2.934776
Epoch: 32         Training Loss: 2.841522        Validation Loss: 2.834679
Validation loss decreased (2.878753 --> 2.834679).  Saving model ...
Epoch: 33         Training Loss: 2.783911        Validation Loss: 2.884225
Epoch: 34         Training Loss: 2.777228        Validation Loss: 2.843405
Epoch: 35         Training Loss: 2.719241        Validation Loss: 2.789025
Validation loss decreased (2.834679 --> 2.789025).  Saving model ...
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [15]: 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: 2.690640


Test Accuracy: 32% (270/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)
You will now use transfer learning to create a CNN that can identify dog breed from images. Your CNN must attain at least 60% accuracy on the test set.

1.1.12 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

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

```
In [ ]: ## TODO: Specify data loaders
```

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 [16]:
```
import torchvision.models as models
import torch.nn as nn

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

# Freeze weights
for param in model_transfer.parameters():
    param.requires_grad = False


num_features = model_transfer.fc.in_features

#retrieve the fully model and replace the last layer we have 133 classes

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

print(model_transfer)


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

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:01<00:00, 95572824.28it/s]
```

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

```
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
```

```
      )
      (3): Bottleneck(
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
      )
    )
    (layer3): Sequential(
      (0): Bottleneck(
        (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
        (downsample): Sequential(
          (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): Bottleneck(
        (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
      )
      (2): Bottleneck(
        (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
      )
      (3): Bottleneck(
        (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

```
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
  (fc): Linear(in_features=2048, out_features=133, bias=True)
)
```

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

Answer:

- downloaded resnet50
- Model has multiple convolution layers with batch normalization, positioned well to produce good feature maps
- Freezed all the weights
- Changed the last layer with new linear layer
- Once training the last layer the model should perform well

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 [17]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(model_transfer.fc.parameters(), lr=0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [18]: # train the model
         #model_transfer = # train(n_epochs, loaders_transfer, model_transfer, optimizer_transfe

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

         use_cuda = torch.cuda.is_available()
         n_epochs = 15
         loaders_transfer = loaders_data
         model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_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: 2.745427 	Validation Loss: 0.979306
Validation loss decreased (inf --> 0.979306).  Saving model ...
Epoch: 2 	Training Loss: 1.496151 	Validation Loss: 0.736856
Validation loss decreased (0.979306 --> 0.736856).  Saving model ...
Epoch: 3 	Training Loss: 1.326900 	Validation Loss: 0.685165
Validation loss decreased (0.736856 --> 0.685165).  Saving model ...
Epoch: 4 	Training Loss: 1.246157 	Validation Loss: 0.568959
Validation loss decreased (0.685165 --> 0.568959).  Saving model ...
Epoch: 5 	Training Loss: 1.159694 	Validation Loss: 0.594749
Epoch: 6 	Training Loss: 1.170727 	Validation Loss: 0.514789
Validation loss decreased (0.568959 --> 0.514789).  Saving model ...
Epoch: 7 	Training Loss: 1.140349 	Validation Loss: 0.565717
Epoch: 8 	Training Loss: 1.106199 	Validation Loss: 0.536667
Epoch: 9 	Training Loss: 1.070683 	Validation Loss: 0.532929
Epoch: 10 	Training Loss: 1.097254 	Validation Loss: 0.546130
Epoch: 11 	Training Loss: 1.114051 	Validation Loss: 0.583726
Epoch: 12 	Training Loss: 1.053657 	Validation Loss: 0.590684
Epoch: 13 	Training Loss: 1.043424 	Validation Loss: 0.541269
Epoch: 14 	Training Loss: 1.059751 	Validation Loss: 0.608782
Epoch: 15 	Training Loss: 1.033329 	Validation Loss: 0.516305
```

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%.

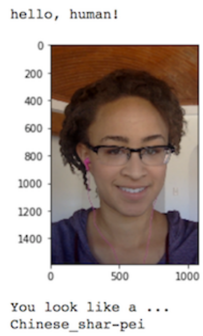
```
In [19]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.556641


Test Accuracy: 82% (693/836)
```

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 [20]: ### 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'].classes]

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             img = Image.open(img_path)
```



Sample Human Output

```
transform = transforms.Compose([
    transforms.Resize(225),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                         std=[0.229, 0.224, 0.225])
])

img = transform(img)
img = torch.unsqueeze(img, 0)
if use_cuda:
    img = img.cuda()

ps = model_transfer(img)
idx = torch.argmax(ps)

return class_names[idx]
```

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

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             if dog_detector(img_path):
                 img = Image.open(img_path)
                 plt.imshow(img)
                 plt.show()
                 print("This Dog is :")
                 print(predict_breed_transfer(img_path))

             elif face_detector(img_path):
                 print("Hello, Human !")
                 img = Image.open(img_path)
                 plt.imshow(img)
                 plt.show()
                 print("You look like a.........:")
                 print(predict_breed_transfer(img_path))

             else:
                 print("Neither Dog nor Human face is detected")
                 plt.imshow(img)
```

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)

- The transfer model is performing fine, better than the scratch model with 82% accuracy

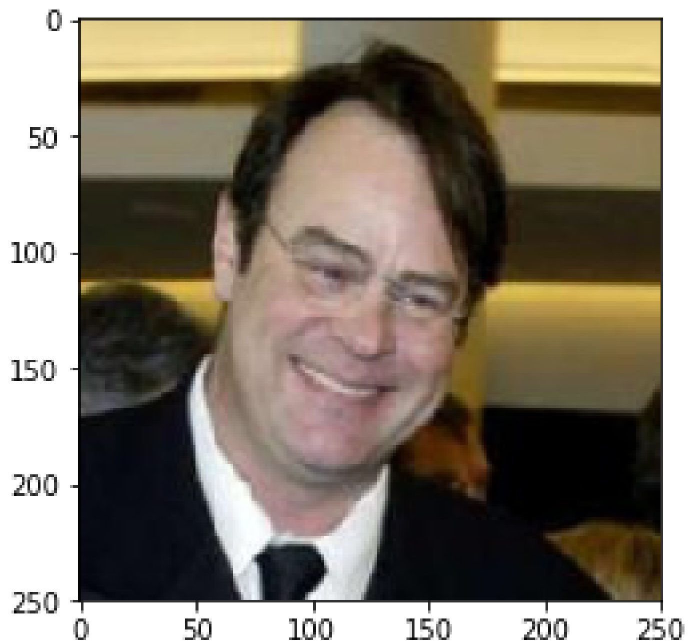
Improving the model :

- during the training phase after epoch 6 the validation loss did not decrease! I would try diffrent hyperparameter for learning rate, the default value is quite low
- Randomly Shuffle the dataset

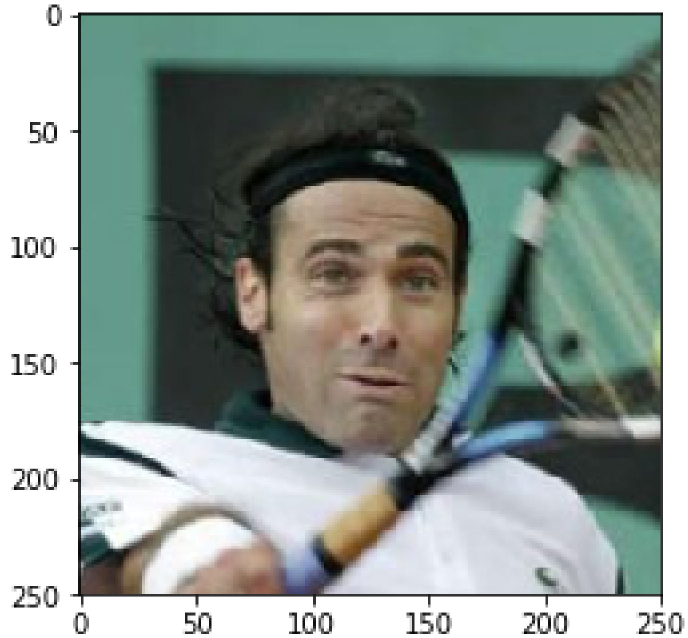
- Explore a diffrent pretrained model
- utilize SGD with momentum as the optimzer instead of Adam optimizer to check if the accuracy improves further
- utilize K-fold cross validation

In [22]:
```
## 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)
```

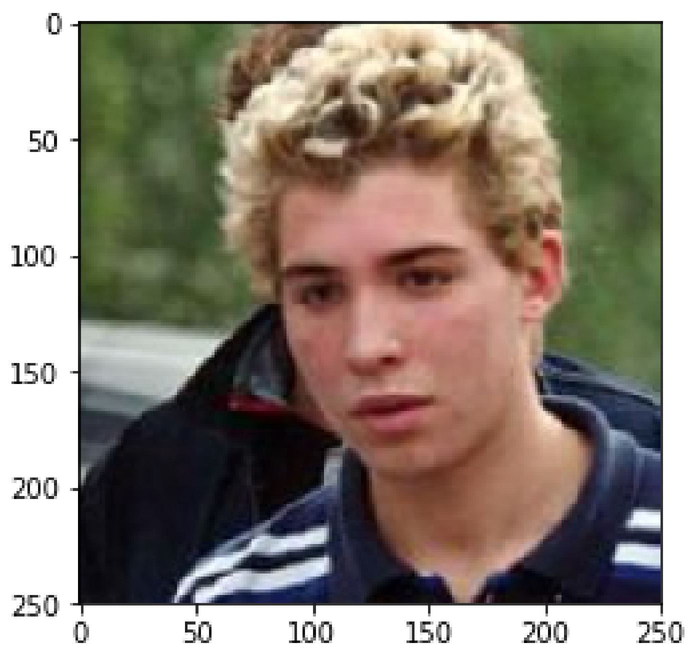
```
Hello, Human !
```



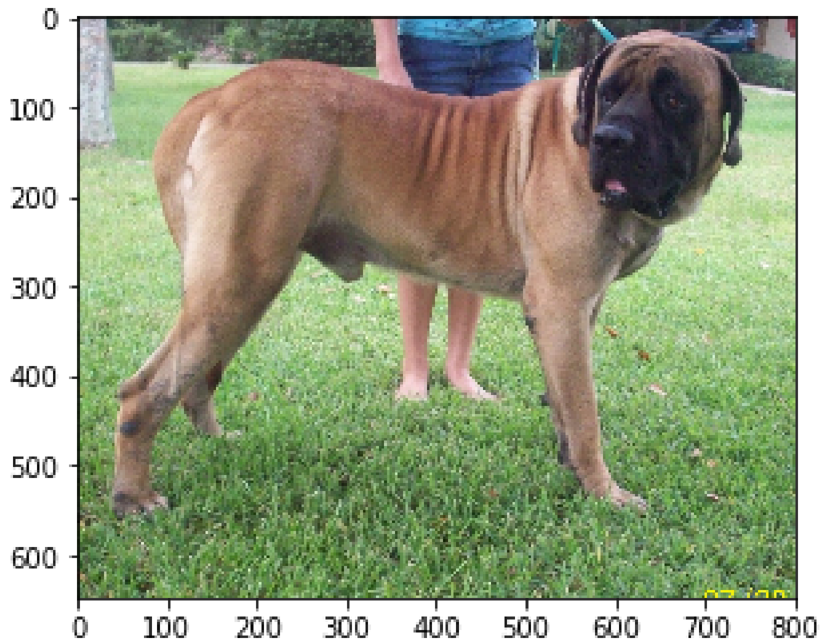

```
You look like a...:
Chihuahua
Hello, Human !
```



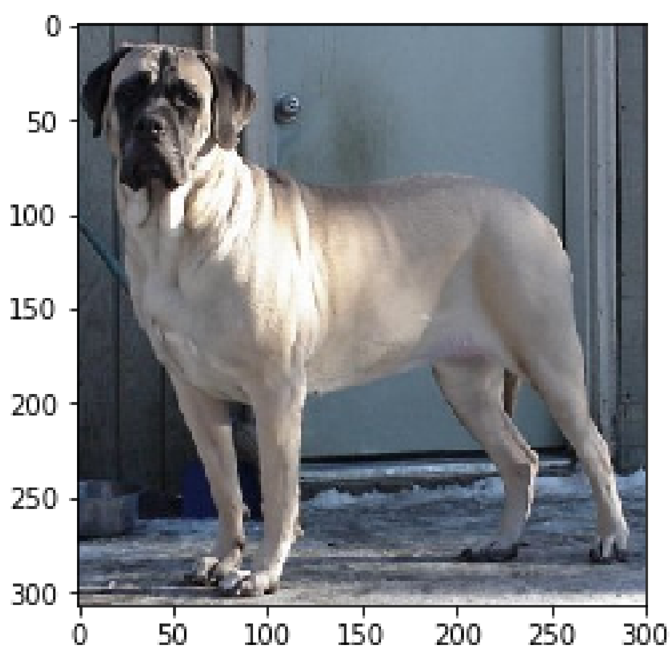

```
You look like a...:
Cardigan welsh corgi
Hello, Human !
```



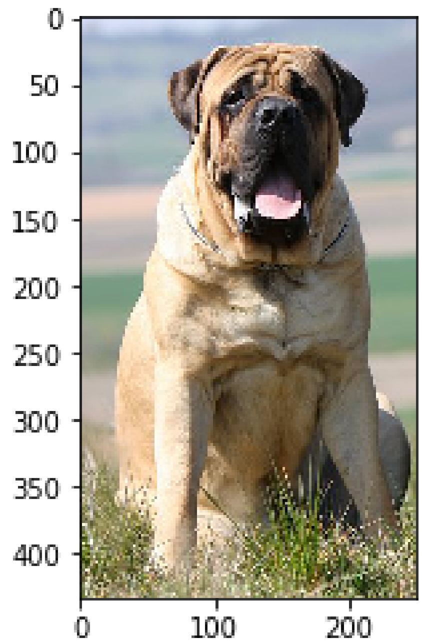
```
You look like a...:
Australian cattle dog
```




```
This Dog is :
Mastiff
```



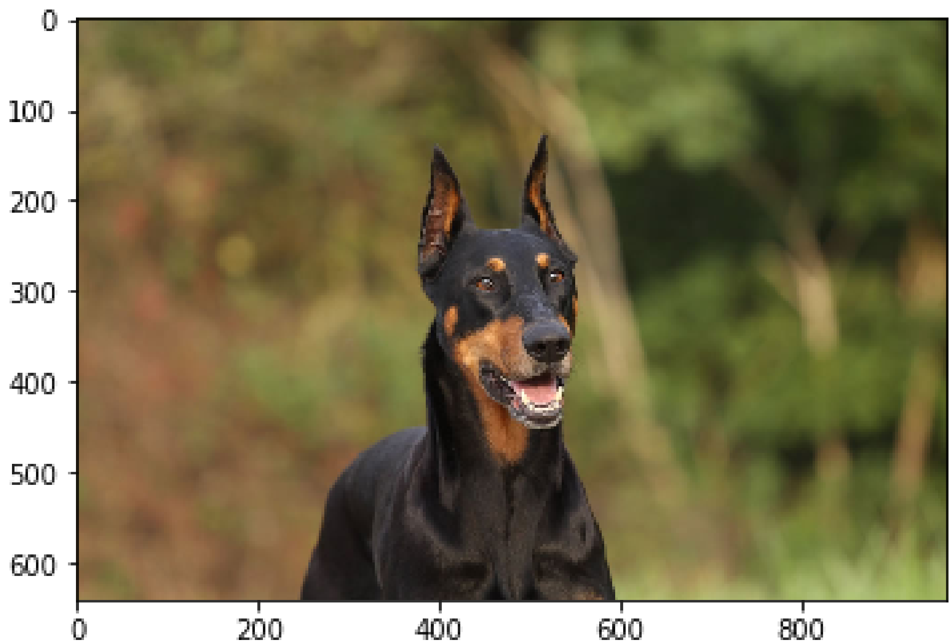
```
This Dog is :
Mastiff
```




```
This Dog is :
Bullmastiff
```

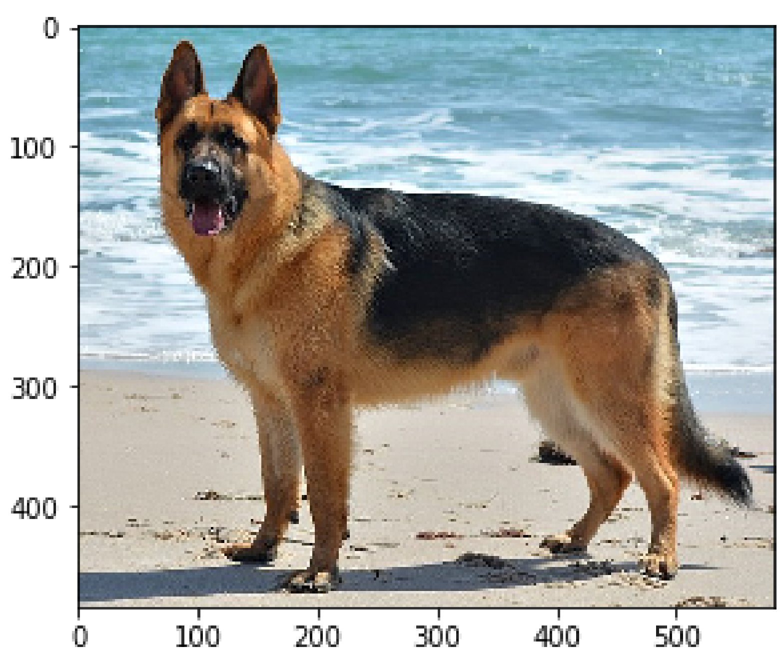
1.2 Testing the algorithm on six images that's not in the dataset.

```
In [23]: run_app("images/Dobermann.jpg")
```



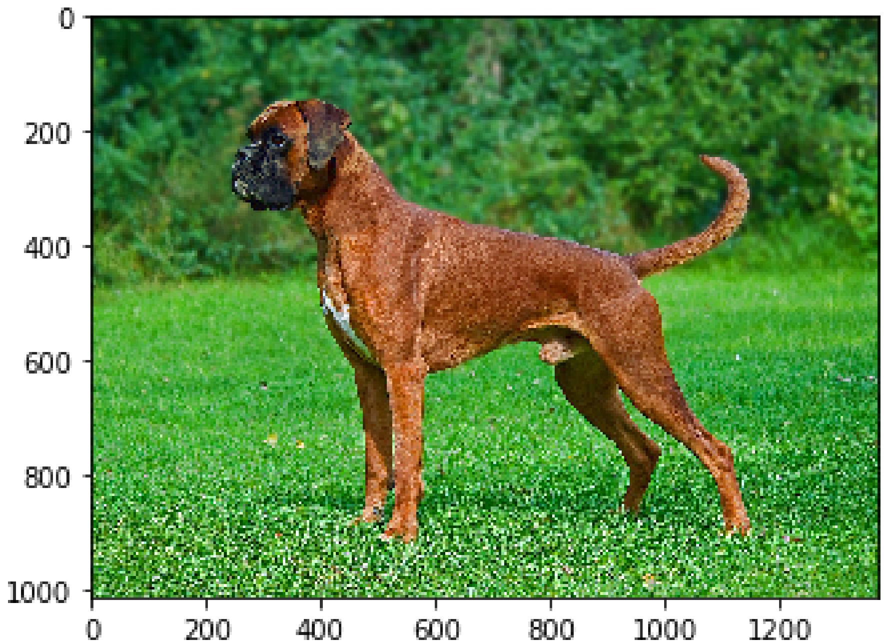
```
This Dog is :
Doberman pinscher
```

```
In [24]: run_app("images/German_Shepherd_-_DSC_0346_(10096362833).jpg")
```



```
This Dog is :
German shepherd dog
```

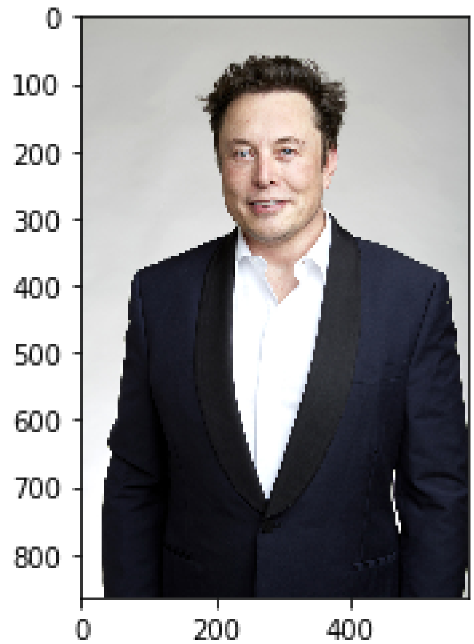
```
In [25]: run_app("images/Male_fawn_Boxer_undocked.jpg")
```



```
This Dog is :
Boxer
```

```
In [26]: run_app("images/Elon_Musk_Royal_Society.jpg")
```

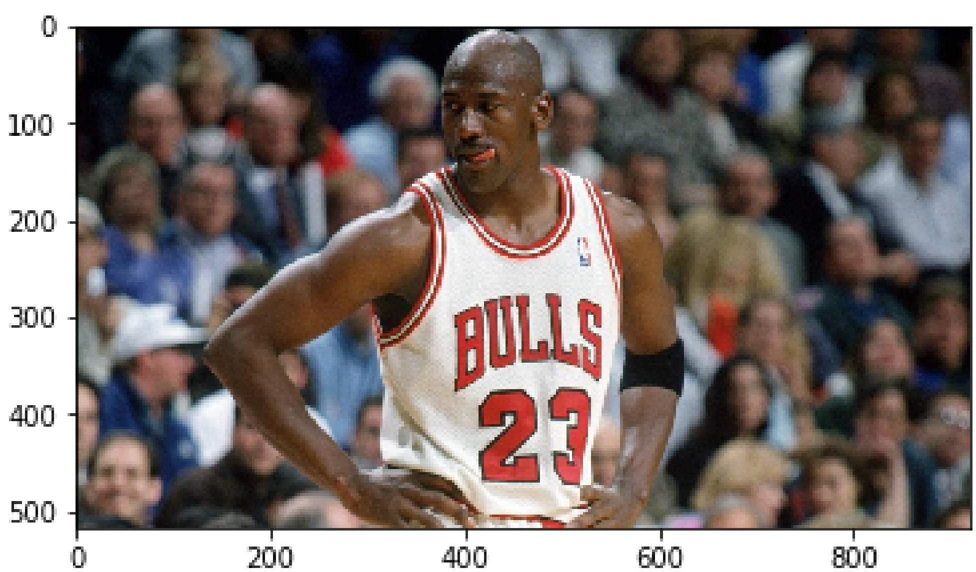
```
Hello, Human !
```



```
You look like a...:
Giant schnauzer
```

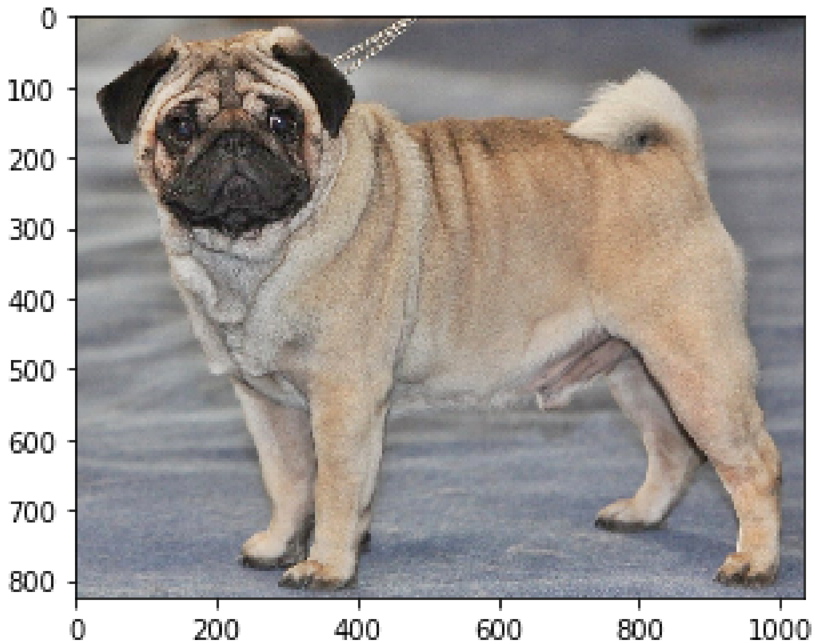
```
In [27]: run_app("images/MJ.jpg")
```

```
Hello, Human !
```



```
You look like a...:
German shorthaired pointer
```

```
In [28]: run_app("images/Pug.jpg")
```



```
This Dog is :
Chinese shar-pei
```

```
In [ ]:
```