dog_app

May 12, 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

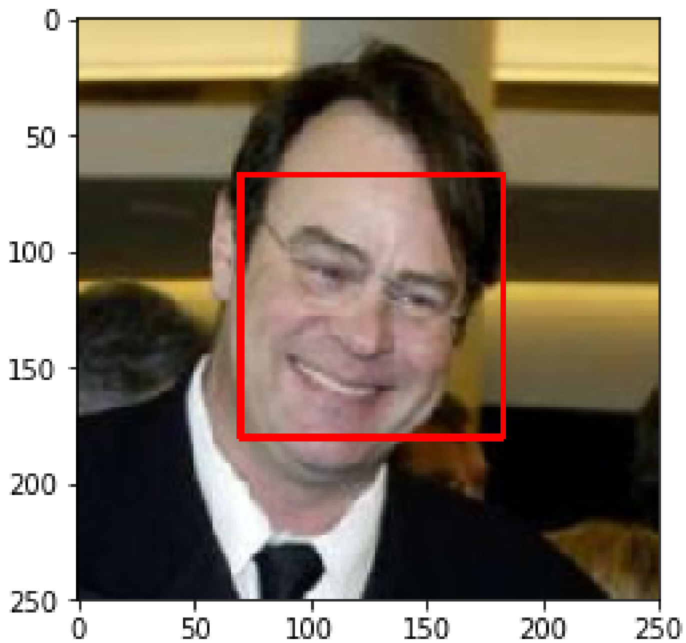
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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))
```

```python
# get bounding box for each detected face
for (x,y,w,h) in faces:
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(0,0,255),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: There are 98.0% images of the first 100 human files that have a detected humnan face. There are 17.0% images of the first dog files that have a detected human face

```
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. #-#-#

        human_faces = [face_detector(human_file) for human_file in human_files_short]
        dog_faces = [face_detector(dog_file) for dog_file in dog_files_short]
        perc_hum = 100 *(np.sum(human_faces)/len(human_files_short))
        ## TODO: Test the performance of the face_detector algorithm
        print('There are %.1f%% images of the  first 100 human files that have a detected humnan
        ## on the images in human_files_short and dog_files_short.
        perc_dog = 100 *(np.sum(dog_faces)/len(dog_files_short))
        print('There are %.1f%% images of the first dog files that have a detected human face' %

There are 98.0% images of the  first 100 human files that have a detected humnan face.
There are 17.0% images of the first dog files that have a detected human face
```

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)
print(VGG16)
# 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 [00:06<00:00, 79617297.67it/s]


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=1000, bias=True)
  )
)
```

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)
    #convert img to tensor , to give it as a parameter for VGG16
    #human  face jpg file widt 250 and resize to 250
    trans_pip= transforms.Compose([transforms.RandomResizedCrop(250),transforms.ToTensor
    img_tensor =trans_pip(img)
    img_tensor =img_tensor.unsqueeze(0)
    # move tensor to cuda
    if torch.cuda.is_available():
        img_tensor = img_tensor.cuda()
    prediction = VGG16(img_tensor)

    #move tensor to cpu
    if torch.cuda.is_available():
        prediction =prediction.cpu()
    index = prediction.data.numpy().argmax()

    return index  # predicted class index
VGG16_predict(dog_files[0])
```

Out[7]: 208

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

```
print(dog_detector(dog_files_short[5]))
print(dog_detector(human_files_short[5]))
```

```
True
False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

__Answer:_ _0.0% image of the first 100 human_files were detected as dog. 84.0% image of te first 100 dog_files were detected a dog.

```
In [10]: ### 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]
         co_humans = 0
         co_dogs = 0

         for file in human_files_short:
             if dog_detector(file):
                 co_humans +=1
         for file in dog_files_short:
             if dog_detector(file):
                 co_dogs +=1
         print('%.1f%% image of the first 100 human_files were detected as dog.' %co_humans)
         print('%.1f%% image of te first 100 dog_files were detected a dog.'%co_dogs)
```

```
0.0% image of the first 100 human_files were detected as dog.
84.0% image of te first 100 dog_files were detected a dog.
```

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 [11]: ### (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 [12]: import os
         from torchvision import datasets
         import torch
         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
         root_dir_path = '/data/dog_images/'
```

```python
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
transform_pip = transforms.Compose([transforms.RandomResizedCrop(224),transforms.ToTens

train_data = datasets.ImageFolder('/data/dog_images/train' , transform=transform_pip)
valid_data = datasets.ImageFolder('/data/dog_images/valid' , transform = transforms.Res
test_data = datasets.ImageFolder('/data/dog_images/test',transform= transforms.Resize(2
datasets_transforms = {'train' : transforms.Compose([transforms.RandomResizedCrop(256,
                                                      transforms.RandomRotation(25),
                                                      transforms.RandomHorizontalFlip(),
                                                      transforms.ColorJitter(),
                                                      transforms.CenterCrop(224),
                                                      transforms.ToTensor(),
                                                      transforms.Normalize((0.485, 0.456,
                                                                            (0.229, 0.224,
                       'valid' : transforms.Compose([transforms.Resize(255),
                                                      transforms.CenterCrop(224),
                                                      transforms.ToTensor(),
                                                      transforms.Normalize((0.485, 0.456,
                                                                            (0.229, 0.224,
                       'test' : transforms.Compose([transforms.Resize(255),
                                                     transforms.CenterCrop(224),
                                                     transforms.ToTensor(),
                                                     transforms.Normalize((0.485, 0.456,
                                                                           (0.229, 0.224,
batch_size = 10
num_workers = 0
images_datasets = {'train' : datasets.ImageFolder(os.path.join(root_dir_path + '/train'
                   'valid' : datasets.ImageFolder(os.path.join(root_dir_path + '/valid'
                   'test' : datasets.ImageFolder(os.path.join(root_dir_path + '/test'),
train_loader = torch.utils.data.DataLoader(train_data,batch_size=batch_size,num_workers
test_loader = torch.utils.data.DataLoader(test_data,batch_size=batch_size,num_workers=n
valid_loader = torch.utils.data.DataLoader(valid_data,batch_size=batch_size,num_workers

loaders_scratch = { 'train':train_loader,'valid':valid_loader,'test':test_loader}
images_dataloaders = {'train' : torch.utils.data.DataLoader(images_datasets['train'], b
                      'valid' : torch.utils.data.DataLoader(images_datasets['valid'], b
                      'test' : torch.utils.data.DataLoader(images_datasets['test'], bat

print('Number of Training Images: ', len(images_datasets['train']))
print('Number of Validation Images: ', len(images_datasets['valid']))
print('Number of Testing Images: ', len(images_datasets['test']))
```

```
Number of Training Images:  6680
Number of Validation Images:  835
Number of Testing Images:  836
```

Question 3: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why? - Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: Resize images randomly by flipping them horizontally first and then cropping them to 224 x 224 as the input tensioner because my images are colored (RGB depth 3) and the required input in CNN structure is 224 x 224 x 3. I used data augmentation (scale random resize, flip, rotate and color jitter)

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [13]: import torch.nn as nn
         import torch.nn.functional as F
         total_dog_classes = 133
         # define the CNN architecture
         class Net(nn.Module):
             ### TODO: choose an architecture, and complete the class
             def __init__(self):
                 super(Net, self).__init__()
                 # 1st convolutional layer
                 self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
                 # 2nd convolutional layer
                 self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
                 # 3rd convolutional layer
                 self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
                 # 4t convolutional layer
                 self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
                 # 5th convolutional layer
                 self.conv5 = nn.Conv2d(128, 256, 3, padding=1)
                 # max pooling layer
                 self.pool = nn.MaxPool2d(2, 2)
                 # 1st fully connected hidden linear layer
                 self.fc1 = nn.Linear(256 * 7 * 7, 1920)
                 # 2nd fully connected hidden linear layer
                 self.fc2 = nn.Linear(1920, 1000)
                 # final output layer
                 self.fc3 = nn.Linear(1000, 133)
                 # dropout layer (p=0.45)
                 self.dropout = nn.Dropout(0.45)

             def forward(self, x):
                 ## Define forward behavior
                 # sequence of 5 convolutional and max pooling layers with relu activation funct
                 x = self.pool(F.relu(self.conv1(x)))
                 x = self.pool(F.relu(self.conv2(x)))
                 x = self.pool(F.relu(self.conv3(x)))
```

```python
        x = self.pool(F.relu(self.conv4(x)))
        x = self.pool(F.relu(self.conv5(x)))
        # flatten image input for fully connected layers
        x = x.view(-1, 256 * 7 * 7)
        # dropout layer
        x = self.dropout(x)
        # 1st hidden layer, with relu activation function
        x = F.relu(self.fc1(x))
        # dropout layer
        x = self.dropout(x)
        # 2nd hidden layer, with relu activation function
        x = F.relu(self.fc2(x))
        # dropout layer
        x = self.dropout(x)
        # final output layers for network
        x = self.fc3(x)
        return x

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

# instantiate the CNN
model_scratch = Net()
print(model_scratch)
# move tensors to GPU if CUDA is available
if use_cuda:
    model_scratch.cuda()
```

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (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)
  (fc1): Linear(in_features=12544, out_features=1920, bias=True)
  (fc2): Linear(in_features=1920, out_features=1000, bias=True)
  (fc3): Linear(in_features=1000, out_features=133, bias=True)
  (dropout): Dropout(p=0.45)
)
```

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

Answer: The following steps:

Under the network init function i defined the CNN layers as follows: (a) 5 convolution layers and their parameters (input image depth of 3 for RGB image, 16 initial depth of filters for the input image which doubled across each convolution layer, 3x3 kernel/filter size, stride=1 and padding=1 to maintain image dimensions. (b) Each convolution layer had a maxpooling layer (with (2 x 2) filter size and stride) after it to discard some spatial information about each convolution layer thereby decreasing their height and weight. (c) 2 fully connected hidden layers with the first fully connected layer taking flattened downsized stack of feature maps as its input and passing it to the next fully connected hidden layer and then to the final output for class scores prediction for the dog breeds (d) A dropout function (45% p=0.45) to avoid overfitting. Under the feed forward of the network with input image (x), I did the following: (a) Resultant input (x) is flattened into a vector shape and passed as input into fully connected layer. (b) Passed input in sequence across convolutional layers applying Relu activation function where outputs are passed to pooling layers to produce down sampled transformed inputs (x) which would be returned by the function. (c) The dropout function to prevent overfitting and relu activation function are passed in-between the flattened vector input image and the first fully connected layer and then between other fully connected hidden layers and finally a dropout function before the final output layer to produce my desired class score output of 133 possible dog breed outputs. After defining network model architecture, it was instantiated and moved to GPU for faster training. Using CrossEntropyLoss function and Adam optimization function for the model and training for 70 epochs, i achieved a test accuracy of 23%.

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 [14]: import torch.optim as optim

         ### TODO: select loss function
         criterion_scratch = nn.CrossEntropyLoss()
         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(),lr=0.001,momentum=0.9)

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

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 [15]: 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 out any gradients calculations at the start of every batch loop
    optimizer.zero_grad()
    #call model and perfrom a forward pass by model taking input images which a
    output = model(data)
    #defined loss function to compare the predicted predicted outputs and the t
    loss = criterion(output, target)
    #completes the backpropagation steps by performing a backward pass to compu
    loss.backward()
    #perform a single optimization step responsible for updating the values of
    optimizer.step()
    #compute the average running 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
    #call model and perfrom a forward pass by model taking input images which a
    output = model(data)
    #defined loss function to compare the predicted predicted outputs and the t
    loss = criterion(output, target)
    #compute the 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 has decreased ({:.6f} --> {:.6f}).  Saving model ...
                valid_loss_min,
                valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss

        # return trained model
        return model
```

```
In [16]: # defining the dataloaders
         loaders_scratch = {'train': images_dataloaders['train'], 'valid': images_dataloaders['v
```

```
In [17]: # train the model
         model_scratch = train(70, loaders_scratch, model_scratch, optimizer_scratch,
                               criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1         Training Loss: 4.889468         Validation Loss: 4.887075
Validation loss has decreased (inf --> 4.887075).  Saving model ...
Epoch: 2         Training Loss: 4.885875         Validation Loss: 4.883929
Validation loss has decreased (4.887075 --> 4.883929).  Saving model ...
Epoch: 3         Training Loss: 4.881849         Validation Loss: 4.879241
Validation loss has decreased (4.883929 --> 4.879241).  Saving model ...
Epoch: 4         Training Loss: 4.875462         Validation Loss: 4.869133
Validation loss has decreased (4.879241 --> 4.869133).  Saving model ...
Epoch: 5         Training Loss: 4.868826         Validation Loss: 4.863940
Validation loss has decreased (4.869133 --> 4.863940).  Saving model ...
Epoch: 6         Training Loss: 4.861566         Validation Loss: 4.850121
Validation loss has decreased (4.863940 --> 4.850121).  Saving model ...
Epoch: 7         Training Loss: 4.832983         Validation Loss: 4.793720
Validation loss has decreased (4.850121 --> 4.793720).  Saving model ...
Epoch: 8         Training Loss: 4.762206         Validation Loss: 4.721498
Validation loss has decreased (4.793720 --> 4.721498).  Saving model ...
Epoch: 9         Training Loss: 4.686471         Validation Loss: 4.642626
Validation loss has decreased (4.721498 --> 4.642626).  Saving model ...
Epoch: 10         Training Loss: 4.619127         Validation Loss: 4.590841
Validation loss has decreased (4.642626 --> 4.590841).  Saving model ...
Epoch: 11         Training Loss: 4.575981         Validation Loss: 4.574237
Validation loss has decreased (4.590841 --> 4.574237).  Saving model ...
Epoch: 12         Training Loss: 4.544353         Validation Loss: 4.529748
Validation loss has decreased (4.574237 --> 4.529748).  Saving model ...
Epoch: 13         Training Loss: 4.500597         Validation Loss: 4.491490
Validation loss has decreased (4.529748 --> 4.491490).  Saving model ...
Epoch: 14         Training Loss: 4.444061         Validation Loss: 4.418908
Validation loss has decreased (4.491490 --> 4.418908).  Saving model ...
Epoch: 15         Training Loss: 4.351595         Validation Loss: 4.316721
Validation loss has decreased (4.418908 --> 4.316721).  Saving model ...
Epoch: 16         Training Loss: 4.268245         Validation Loss: 4.270220
```

```
Validation loss has decreased (4.316721 --> 4.270220).  Saving model ...
Epoch: 17         Training Loss: 4.225286        Validation Loss: 4.200246
Validation loss has decreased (4.270220 --> 4.200246).  Saving model ...
Epoch: 18         Training Loss: 4.173330        Validation Loss: 4.165174
Validation loss has decreased (4.200246 --> 4.165174).  Saving model ...
Epoch: 19         Training Loss: 4.125032        Validation Loss: 4.086306
Validation loss has decreased (4.165174 --> 4.086306).  Saving model ...
Epoch: 20         Training Loss: 4.068491        Validation Loss: 4.108418
Epoch: 21         Training Loss: 4.016416        Validation Loss: 4.060518
Validation loss has decreased (4.086306 --> 4.060518).  Saving model ...
Epoch: 22         Training Loss: 3.960154        Validation Loss: 3.980725
Validation loss has decreased (4.060518 --> 3.980725).  Saving model ...
Epoch: 23         Training Loss: 3.917574        Validation Loss: 3.943431
Validation loss has decreased (3.980725 --> 3.943431).  Saving model ...
Epoch: 24         Training Loss: 3.875296        Validation Loss: 3.920422
Validation loss has decreased (3.943431 --> 3.920422).  Saving model ...
Epoch: 25         Training Loss: 3.822846        Validation Loss: 3.920123
Validation loss has decreased (3.920422 --> 3.920123).  Saving model ...
Epoch: 26         Training Loss: 3.765573        Validation Loss: 3.832049
Validation loss has decreased (3.920123 --> 3.832049).  Saving model ...
Epoch: 27         Training Loss: 3.714671        Validation Loss: 3.817132
Validation loss has decreased (3.832049 --> 3.817132).  Saving model ...
Epoch: 28         Training Loss: 3.661752        Validation Loss: 3.759655
Validation loss has decreased (3.817132 --> 3.759655).  Saving model ...
Epoch: 29         Training Loss: 3.609350        Validation Loss: 3.738640
Validation loss has decreased (3.759655 --> 3.738640).  Saving model ...
Epoch: 30         Training Loss: 3.555688        Validation Loss: 3.714181
Validation loss has decreased (3.738640 --> 3.714181).  Saving model ...
Epoch: 31         Training Loss: 3.505713        Validation Loss: 3.682357
Validation loss has decreased (3.714181 --> 3.682357).  Saving model ...
Epoch: 32         Training Loss: 3.467778        Validation Loss: 3.650329
Validation loss has decreased (3.682357 --> 3.650329).  Saving model ...
Epoch: 33         Training Loss: 3.399888        Validation Loss: 3.664252
Epoch: 34         Training Loss: 3.352349        Validation Loss: 3.583012
Validation loss has decreased (3.650329 --> 3.583012).  Saving model ...
Epoch: 35         Training Loss: 3.297228        Validation Loss: 3.585888
Epoch: 36         Training Loss: 3.239390        Validation Loss: 3.544166
Validation loss has decreased (3.583012 --> 3.544166).  Saving model ...
Epoch: 37         Training Loss: 3.194479        Validation Loss: 3.524099
Validation loss has decreased (3.544166 --> 3.524099).  Saving model ...
Epoch: 38         Training Loss: 3.126360        Validation Loss: 3.499434
Validation loss has decreased (3.524099 --> 3.499434).  Saving model ...
Epoch: 39         Training Loss: 3.087620        Validation Loss: 3.453141
Validation loss has decreased (3.499434 --> 3.453141).  Saving model ...
Epoch: 40         Training Loss: 3.032374        Validation Loss: 3.435632
Validation loss has decreased (3.453141 --> 3.435632).  Saving model ...
Epoch: 41         Training Loss: 2.962205        Validation Loss: 3.469011
Epoch: 42         Training Loss: 2.909074        Validation Loss: 3.370030
```

```
Validation loss has decreased (3.435632 --> 3.370030).  Saving model ...
Epoch: 43 	Training Loss: 2.837904 	Validation Loss: 3.424322
Epoch: 44 	Training Loss: 2.806828 	Validation Loss: 3.408557
Epoch: 45 	Training Loss: 2.716029 	Validation Loss: 3.352555
Validation loss has decreased (3.370030 --> 3.352555).  Saving model ...
Epoch: 46 	Training Loss: 2.704828 	Validation Loss: 3.354591
Epoch: 47 	Training Loss: 2.620496 	Validation Loss: 3.397565
Epoch: 48 	Training Loss: 2.587734 	Validation Loss: 3.310738
Validation loss has decreased (3.352555 --> 3.310738).  Saving model ...
Epoch: 49 	Training Loss: 2.505198 	Validation Loss: 3.344656
Epoch: 50 	Training Loss: 2.460754 	Validation Loss: 3.241125
Validation loss has decreased (3.310738 --> 3.241125).  Saving model ...
Epoch: 51 	Training Loss: 2.391278 	Validation Loss: 3.264210
Epoch: 52 	Training Loss: 2.323534 	Validation Loss: 3.230376
Validation loss has decreased (3.241125 --> 3.230376).  Saving model ...
Epoch: 53 	Training Loss: 2.283247 	Validation Loss: 3.309891
Epoch: 54 	Training Loss: 2.264182 	Validation Loss: 3.395674
Epoch: 55 	Training Loss: 2.166710 	Validation Loss: 3.399294
Epoch: 56 	Training Loss: 2.113447 	Validation Loss: 3.349519
Epoch: 57 	Training Loss: 2.107673 	Validation Loss: 3.257889
Epoch: 58 	Training Loss: 2.040824 	Validation Loss: 3.357547
Epoch: 59 	Training Loss: 1.990901 	Validation Loss: 3.233099
Epoch: 60 	Training Loss: 1.920649 	Validation Loss: 3.306247
Epoch: 61 	Training Loss: 1.905487 	Validation Loss: 3.370018
Epoch: 62 	Training Loss: 1.873820 	Validation Loss: 3.266130
Epoch: 63 	Training Loss: 1.797884 	Validation Loss: 3.373369
Epoch: 64 	Training Loss: 1.758568 	Validation Loss: 3.359320
Epoch: 65 	Training Loss: 1.727158 	Validation Loss: 3.238922
Epoch: 66 	Training Loss: 1.651915 	Validation Loss: 3.387691
Epoch: 67 	Training Loss: 1.639060 	Validation Loss: 3.387869
Epoch: 68 	Training Loss: 1.565873 	Validation Loss: 3.440488
Epoch: 69 	Training Loss: 1.566774 	Validation Loss: 3.416880
Epoch: 70 	Training Loss: 1.535107 	Validation Loss: 3.443890
```

```
In [18]: # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [19]: 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: 3.241983


Test Accuracy: 23% (195/836)
```

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

1.1.13 (IMPLEMENTATION) Model Architecture

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

```
In [21]: ## TODO: Specify model architecture
         model_transfer = models.resnet152(pretrained=True)

         # Freeze parameters by turning of gradient for model
         for param in model_transfer.parameters():
             param.requires_grad = False

         model_transfer.fc = nn.Sequential(nn.Linear(2048, 2048),
                                           nn.ReLU(),
                                           nn.Dropout(0.25),
                                           nn.Linear(2048, 133))

         print(model_transfer)

         #Move model to GPU
         if use_cuda:
             model_transfer = model_transfer.cuda()
```

```
Downloading: "https://download.pytorch.org/models/resnet152-b121ed2d.pth" to /root/.torch/models
100%|| 241530880/241530880 [00:08<00:00, 27069666.02it/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)
    )
    (4): 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)
    )
    (5): 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)
    )
    (6): 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)
    )
    (7): 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)
)
(6): 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)
)
(7): 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)
)
(8): 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)
)
(9): 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)
)
(10): 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)
  )
  (11): 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)
  )
  (12): 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)
  )
  (13): 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)
  )
  (14): 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)
  )
  (15): 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)
  )
  (16): 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)
  )
  (17): 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)
  )
  (18): 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)
  )
  (19): 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)
  )
  (20): 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)
  )
```

```
(21): 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)
)
(22): 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)
)
(23): 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)
)
(24): 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)
)
(25): 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)
)
(26): 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)
  )
  (27): 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)
  )
  (28): 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)
  )
  (29): 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)
  )
  (30): 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)
  )
  (31): 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)
    )
    (32): 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)
    )
    (33): 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)
    )
    (34): 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)
    )
    (35): 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): Sequential(
    (0): Linear(in_features=2048, out_features=2048, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.25)
    (3): 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: Steps to get The final CNN architecture:

First I chose resnet152 as a pretrained model because it has been trained on millions of images from imagenet database and it uses deep residual networks and skip connections to fit inputs of previous layers to the next layer without modifications allowing for very deep networks. I froze all weights at the convolution layers and the adjusted the last layer of fully connected (fc) layer to 133 which is the number of output classes based on the number of dog breeds using nn.Sequential module allowed me to specify each fc layer in sequence using Relu activation function and a dropout of 25%. I used CrossEntropyLoss as my loss function to keep track of the loss and gradients of loss of the weights during the training and Adam as my optimization function which updates the weights during training after each epoch. The weights of the fc layer by default were unfrozen and trained because I modified the final fc layer to 133 which is the number of the classes of the dog breeds. I trained the fully connected (fc) layers for 20 epochs on preprocessed dog images of size 224x224x3 that have been augmented using random scale, random crop, random horizontal flip and color jitter and saved the validation losses as they decreased across the training epochs in order to be able to load the best model for dog breed prediction after training and was able to get a test accuracy of 83%.

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

```
In [23]: loaders_transfer = loaders_scratch
```

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 [24]: # train the model
         n_epochs = 20
         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: 3.147409 	Validation Loss: 1.200413
Validation loss has decreased (inf --> 1.200413).  Saving model ...
Epoch: 2 	Training Loss: 1.681823 	Validation Loss: 0.772588
Validation loss has decreased (1.200413 --> 0.772588).  Saving model ...
Epoch: 3 	Training Loss: 1.411786 	Validation Loss: 0.660662
Validation loss has decreased (0.772588 --> 0.660662).  Saving model ...
Epoch: 4 	Training Loss: 1.355508 	Validation Loss: 0.591749
Validation loss has decreased (0.660662 --> 0.591749).  Saving model ...
Epoch: 5 	Training Loss: 1.243111 	Validation Loss: 0.558057
Validation loss has decreased (0.591749 --> 0.558057).  Saving model ...
Epoch: 6 	Training Loss: 1.232289 	Validation Loss: 0.526710
Validation loss has decreased (0.558057 --> 0.526710).  Saving model ...
Epoch: 7 	Training Loss: 1.184049 	Validation Loss: 0.498732
Validation loss has decreased (0.526710 --> 0.498732).  Saving model ...
Epoch: 8 	Training Loss: 1.192403 	Validation Loss: 0.505184
Epoch: 9 	Training Loss: 1.141256 	Validation Loss: 0.471295
Validation loss has decreased (0.498732 --> 0.471295).  Saving model ...
Epoch: 10 	Training Loss: 1.127628 	Validation Loss: 0.510309
Epoch: 11 	Training Loss: 1.129808 	Validation Loss: 0.511261
Epoch: 12 	Training Loss: 1.130991 	Validation Loss: 0.476664
Epoch: 13 	Training Loss: 1.112723 	Validation Loss: 0.526636
Epoch: 14 	Training Loss: 1.112586 	Validation Loss: 0.491743
```

```
Epoch: 15       Training Loss: 1.090452         Validation Loss: 0.477124
Epoch: 16       Training Loss: 1.048788         Validation Loss: 0.522733
Epoch: 17       Training Loss: 1.090356         Validation Loss: 0.472262
Epoch: 18       Training Loss: 1.071066         Validation Loss: 0.498838
Epoch: 19       Training Loss: 1.044588         Validation Loss: 0.450347
Validation loss has decreased (0.471295 --> 0.450347).  Saving model ...
Epoch: 20       Training Loss: 1.048192         Validation Loss: 0.454055
```

```
In [28]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

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

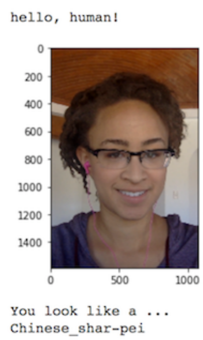
```
Test Loss: 0.511994


Test Accuracy: 83% (702/836)
```

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 [34]: def preprocess_image(img_path):
             pil_image = Image.open(img_path)
             #preprocess image
             preprocess_image_transforms = transforms.Compose([transforms.Resize(255),
                                                    transforms.CenterCrop(224),
                                                    transforms.ToTensor(),
                                                    transforms.Normalize(mean=[0.485, 0.456, 0.4
                                                                         std=[0.229, 0.224, 0.22

             pil_image = preprocess_image_transforms(pil_image).unsqueeze(0)
             if use_cuda:
                 pil_image = pil_image.cuda()
             return pil_image
```

```
In [35]: ### 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]
         data_transfer = loaders_transfer
         class_names = [item[4:].replace("_", " ") for item in data_transfer['train'].dataset.cl
```



Sample Human Output

```
def predict_breed_transfer(img_path):

    # load the image and return the predicted breed
    dog_image = preprocess_image(img_path)

    model_transfer.eval()
    output = torch.argmax(model_transfer(dog_image)).item()
    return output # predicted class index

predict_breed_transfer(dog_files[0])
predict_breed = class_names[predict_breed_transfer(dog_files[0])]
print(predict_breed_transfer(dog_files[0]))
```

```
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```

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.

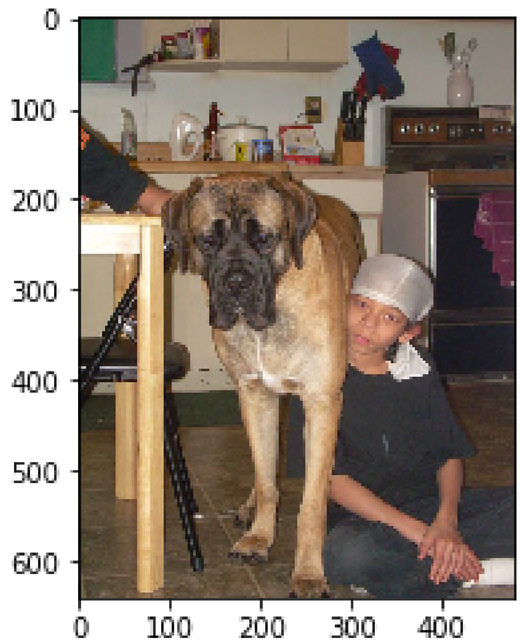
You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

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 [41]: ### 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
    img = Image.open(img_path)
    plt.imshow(img)
    plt.show()

    dog_face = dog_detector(img_path)
    human_face = face_detector(img_path)
    predict_breed = class_names[predict_breed_transfer(img_path)]

    if dog_face:
        print('Detected a dog thats look like a {} breed.'.format(predict_breed))
    elif human_face:
        print('hello, human! \nYou are not a dog but look like the ....\n{} dog breed.'
    else:
        print('Error! - no  human faces no  dog faces in it.')
    return

# Test to see if dog breed is predicted
run_app(dog_files[1])
```



```
Detected a dog thats look like a Mastiff breed.
```

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?

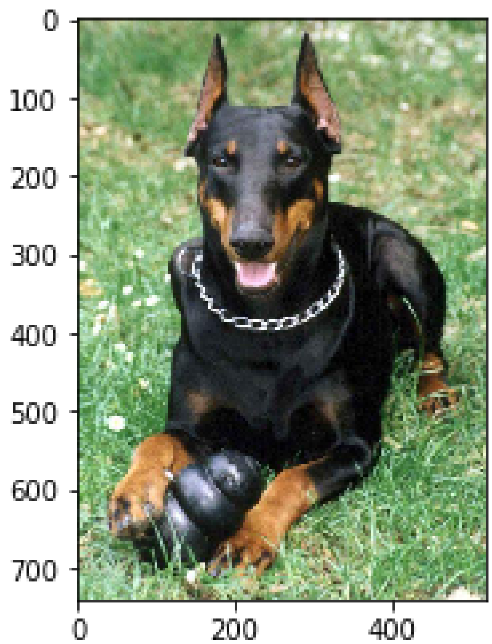
1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

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) (Three possible points for improvement) Some times predict very good and some times there are some errors. It predicts dog_faces well and is able to suggest similarities to dog faces from human faces like one appear. However, test accuracy from the modified pretrained model was 83% i think we can improve by the following adjustments: 1.Use anoter pre-trained model . 2.By providing more data for the training. 3.increasing the depth of the neural network

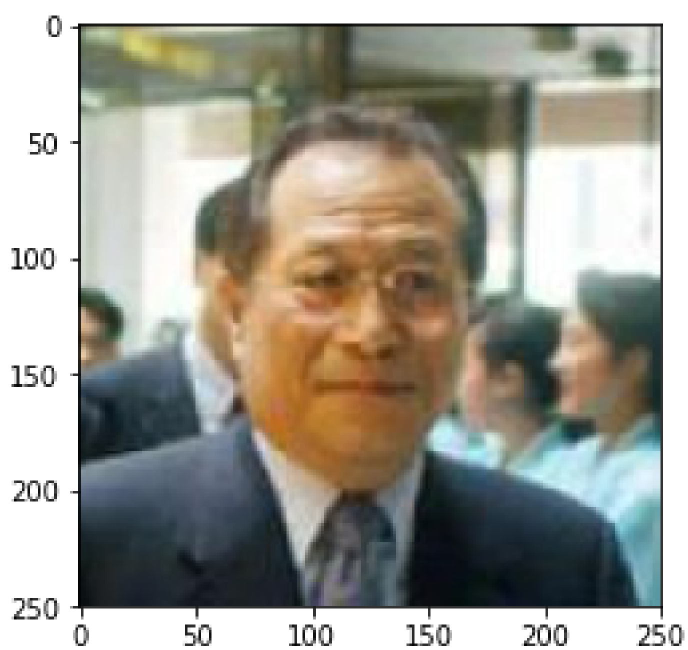
```
In [45]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.
         import random
         random.seed(95)
         random.shuffle(dog_files[:100])
         random.shuffle(human_files[:100])

         dog_pics = dog_files[:3]
         human_pics = human_files[:3]
         other_pics = ('other_img/image1.jpg', 'other_img/image2.jpg', 'other_img/image3.jpg', '
         ## suggested code, below
         for files in np.hstack((dog_pics, human_pics,other_pics)):
             run_app(files)
```



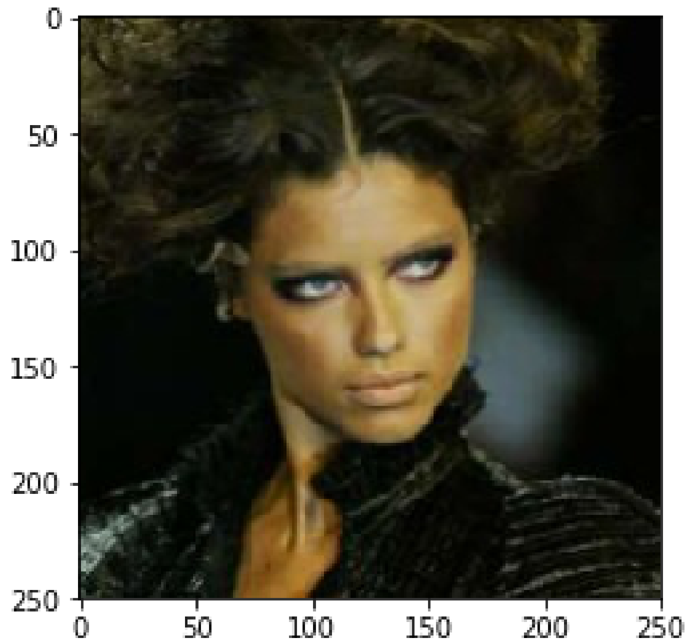
```
Detected a dog thats look like a Doberman pinscher breed.
```

```
Detected a dog thats look like a Plott breed.
```

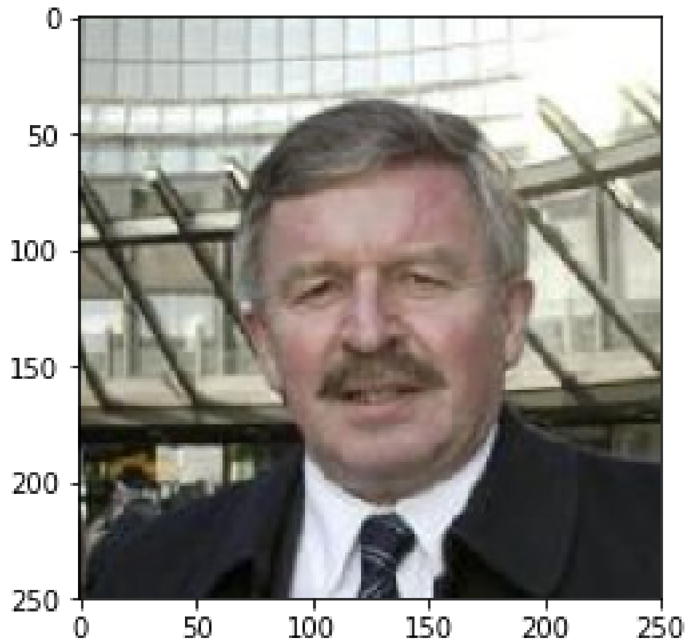

```
Detected a dog thats look like a Doberman pinscher breed.
```



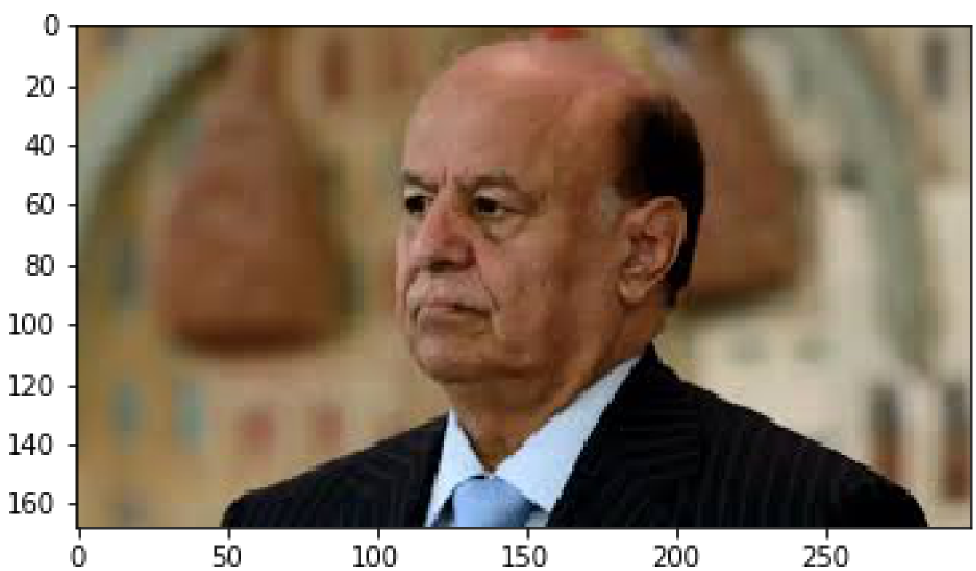
```
hello, human!
You are not a dog but look like the ...
Chihuahua dog breed.
```



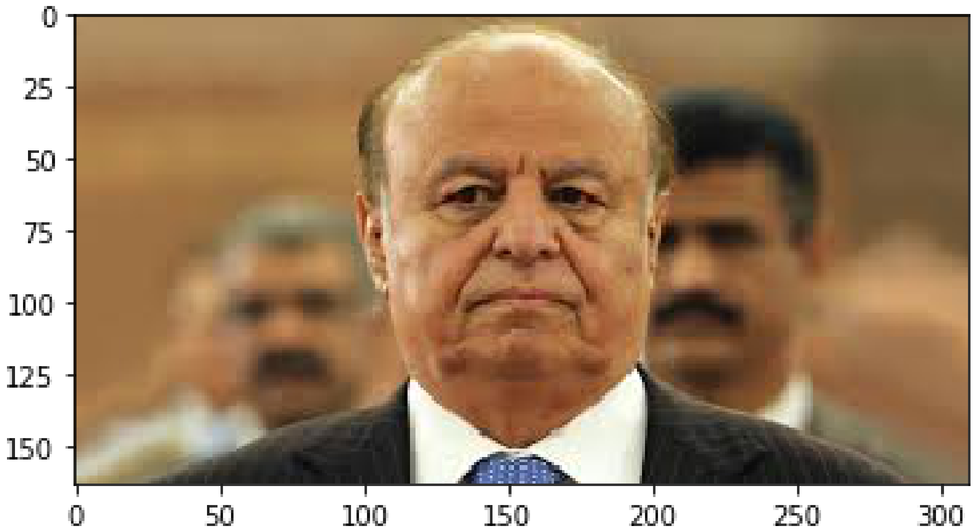

```
hello, human!
You are not a dog but look like the ...
Chinese crested dog breed.
```



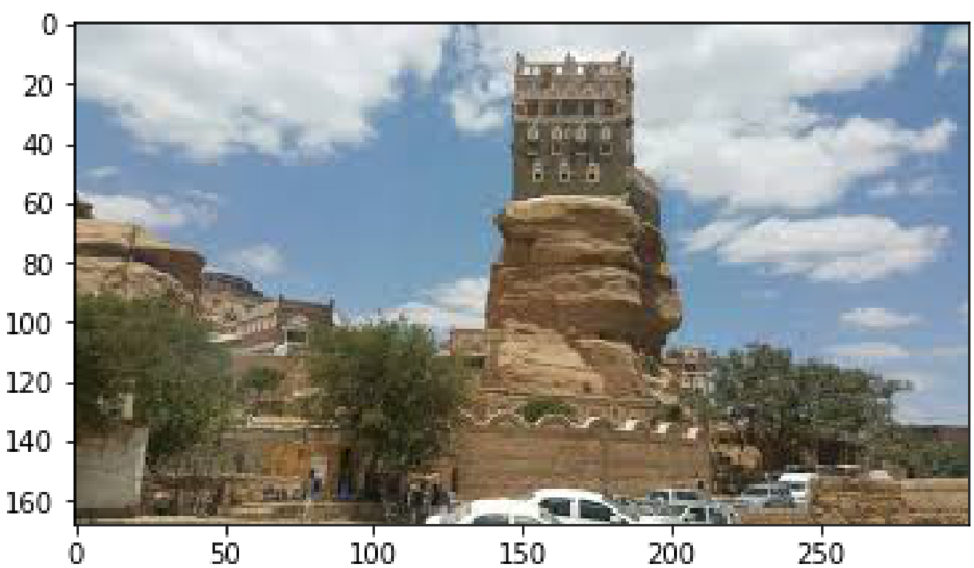

```
hello, human!
You are not a dog but look like the ...
Dachshund dog breed.
```



```
hello, human!
You are not a dog but look like the ...
Chihuahua dog breed.
```




```
hello, human!
You are not a dog but look like the ...
Chihuahua dog breed.
```



```
Error! - no  human faces no  dog faces in it.
```


```
Detected a dog thats look like a German shepherd dog breed.
```

```
In [ ]:
```