dog_app

February 3, 2019

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.
Step 0: Import Datasets
Make sure that you've downloaded the required human and dog datasets: * Download the [dog dataset](). Unzip the folder and place it in this project's home directory, at the location `/dogImages`.

- Download the [human dataset](). Unzip the folder and place it in the home diretcory, 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 [34]:
```
import numpy as np
from glob import glob
import os

# prefix of the images
images_dir = r"F:\datasets\udacity"

# load filenames for human and dog images
human_files = np.array(glob("{0}/lfw/*/*/*".format(images_dir)))
dog_files = np.array(glob("{0}/dogImages/*/*/*".format(images_dir)))

# 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 18982 total human images.
There are 8351 total dog images.
```

Step 1: Detect Humans

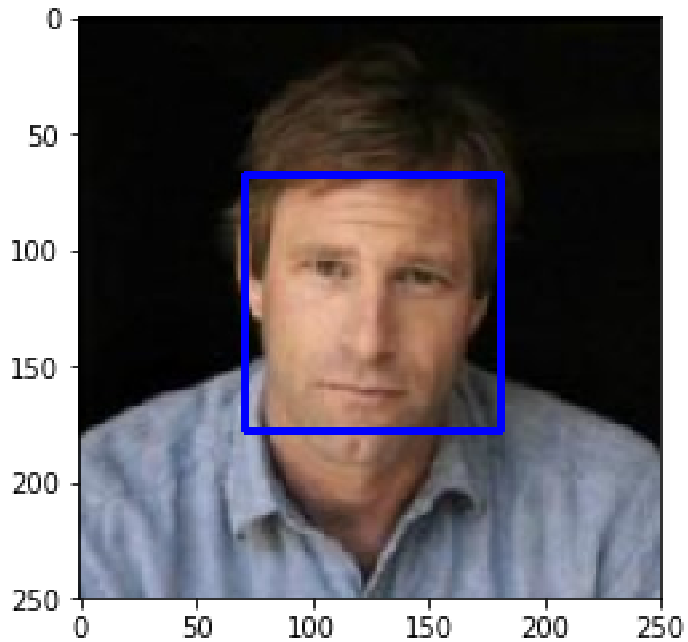
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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 [35]:
```
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 [36]: # 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 [37]: from tqdm import tqdm

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

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

         ## DONE: Test the performance of the face_detector algorithm
         def num_human_faces(image_list):
             is_human_face = list(map(face_detector, image_list))
             return np.array(is_human_face).sum()


         ## on the images in human_files_short and dog_files_short.
         print("Number of human faces in human_files_short: {0}".format(num_human_faces(human_
         print("Number of human faces in dog_files_short: {0}".format(num_human_faces(dog_files

Number of human faces in human_files_short: 96
Number of human faces in dog_files_short: 18
```

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 [38]: ### (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 [39]: import torch
         import torchvision.models as models

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

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

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

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

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

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

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

```
In [40]: from PIL import Image
         import torchvision.transforms as transforms

         # Transforms
         normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                          std=[0.229, 0.224, 0.225])

         img_transform = transforms.Compose([
                     transforms.RandomResizedCrop(224),
                     transforms.RandomHorizontalFlip(),
                     transforms.ToTensor(),
                     normalize])
```

```python
def image_preprocess(img_path):
    """
    Process the image so that it can be fed to the pre-trained classifier.

    Args:
        img_path: Path of an image.
    Returns:
        image loaded as a tensor.
    """
    image = Image.open(img_path)
    image = img_transform(image).float()
    image.unsqueeze_(0)

    if use_cuda:
        image = image.cuda()
    return image

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
    '''

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

    predictions = VGG16(image_preprocess(img_path))
    top_class = predictions.argmax().cpu().numpy()

    return top_class # predicted class index
```

1.1.5 (IMPLEMENTATION) Write a Dog Detector

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

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

```
In [41]: ### returns "True" if a dog is detected in the image stored at img_path
         dog_class = range(151, 269)
         def dog_detector(img_path):

             top_class = int(VGG16_predict(img_path))
             return top_class in dog_class # 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:

```
In [42]: ### DONE: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         def percent_dogs(image_set):
             dogs_t = np.array(list(map(dog_detector, image_set))).sum()
             dogs_percent = dogs_t * 100.0 / len(image_set)
             return dogs_t, dogs_percent

         human_files_dogs_t, human_files_dogs_percent = percent_dogs(human_files_short)
         dog_files_dogs_t, dog_files_dogs_percent = percent_dogs(dog_files_short)


         print("Percentage of dogs detected in human_files_short: {0}".format(human_files_dogs_
         print("Percentage of dogs detected in dog_files_short: {0}".format(dog_files_dogs_perc

Percentage of dogs detected in human_files_short: 2.0
Percentage of dogs detected in dog_files_short: 91.0
```

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 [43]: ### (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 `dogImages/train`, `dogImages/valid`, and `dogImages/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 [44]: import torch
         use_cuda = torch.cuda.is_available()
```

```
In [45]: import os
         import multiprocessing
         import torch
         import torchvision.transforms as transforms
         from torchvision import datasets

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

```python
# Folders
train_folder = os.path.join(images_dir, r"dogimages\train")
valid_folder = os.path.join(images_dir, r"dogimages\valid")
test_folder = os.path.join(images_dir, r"dogimages\test")

# Batch sizes
min_batch_size = 64
image_input_size = 224
num_workers = np.int(multiprocessing.cpu_count() / 2)

std_normalize = transforms.Normalize(
   mean=[0.485, 0.456, 0.406],
   std=[0.229, 0.224, 0.225]
)

# TODO Improve loaders.
img_transforms = {'train': transforms.Compose([transforms.RandomHorizontalFlip(),
                                    transforms.RandomRotation(10),
                                    transforms.RandomResizedCrop(image_input_size),
                                    transforms.ToTensor(),
                                    std_normalize]),
                   'valid': transforms.Compose([transforms.Resize(256),
                                    transforms.CenterCrop(image_input_size),
                                    transforms.ToTensor(),
                                    std_normalize]),
                   'test': transforms.Compose([transforms.Resize(size=(image_input_si
                                    transforms.ToTensor(),
                                    std_normalize])
                  }

def get_loader(folder, transform, batchsize=min_batch_size, num_workers=num_workers, i
    """
    Load dataset based on the folder.

    Args:
        folder: Image folder from which to load data.
        transform: Transform to apply to images.
        batchsize: Batchsize for training (default = 128).
        num_workers: Number of workers.
        is_shuffle: True if shuffling of dataset is reauired; False otherwise.

    Returns:
        loader variable based on the input.
    """
    img_dataset = datasets.ImageFolder(root=folder, transform=transform)
    loader = torch.utils.data.DataLoader(
        img_dataset,
        batch_size=batchsize,
```

```
            num_workers=num_workers,
            shuffle=is_shuffle)

        return loader

    # Create Loaders
    train_loader = get_loader(train_folder, img_transforms['train'])
    valid_loader = get_loader(valid_folder, img_transforms['valid'])
    test_loader = get_loader(test_folder, img_transforms['test'])
    loaders = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

1.1.8 Code to handle the OS error issue.

This is only run once to remove the images that are giving an OS error.

```
In [46]: import os
         import sys
         from PIL import Image, ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = False

         def adjust_image(img_path):
             im = Image.open(img_path)
             try:
                 im.save(r"c:\temp.jpg")
             except:
                 print("Corrupt image: ",img_path)
                 ImageFile.LOAD_TRUNCATED_IMAGES = True
                 im.save(img_path)
                 ImageFile.LOAD_TRUNCATED_IMAGES = False

         def process_truncated_images(folder):
             # Adjust files that have load problems.
             for root, subdirs, files in os.walk(train_folder):
                 for file in os.listdir(root):
                     filePath = os.path.join(root, file)
                     if os.path.isdir(filePath):
                         continue
                     adjust_image(filePath)

         # Process truncated images
         # process_truncated_images(train_folder)
         # process_truncated_images(valid_folder)
         # process_truncated_images(test_folder)
```

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:

A random size crop was performed so that a bit of randomness can be injected due to the scaling and it is cropped to the desired input size. The image input size used was 224 x 224 and the main reason for these choices was to follow this example and I've seen that this size seems to be giving good results across a number of other applications

The augmentation was done using the following operations: random horizontal flip and random rotation

1.1.9 (IMPLEMENTATION) Model Architecture

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

```
In [47]: # DEBUG
         device = torch.device("cuda:0" if use_cuda else "cpu")
         for batch_idx, (data, lbl) in enumerate(train_loader):
             break
         if use_cuda:
             data = data.cuda()
         lbl = lbl.to(device)
         print("Data Device: {0}".format(data.device))
         print("lbl Device: {0}".format(lbl.device))
```

```
Data Device: cuda:0
lbl Device: cuda:0
```

```
In [48]: 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__()

                 # Net properties
                 self._num_pool_layers = 4
                 self._conv_filters = [24, 48, 72, 128]

                 self.conv1 = nn.Conv2d(3, self._conv_filters[0], 3, padding=1)
                 self.batchnorm1 = nn.BatchNorm2d(self._conv_filters[0])

                 self.conv2 = nn.Conv2d(self._conv_filters[0], self._conv_filters[1], 3, paddi
                 self.batchnorm2 = nn.BatchNorm2d(self._conv_filters[1])

                 self.conv3 = nn.Conv2d(self._conv_filters[1], self._conv_filters[2], 3, paddi
                 self.batchnorm3 = nn.BatchNorm2d(self._conv_filters[2])

                 self.conv4 = nn.Conv2d(self._conv_filters[2], self._conv_filters[3], 3, paddi
```

```
            self.batchnorm4 = nn.BatchNorm2d(self._conv_filters[3])

            # Max Pooling
            self.pool = nn.MaxPool2d(2, 2)

            # Image size after passing through pooling layers
            self.downsample_size = np.int(image_input_size / np.power(2, self._num_pool_la

            # Flatted size
            self._flatten_size = self._conv_filters[self._num_pool_layers - 1] * self.down
            self.fc1 = nn.Linear(self._flatten_size, 1024)
            self.batchnorm_lin1 = nn.BatchNorm1d(1024)
            self.fc2 = nn.Linear(1024, 1024)
            self.batchnorm_lin2 = nn.BatchNorm1d(1024)
            self.fc3 = nn.Linear(1024, 133)

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

        def forward(self, x):

           # CONVOLUTION LAYERS
            x = self.pool(F.relu(self.batchnorm1(self.conv1(x))))
            x = self.pool(F.relu(self.batchnorm2(self.conv2(x))))
            x = self.pool(F.relu(self.batchnorm3(self.conv3(x))))
            x = self.pool(F.relu(self.batchnorm4(self.conv4(x))))

            # FLATTEN IMAGE
            x = x.view(-1, self._flatten_size)

            # LINEAR LAYERS
            x = self.dropout(x)
            x = F.relu(self.batchnorm_lin1(self.fc1(x)))
            x = self.dropout(x)
            x = F.relu(self.batchnorm_lin2(self.fc2(x)))
            x = self.fc3(x)
            return x

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

    # instantiate the CNN
    model_scratch = Net()

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

```
In [49]: model_scratch
```

Out[49]:
```
Net(
  (conv1): Conv2d(3, 24, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (batchnorm1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (conv2): Conv2d(24, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (batchnorm2): BatchNorm2d(48, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (conv3): Conv2d(48, 72, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (batchnorm3): BatchNorm2d(72, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (conv4): Conv2d(72, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (batchnorm4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=25088, out_features=1024, bias=True)
  (batchnorm_lin1): BatchNorm1d(1024, eps=1e-05, momentum=0.1, affine=True, track_runn
  (fc2): Linear(in_features=1024, out_features=1024, bias=True)
  (batchnorm_lin2): BatchNorm1d(1024, eps=1e-05, momentum=0.1, affine=True, track_runn
  (fc3): Linear(in_features=1024, out_features=133, bias=True)
  (dropout): Dropout(p=0.25)
)
```

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

Answer: The main inspiration for the architecture was taken from the AlexNet paper. While I did not use the same filter banks, I experimented with the size and found this architecture provided satisfactory results. Once I was able to comfortably cross the 10% cut-off, I did not experiment further and moved on to the next steps.

1.1.10 (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 [50]:
```
import torch.optim as optim

criterion_scratch = nn.CrossEntropyLoss()

#optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.01)
optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.001)
```

1.1.11 (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 [51]:
```
# DEBUG
# print("CUDA memory allocated: {0}".format(torch.cuda.memory_allocated()))
# print("CUDA memory cached: {0}".format(torch.cuda.memory_cached()))
# torch.cuda.empty_cache()
```

In [52]:
```
from PIL import Image, ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
```

```
num_epochs=30
```

In [53]:
```
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
    model_best = model

    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_cnt = 0
        valid_cnt = 0
        prev_valid_loss = 1.0E6 # some high value to get started

        ###################
        # train the model #
        ###################
        model.train()
        try:
            for batch_idx, (train_data, train_target) in enumerate(loaders['train']):
                # move to GPU
                if use_cuda:
                    train_data, train_target = train_data.cuda(), train_target.cuda(a
                ## 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 - tr
                optimizer.zero_grad()
                output = model(train_data)
                loss = criterion(output, train_target).cuda()
                loss.backward()
                optimizer.step()
                train_loss += loss.item()*train_data.size(0)
                train_cnt += train_data.size(0)

                if (batch_idx % 10 == 0):
                    print("Training batch: {0}".format(batch_idx))
        except OSError:
            print("Train Batch {0} could not be loaded due to an OSError".format(batc
            pass

        ######################
        # 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
                output = model(data)
                loss = criterion(output, target)
                valid_loss += loss.item()*data.size(0)
                valid_cnt += data.size(0)

             # calculate average losses
            train_loss = train_loss/train_cnt
            valid_loss = valid_loss/valid_cnt

            # 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):
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss


        # return trained model
        return model


    # train the model
    model_scratch = train(num_epochs, loaders, 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'))
```

```
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 1        Training Loss: 4.651498         Validation Loss: 4.332928
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 2        Training Loss: 4.346211         Validation Loss: 4.130014
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 3        Training Loss: 4.212510         Validation Loss: 4.098220
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 4        Training Loss: 4.068499         Validation Loss: 3.933106
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 5        Training Loss: 3.939085         Validation Loss: 3.816866
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 6        Training Loss: 3.824931         Validation Loss: 3.745406
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 7        Training Loss: 3.711876         Validation Loss: 3.608319
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 8        Training Loss: 3.638411         Validation Loss: 3.678886
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 9        Training Loss: 3.529255         Validation Loss: 3.478754
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 10        Training Loss: 3.439738         Validation Loss: 3.497873
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 11        Training Loss: 3.371656         Validation Loss: 3.427671
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 12        Training Loss: 3.283902         Validation Loss: 3.176346
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 13         Training Loss: 3.212064         Validation Loss: 3.223150
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 14         Training Loss: 3.143266         Validation Loss: 3.105325
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 15         Training Loss: 3.059785         Validation Loss: 3.395668
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 16         Training Loss: 3.015334         Validation Loss: 3.112940
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 17          Training Loss: 2.977889          Validation Loss: 3.020487
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 18          Training Loss: 2.890229          Validation Loss: 3.047710
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 19          Training Loss: 2.821364          Validation Loss: 2.938056
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 20          Training Loss: 2.776229          Validation Loss: 2.963174
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 21         Training Loss: 2.732145         Validation Loss: 3.013561
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 22         Training Loss: 2.682372         Validation Loss: 3.443680
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 23         Training Loss: 2.629838         Validation Loss: 2.893286
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 24         Training Loss: 2.602000         Validation Loss: 2.973519
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 25         Training Loss: 2.531263         Validation Loss: 2.819042
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 26         Training Loss: 2.479668         Validation Loss: 2.855199
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 27         Training Loss: 2.455834         Validation Loss: 2.732893
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 28         Training Loss: 2.396471         Validation Loss: 2.959817
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
```

```
Epoch: 29         Training Loss: 2.345703         Validation Loss: 2.801879
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 30         Training Loss: 2.328592         Validation Loss: 2.783004
```

1.1.12 (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 [54]: import os
         def dog_classes(dir):
             classes = os.listdir(dir)
             classes = [classes[i].split('.')[-1] for i in range(len(classes))]
             classes.sort()
             class_to_idx = {classes[i]: i for i in range(len(classes))}
             return classes, class_to_idx

         dog_classes, dog_class_idx = dog_classes(train_folder)
```

```
In [55]: def test(loaders, model, criterion, use_cuda):

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

             misclassification_map = {}

             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)

            # Add to the misclassification map if you get classification wrong.
            error_vector = 1 - pred.eq(target.data.view_as(pred)).cpu().numpy()
            errors = np.where(error_vector == 1)[0]
            error_labels = [dog_classes[int(target.data[errors[i]].cpu().numpy())] for i i
            for error_label in error_labels:

                if error_label not in misclassification_map:
                    misclassification_map[error_label] = 1
                else:
                    misclassification_map[error_label] += 1

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

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

        # Sort the misclassification map by descending order of value.
        misclassification_map = sorted(misclassification_map.items(), key=lambda kv: kv[1
        return misclassification_map


    misclassification_map = test(loaders, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.034119


Test Accuracy: 26% (225/836)
```

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.

1.1.13 (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 [56]: loaders_transfer = loaders.copy()
```

1.1.14 (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 [57]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.densenet121(pretrained=True)

         # Freeze parameters so we don't backprop through them
         for param in model_transfer.parameters():
             param.requires_grad = False

         from collections import OrderedDict
         classifier = nn.Sequential(OrderedDict([
                                   ('fc1', nn.Linear(1024, 500)),
                                   ('relu', nn.ReLU()),
                                   ('fc2', nn.Linear(500, 133))
                                   ]))

         model_transfer.classifier = classifier

         if use_cuda:
             model_transfer = model_transfer.cuda()

         model_transfer
```

```
Out[57]: DenseNet(
           (features): Sequential(
             (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=Fal
             (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats
             (relu0): ReLU(inplace)
             (pool0): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False
             (denseblock1): _DenseBlock(
               (denselayer1): _DenseLayer(
                 (norm1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
                 (relu1): ReLU(inplace)
                 (conv1): Conv2d(64, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
                 (relu2): ReLU(inplace)
                 (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
               )
```

```
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(96, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
    )
    (denselayer5): _DenseLayer(
      (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
    )
  )
  (transition1): _Transition(
    (norm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_sta
    (relu): ReLU(inplace)
    (conv): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (denseblock2): _DenseBlock(
```

```
(denselayer1): _DenseLayer(
  (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer2): _DenseLayer(
  (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer3): _DenseLayer(
  (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer4): _DenseLayer(
  (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer5): _DenseLayer(
  (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer10): _DenseLayer(
  (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer11): _DenseLayer(
  (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer12): _DenseLayer(
  (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
)
(transition2): _Transition(
  (norm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_sta
  (relu): ReLU(inplace)
  (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
)
(denseblock3): _DenseBlock(
  (denselayer1): _DenseLayer(
    (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer2): _DenseLayer(
    (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer3): _DenseLayer(
    (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
```

```
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer10): _DenseLayer(
  (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer11): _DenseLayer(
  (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
(denselayer12): _DenseLayer(
  (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer13): _DenseLayer(
  (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer14): _DenseLayer(
  (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer15): _DenseLayer(
  (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer16): _DenseLayer(
  (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer17): _DenseLayer(
  (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
(denselayer18): _DenseLayer(
  (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer19): _DenseLayer(
  (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer20): _DenseLayer(
  (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer21): _DenseLayer(
  (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer22): _DenseLayer(
  (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer23): _DenseLayer(
  (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
  (denselayer24): _DenseLayer(
    (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
)
(transition3): _Transition(
  (norm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_st
  (relu): ReLU(inplace)
  (conv): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
)
(denseblock4): _DenseBlock(
  (denselayer1): _DenseLayer(
    (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer2): _DenseLayer(
    (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer3): _DenseLayer(
    (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
  )
```

```
(denselayer5): _DenseLayer(
  (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer10): _DenseLayer(
  (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
(denselayer11): _DenseLayer(
  (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer12): _DenseLayer(
  (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer13): _DenseLayer(
  (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer14): _DenseLayer(
  (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer15): _DenseLayer(
  (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
(denselayer16): _DenseLayer(
  (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
)
```

```
    )
    (norm5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_sta
  )
  (classifier): Sequential(
    (fc1): Linear(in_features=1024, out_features=500, bias=True)
    (relu): ReLU()
    (fc2): Linear(in_features=500, out_features=133, bias=True)
  )
)
```

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

Answer:

In the final architecture, I started with using DenseNet model as a way of extracting features since it was providing good results on the cat/dog dataset we did in the exercises.

I replaced the classification layer with two fully connected layer of sizes 1024 and 500 respectively. I primarily started with this architecture since it worked so well in the transfer learning scenario. My plan was to experiment with this if it didn't work well but the results were considerably better than 60% so I didn't look any further. I used a cross entropy loss function and an adam optimizer with a learning rate of 0.001. These values seem to be reasonably well researcher and they seem to be working well. 30 epochs seemed to be enough for getting good accuracy.

1.1.15 (IMPLEMENTATION) Specify Loss Function and Optimizer

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

```
In [58]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(model_transfer.classifier.parameters(), lr=0.001)
```

1.1.16 (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 [59]: # train the model
         n_epochs = 10
         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'))
```

```
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
```

```
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 1         Training Loss: 3.017472         Validation Loss: 1.103813
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 2         Training Loss: 1.325382         Validation Loss: 0.692751
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 3         Training Loss: 1.083028         Validation Loss: 0.573796
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 4         Training Loss: 0.972441         Validation Loss: 0.528893
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
```

```
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 5         Training Loss: 0.899759         Validation Loss: 0.528441
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 6         Training Loss: 0.838780         Validation Loss: 0.522133
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 7         Training Loss: 0.809847         Validation Loss: 0.466710
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 8         Training Loss: 0.779986         Validation Loss: 0.452513
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
```

```
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 9         Training Loss: 0.759564         Validation Loss: 0.459405
Training batch: 0
Training batch: 10
Training batch: 20
Training batch: 30
Training batch: 40
Training batch: 50
Training batch: 60
Training batch: 70
Training batch: 80
Training batch: 90
Training batch: 100
Epoch: 10        Training Loss: 0.747965         Validation Loss: 0.441069
```

1.1.17 (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 [60]: model_transfer_missclassification = test(loaders_transfer, model_transfer, criterion_t
         # print("Misclassifications by dog breed: ")
         # print(model_transfer_missclassification)
```

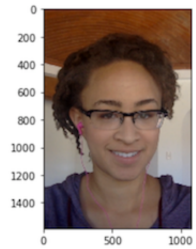
```
Test Loss: 0.602468


Test Accuracy: 79% (665/836)
```

1.1.18 (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 [61]: ### DONE: 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 data_transfer['train'].classes

         def predict_breed_transfer(img_path):
             dog_prediction = model_transfer(image_preprocess(img_path))
             dog_idx = int(dog_prediction.argmax().cpu().numpy())
             return dog_classes[dog_idx]
```

```
hello, human!
```




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

Sample Human Output

Step 5: Write your Algorithm

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

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

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

1.1.19 (IMPLEMENTATION) Write your Algorithm

In [62]:
```python
def show_test_image(img_path):
    # display the image
    img = cv2.imread(img_path)
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.imshow(cv_rgb)
    plt.show()
```

In [63]:
```python
def predict_dog_model_transfer(img_path):
    dog_prediction = model_transfer(image_preprocess(img_path))
    dog_idx = int(dog_prediction.argmax().cpu().numpy())
    dog_name = dog_classes[dog_idx].split('.')[-1]
    return dog_name

# Simple test
# img_path = dog_files_short[13]
# predict_dog_model_transfer(img_path)
```

In [64]:
```python
def run_app(img_path):
    ## handle cases for a human face, dog, and neither

    show_test_image(img_path)
```

```
    # Detect human
    if (face_detector(img_path)):
        print("Human detected. Human looks like dog breed ...")
        dog_breed = predict_breed_transfer(img_path)
        print(dog_breed)
        return dog_breed

    if (dog_detector(img_path)):
        print("Dog breed ...")
        dog_breed = predict_breed_transfer(img_path)
        print(dog_breed)
        return dog_breed

    print("Error: Neither dog nor human detected ...")
    return None
```

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?

1.1.20 (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.

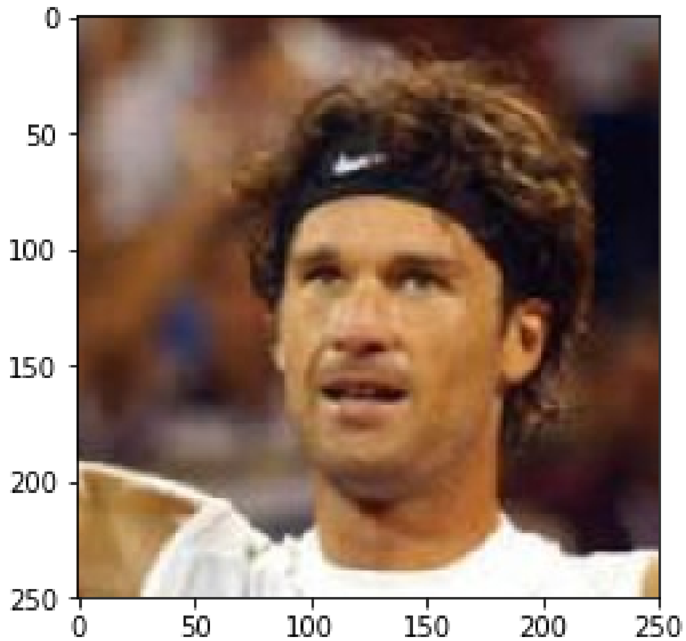
Answer:

The output is better than I expected for the dog classifications. It is a bit hard to measure the closest dog breed match to the human face. Some improvements to the algorithm are.

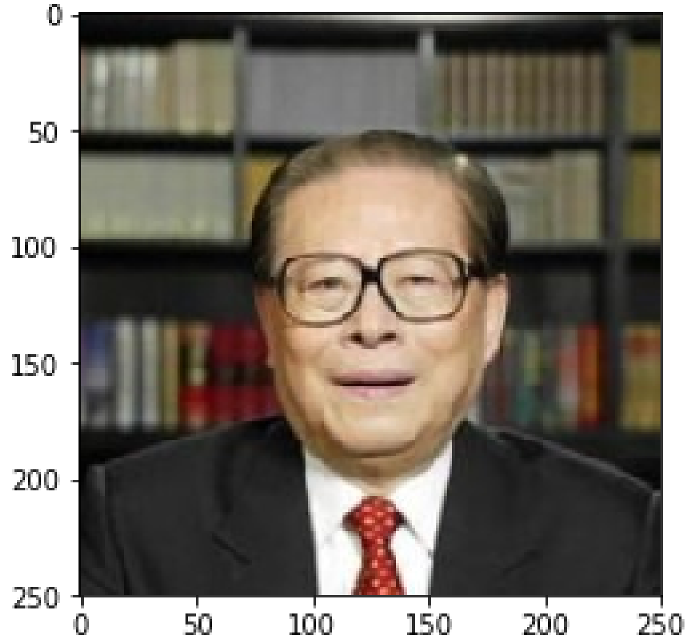
1. The algorithm has some challenges when there are multiple humans in the photo. We could improve accuracy of the current face detector by building a deep network for human faces.
2. There is no easy way to validate how good our classification scheme does in detecting the closest dog breed to a human face. We can collect some label data (by asking users) on whether the prediction was approved by humans by juxtaposing a representative image of a dog next to the human. With those lables, we can train a network to do the closest-human-dog match.
3. The top 5 misclassification among dog breeds is as follows: ('Kuvasz', 'English_cocker_spaniel', 'Silky_terrier', 'Doberman_pinscher', 'Lakeland_terrier'). In order to bring down the misclassification rate, we can collect more images on these dogs that are being misclassified for better discrimination.

In [65]:
```
# Set to true to see true class labels of predictions.
debug_app = False
```

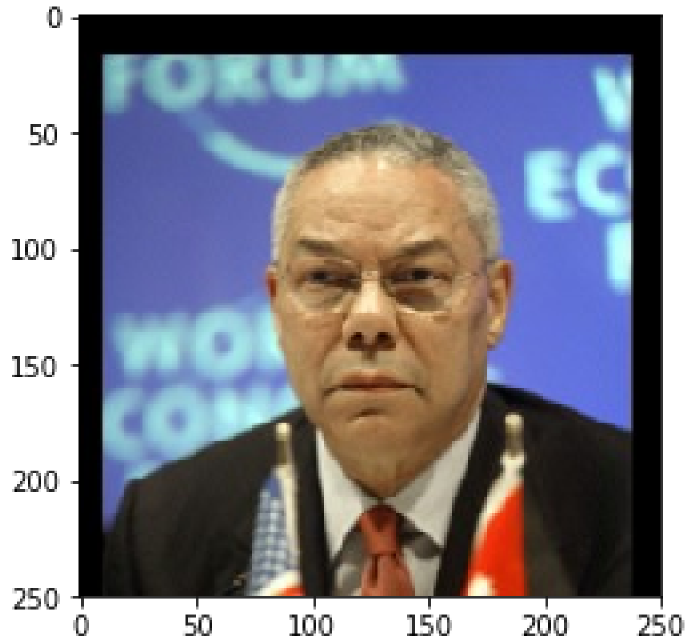
In [66]:
```
from random import randint
num_test_points = 10
img_idx = [randint(0, 8000) for i in range(0, num_test_points - 1)]
img_idx

fn_path_to_name = lambda x: os.path.split(file)[-1].split('.')[0]

for file in np.hstack((human_files[img_idx], dog_files[img_idx])):
    dog_breed = run_app(file)

    if (debug_app):
        print("True class name: {0}".format(fn_path_to_name(file)))
```



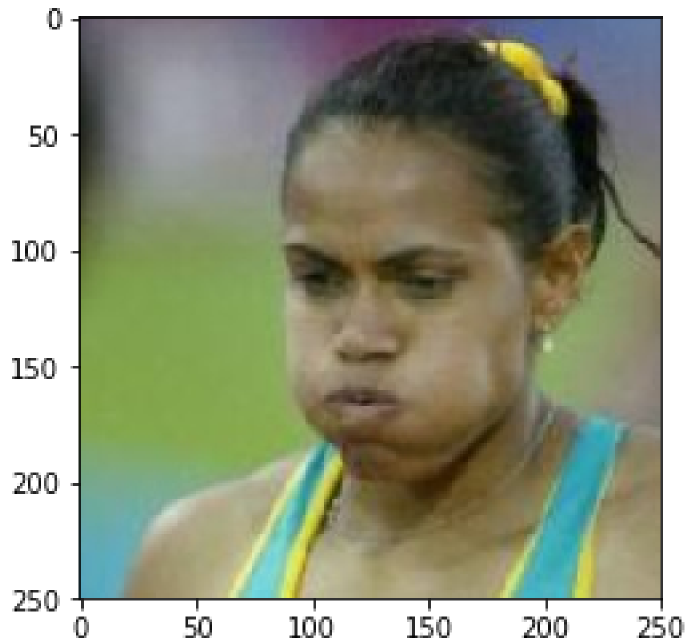

```
Human detected. Human looks like dog breed ...
Dogue_de_bordeaux
```



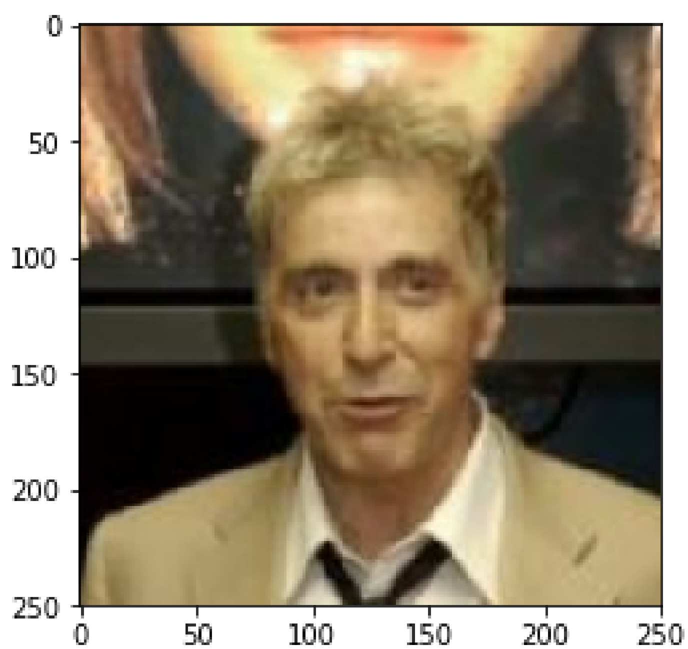

```
Human detected. Human looks like dog breed ...
Dogue_de_bordeaux
```



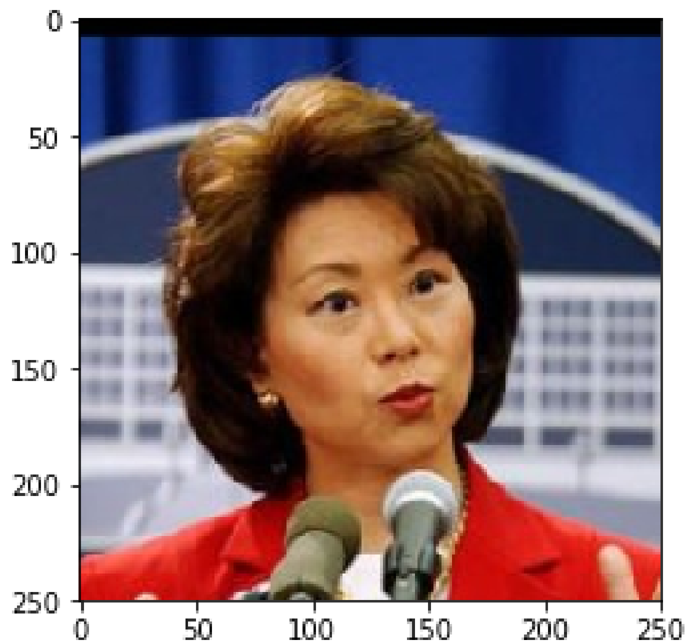
```
Human detected. Human looks like dog breed ...
Dogue_de_bordeaux
```



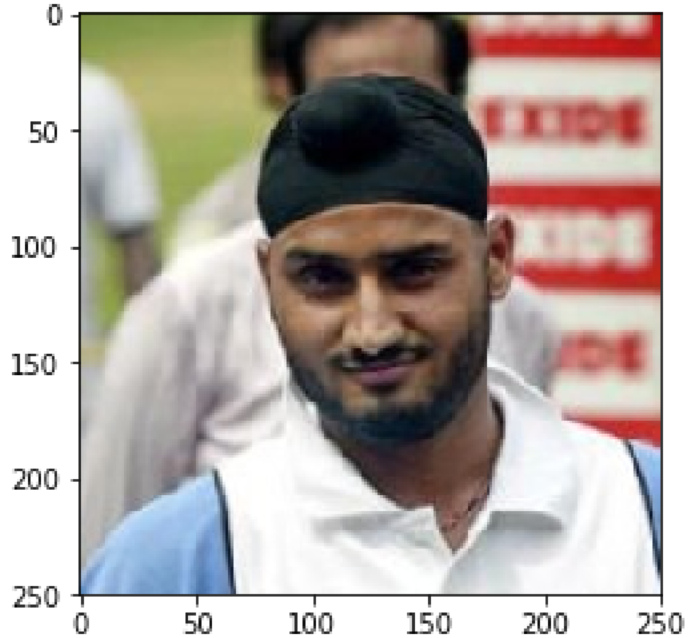
```
Human detected. Human looks like dog breed ...
Dogue_de_bordeaux
```



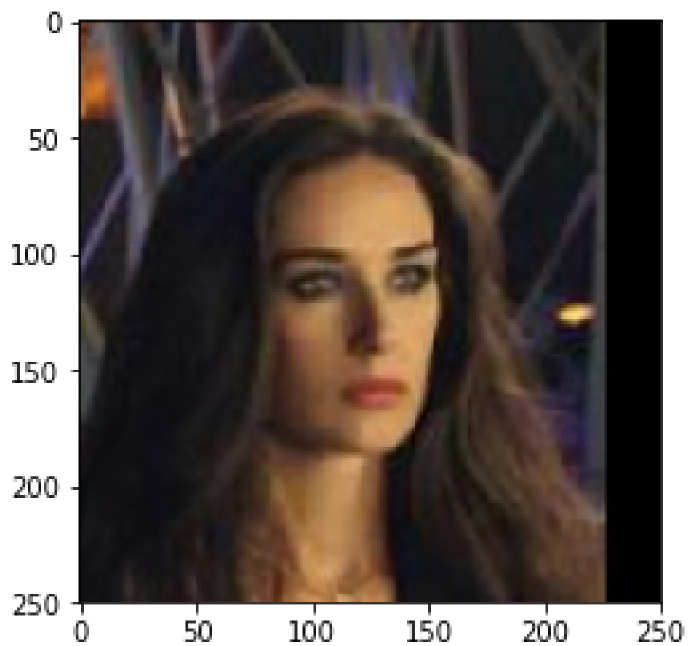
```
Human detected. Human looks like dog breed ...
Irish_water_spaniel
```



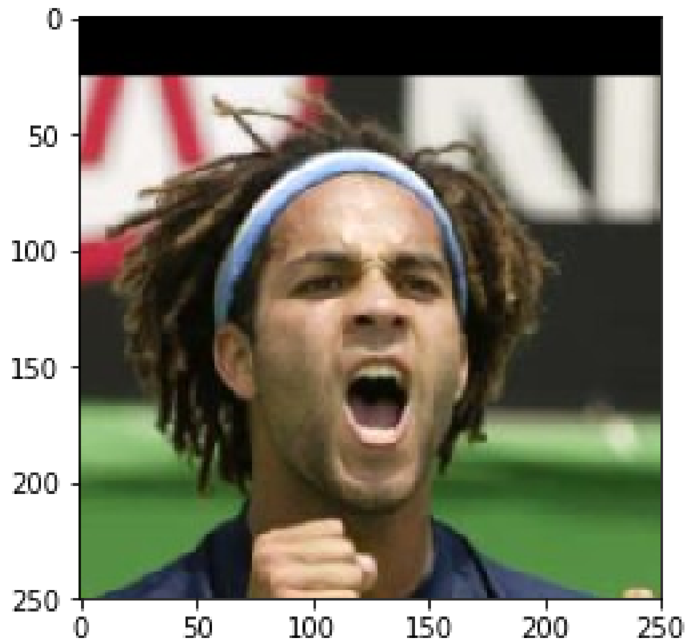

```
Human detected. Human looks like dog breed ...
Dogue_de_bordeaux
```



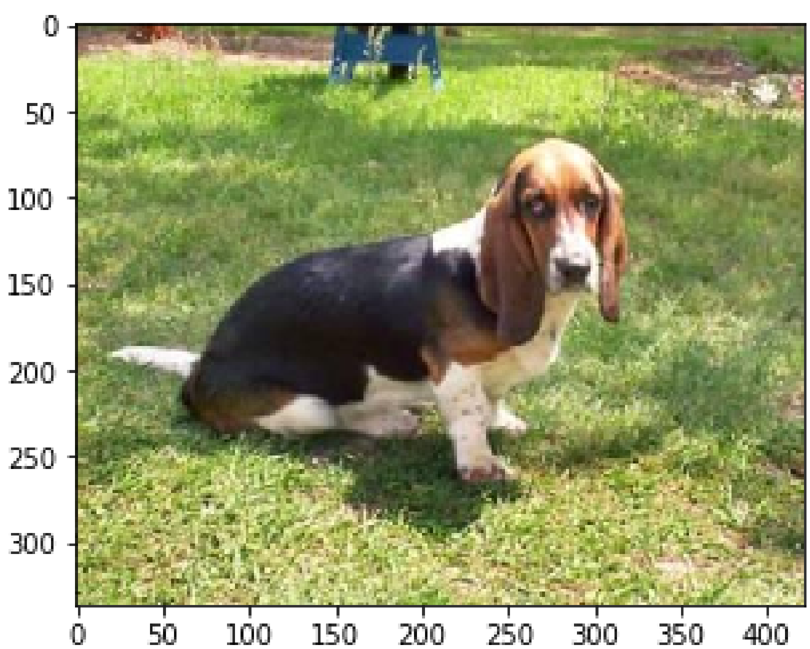

```
Human detected. Human looks like dog breed ...
Otterhound
```



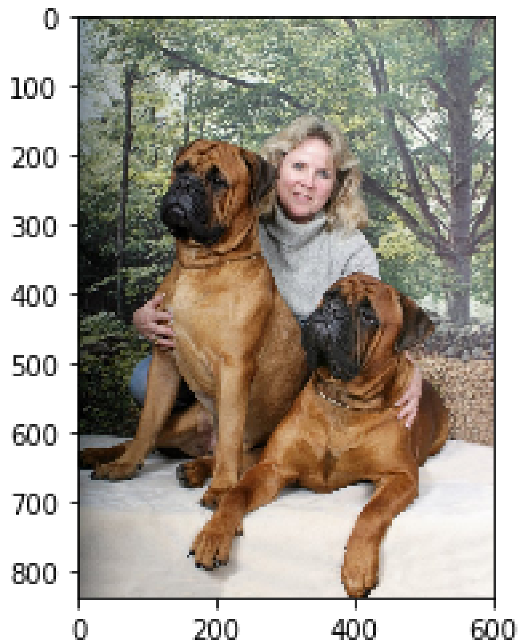
```
Human detected. Human looks like dog breed ...
Afghan_hound
```



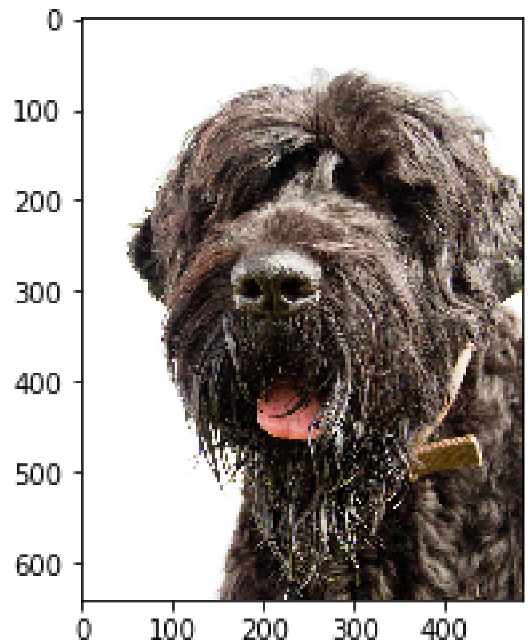

```
Human detected. Human looks like dog breed ...
Bearded_collie
```



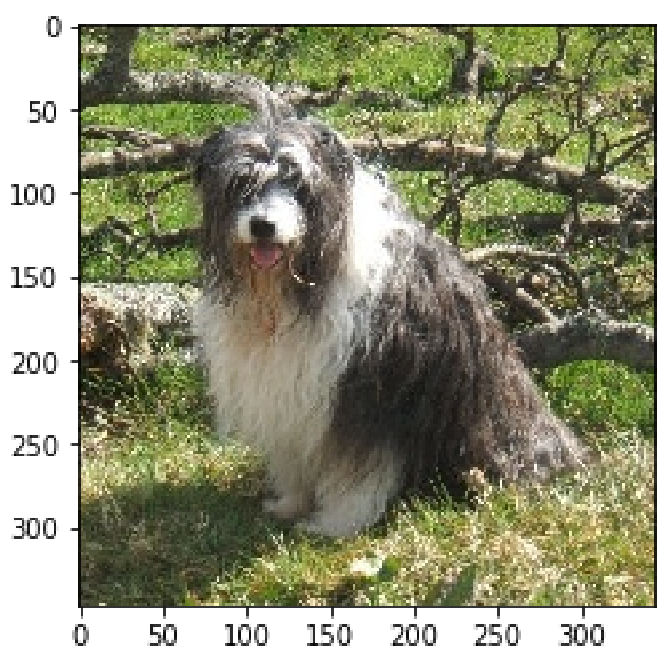
```
Dog breed ...
American_staffordshire_terrier
```



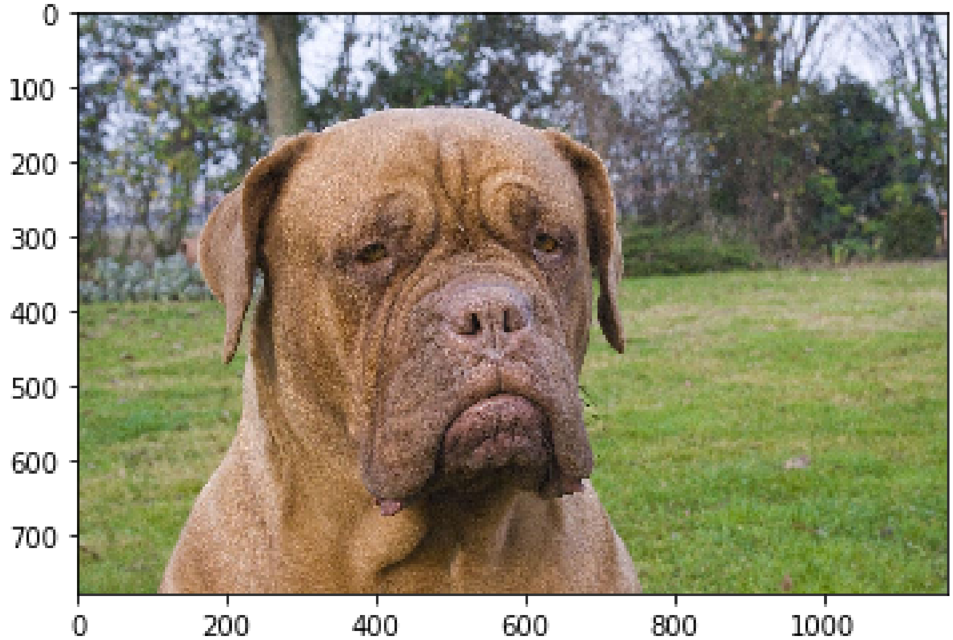
```
Human detected. Human looks like dog breed ...
Bullmastiff
```



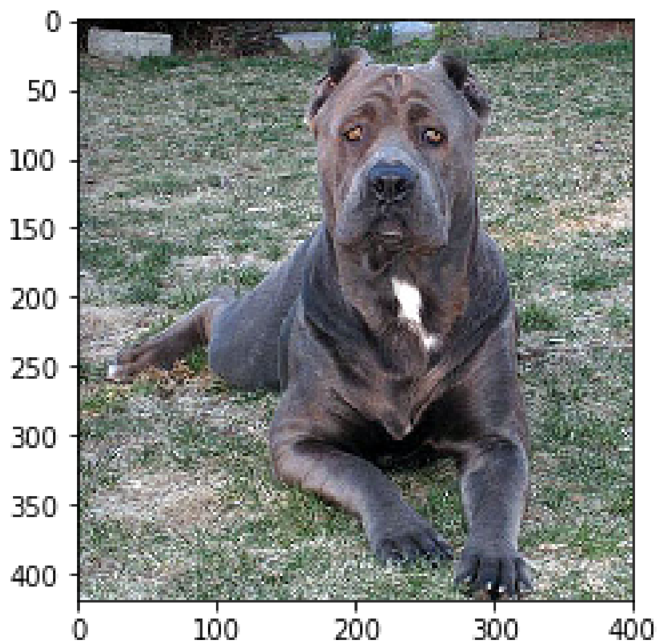

```
Dog breed ...
Wirehaired_pointing_griffon
```



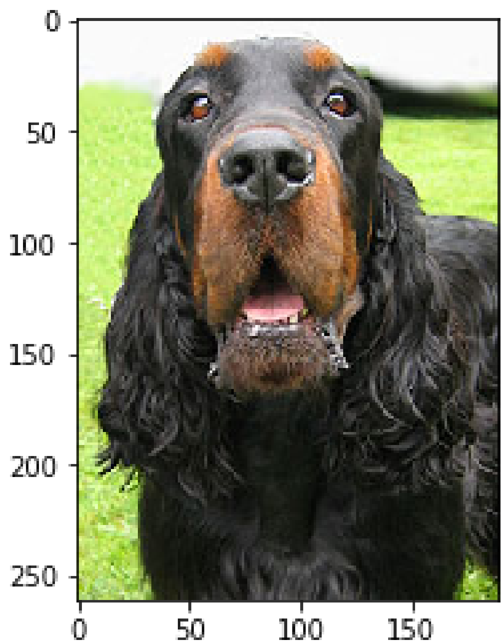
```
Dog breed ...
Bearded_collie
```



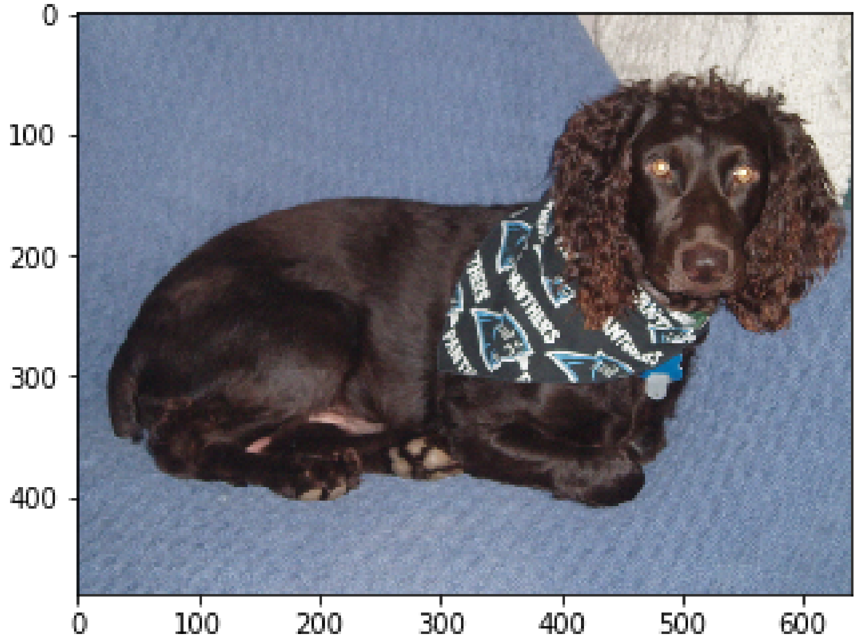

```
Dog breed ...
Dogue_de_bordeaux
```



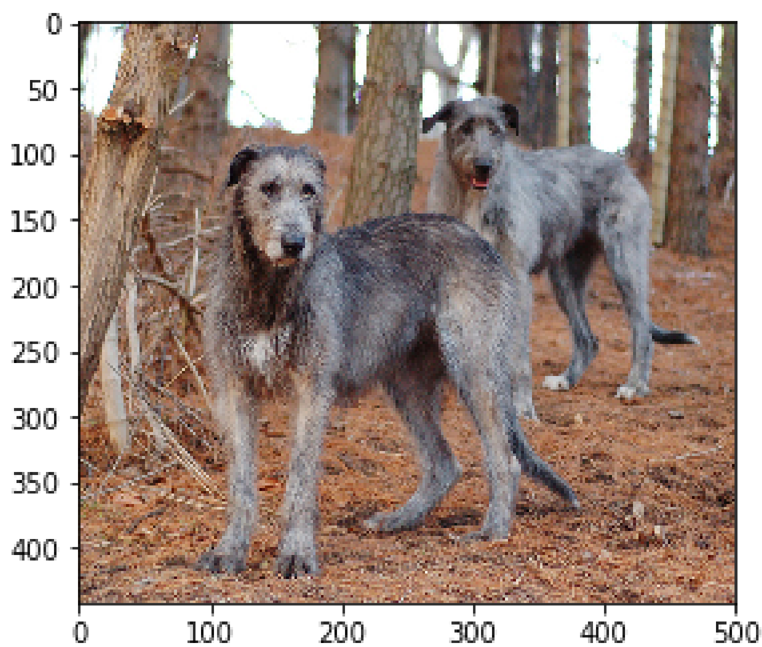
```
Dog breed ...
Neapolitan_mastiff
```




```
Human detected. Human looks like dog breed ...
Gordon_setter
```




```
Dog breed ...
Boykin_spaniel
```



```
Dog breed ...
Irish_wolfhound
```