dog_app

March 13, 2021

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

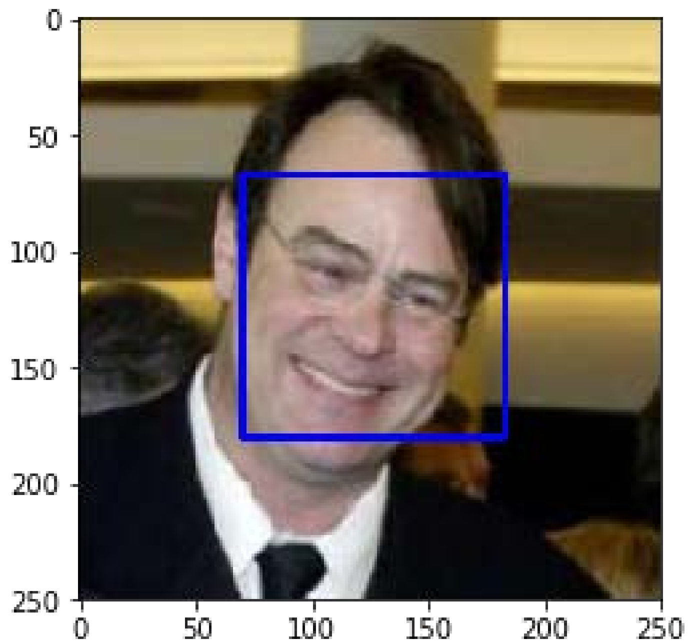
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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),(255,0,0),2)

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer:
We detected 98 % as humans in the human file
We detected 17 % as humans in the dogs file

```
In [4]: from tqdm import tqdm

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        counter_human = 0;
        counter_dog = 0;
        for human in human_files_short:
            if (face_detector(human)):
                counter_human += 1

        for dog in dog_files_short:
            if (face_detector(dog)):
                counter_dog += 1
        print('We detected',counter_human, '% as humans in the human file')
        print('We detected',counter_dog, '% as humans in the dogs file')
```

```
We detected 98 % as humans in the human file
We detected 17 % as humans in the dogs file
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 106740067.07it/s]
```

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

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

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

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

```python
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)
            normalize = transforms.Compose([transforms.Resize((224,224)),transforms.CenterCrop((
            img=normalize(img)
            #display(img)
            img = img.unsqueeze(0).to('cuda') # unsqueeze to add artificial first dimension

            return  torch.argmax(VGG16(img))# 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).

```python
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.
            prediction = VGG16_predict(img_path)
            return ((prediction <= 268) & (prediction >= 151)) # 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:

We detected 3 % as dogs in the human file
We detected 100 % as dogs in the dogs file

In [9]:
```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
counter_human = 0;
counter_dog = 0;
for human in human_files_short:
    #display(Image.open(human))
    if (dog_detector(human)):
        counter_human += 1

for dog in dog_files_short:
    #display(Image.open(dog))
    if (dog_detector(dog)):
        counter_dog += 1
print('We detected',counter_human, '% as dogs in the human file')
print('We detected',counter_dog, '% as dogs in the dogs file')
```

```
We detected 2 % as dogs in the human file
We detected 100 % as dogs in the dogs file
```

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

In [10]:
```
### (Optional)
### TODO: Report the performance of another pre-trained network.
### Feel free to use as many code cells as needed.
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)
Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador

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

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

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

```
In [11]: ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         from torch.utils.data import DataLoader
         from torchvision import datasets
         from skimage import io

         #not sure what the next two lines are doing but they help to avoid error in model...
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         transformation_train = transforms.Compose([
             transforms.Resize(256),
             transforms.CenterCrop(256),
             transforms.RandomHorizontalFlip(),
             transforms.RandomRotation(10),
             transforms.ToTensor(),
             transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
             ])
         transformation_validate = transforms.Compose([
             transforms.Resize(256),
```

```
            transforms.CenterCrop(256),
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
            ])
        transformation_test = transforms.Compose([
            transforms.Resize(256),
            transforms.CenterCrop(256),
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
            ])

        dataset_train = datasets.ImageFolder(root='/data/dog_images/train/',transform=transform
        dataset_validate = datasets.ImageFolder(root='/data/dog_images/valid/',transform=transf
        dataset_test = datasets.ImageFolder(root='/data/dog_images/test/',transform=transformat

        data_loader_train = DataLoader(dataset_train,batch_size = 20,shuffle=True)
        data_loader_validate = DataLoader(dataset_validate,batch_size = 20)
        data_loader_test = DataLoader(dataset_test,batch_size = 20)
```

In [12]:
```
classes = dataset_train.classes
for brew in classes:
    print(brew)
```

```
001.Affenpinscher
002.Afghan_hound
003.Airedale_terrier
004.Akita
005.Alaskan_malamute
006.American_eskimo_dog
007.American_foxhound
008.American_staffordshire_terrier
009.American_water_spaniel
010.Anatolian_shepherd_dog
011.Australian_cattle_dog
012.Australian_shepherd
013.Australian_terrier
014.Basenji
015.Basset_hound
016.Beagle
017.Bearded_collie
018.Beauceron
019.Bedlington_terrier
020.Belgian_malinois
021.Belgian_sheepdog
022.Belgian_tervuren
023.Bernese_mountain_dog
024.Bichon_frise
025.Black_and_tan_coonhound
```

026.Black_russian_terrier
027.Bloodhound
028.Bluetick_coonhound
029.Border_collie
030.Border_terrier
031.Borzoi
032.Boston_terrier
033.Bouvier_des_flandres
034.Boxer
035.Boykin_spaniel
036.Briard
037.Brittany
038.Brussels_griffon
039.Bull_terrier
040.Bulldog
041.Bullmastiff
042.Cairn_terrier
043.Canaan_dog
044.Cane_corso
045.Cardigan_welsh_corgi
046.Cavalier_king_charles_spaniel
047.Chesapeake_bay_retriever
048.Chihuahua
049.Chinese_crested
050.Chinese_shar-pei
051.Chow_chow
052.Clumber_spaniel
053.Cocker_spaniel
054.Collie
055.Curly-coated_retriever
056.Dachshund
057.Dalmatian
058.Dandie_dinmont_terrier
059.Doberman_pinscher
060.Dogue_de_bordeaux
061.English_cocker_spaniel
062.English_setter
063.English_springer_spaniel
064.English_toy_spaniel
065.Entlebucher_mountain_dog
066.Field_spaniel
067.Finnish_spitz
068.Flat-coated_retriever
069.French_bulldog
070.German_pinscher
071.German_shepherd_dog
072.German_shorthaired_pointer
073.German_wirehaired_pointer

074.Giant_schnauzer
075.Glen_of_imaal_terrier
076.Golden_retriever
077.Gordon_setter
078.Great_dane
079.Great_pyrenees
080.Greater_swiss_mountain_dog
081.Greyhound
082.Havanese
083.Ibizan_hound
084.Icelandic_sheepdog
085.Irish_red_and_white_setter
086.Irish_setter
087.Irish_terrier
088.Irish_water_spaniel
089.Irish_wolfhound
090.Italian_greyhound
091.Japanese_chin
092.Keeshond
093.Kerry_blue_terrier
094.Komondor
095.Kuvasz
096.Labrador_retriever
097.Lakeland_terrier
098.Leonberger
099.Lhasa_apso
100.Lowchen
101.Maltese
102.Manchester_terrier
103.Mastiff
104.Miniature_schnauzer
105.Neapolitan_mastiff
106.Newfoundland
107.Norfolk_terrier
108.Norwegian_buhund
109.Norwegian_elkhound
110.Norwegian_lundehund
111.Norwich_terrier
112.Nova_scotia_duck_tolling_retriever
113.Old_english_sheepdog
114.Otterhound
115.Papillon
116.Parson_russell_terrier
117.Pekingese
118.Pembroke_welsh_corgi
119.Petit_basset_griffon_vendeen
120.Pharaoh_hound
121.Plott

```
122.Pointer
123.Pomeranian
124.Poodle
125.Portuguese_water_dog
126.Saint_bernard
127.Silky_terrier
128.Smooth_fox_terrier
129.Tibetan_mastiff
130.Welsh_springer_spaniel
131.Wirehaired_pointing_griffon
132.Xoloitzcuintli
133.Yorkshire_terrier
```

In [ ]:

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

Answer:

I croped and resized the images to size 256 * 256 and turned it in a tensor in the next step. i decided for 256 = 2ˇ8 to have it nicely scalable in the further steps.

I went for basic augmentation by random rotarion of 10ř and random horizontal flip in the training dataset

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

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3,16,3,padding=1)
        self.conv2 = nn.Conv2d(16,32,3,padding=1)
        self.conv3 = nn.Conv2d(32,64,3,padding=1)
        self.conv4 = nn.Conv2d(64,128,3,padding=1)
        #self.conv5 = nn.Conv2d(128,256,3,padding=1)
        self.pool  = nn.MaxPool2d(2,2)

        self.fc1 = nn.Linear(16 * 16 * 128, 2048)
        self.fc2 = nn.Linear(2048,1024)
        self.fc3 = nn.Linear(1024,133)
```

```
        self.conv_bn1 = nn.BatchNorm2d(16)
        self.conv_bn2 = nn.BatchNorm2d(32)
        self.conv_bn3 = nn.BatchNorm2d(64)
        self.conv_bn4 = nn.BatchNorm2d(128)
        #self.conv_bn5 = nn.BatchNorm2d(256)

        self.dropout = nn.Dropout(0.2)


    def forward(self, x):
        ## Define forward behavior
        x = self.pool(self.conv_bn1(F.relu(self.conv1(x))))     # 256 * 256 * 3  -> 128
        x = self.pool(self.conv_bn2(F.relu(self.conv2(x))))     # 128 * 128 * 16 -> 64
        x = self.pool(self.conv_bn3(F.relu(self.conv3(x))))     # 64 * 64* 32 -> 32 * 3
        x = self.pool(self.conv_bn4(F.relu(self.conv4(x))))     # 32 * 32 * 64 -> 16 *
        #x = self.pool(self.conv_bn5(F.relu(self.conv5(x))))     # 16 * 16 * 128 -> 8 *

        x = x.view(-1,16 * 16 * 128)              # 7 * 7 * 256 -> 2048
        x = F.relu(self.fc1(x))                   # 2048 -> 1024 brews
        x = self.dropout(x)
        x = F.relu(self.fc2(x))                   # 1024 -> 133 brews
        x = self.dropout(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()
```

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

Answer:

I increased the depth of the layers step by step and ended with a depth of 128. in between all concolutional layers i added a max pooling layer that resuces the area of the 'image' by factor 4. Besides that research in the internet and other classifiers available online pointed me to a batch normalization layer that normalizes the data of each batch as described here. I added a batch normalization layer between all conv and pooling layers to increase the solution quality. After my convolutional layers I added three fully connected layer that reduce the number of features from 32768 ->2048 -> 1024 -> 133 to end up in the brews of the dogs.

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 = torch.optim.Adam(model_scratch.parameters(), lr=0.001)
```

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, data_loader_train, data_loader_validate, model, optimizer, criterio
             """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(data_loader_train):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()

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

                 ######################
                 # validate the model #
                 ######################
```

```
            model.eval()
            for batch_idx, (data, target) in enumerate(data_loader_validate):
                # move to GPU
                if use_cuda:
                    data, target = data.cuda(), target.cuda()
                ## update the average validation loss
                output = model(data)
                loss = criterion(output,target)
                valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)

            # print training/validation statistics
            print(f'Epoch: {epoch} \tTraining Loss: {train_loss} \tValidation Loss: {valid_

            ## TODO: save the model if validation loss has decreased
            if valid_loss < valid_loss_min:
                print(f'Validation loss decreased from {valid_loss_min} to {valid_loss}.  S
                torch.save(model.state_dict(),save_path)
                valid_loss_min = valid_loss
        # return trained model
        return model


    # train the model
    model_scratch = train(20, data_loader_train, data_loader_validate, model_scratch, optim
                          criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1         Training Loss: 4.810904502868652         Validation Loss: 4.556180477142334
Validation loss decreased from inf to 4.556180477142334.  Saving model ...
Epoch: 2         Training Loss: 4.564329624176025         Validation Loss: 4.387361526489258
Validation loss decreased from 4.556180477142334 to 4.387361526489258.  Saving model ...
Epoch: 3         Training Loss: 4.375672817230225         Validation Loss: 4.258118629455566
Validation loss decreased from 4.387361526489258 to 4.258118629455566.  Saving model ...
Epoch: 4         Training Loss: 4.225637912750244         Validation Loss: 4.116283893585205
Validation loss decreased from 4.258118629455566 to 4.116283893585205.  Saving model ...
Epoch: 5         Training Loss: 4.094132900238037         Validation Loss: 4.011231899261475
Validation loss decreased from 4.116283893585205 to 4.011231899261475.  Saving model ...
Epoch: 6         Training Loss: 3.975861072540283         Validation Loss: 3.8979673385620117
Validation loss decreased from 4.011231899261475 to 3.8979673385620117.  Saving model ...
Epoch: 7         Training Loss: 3.839242458343506         Validation Loss: 3.8559043407440186
Validation loss decreased from 3.8979673385620117 to 3.8559043407440186.  Saving model ...
Epoch: 8         Training Loss: 3.693246603012085         Validation Loss: 3.816957712173462
Validation loss decreased from 3.8559043407440186 to 3.816957712173462.  Saving model ...
Epoch: 9         Training Loss: 3.53468656539917         Validation Loss: 3.8511085510253906
Epoch: 10         Training Loss: 3.3996129035949707         Validation Loss: 3.7740135192871094
Validation loss decreased from 3.816957712173462 to 3.7740135192871094.  Saving model ...
Epoch: 11         Training Loss: 3.22283673286438         Validation Loss: 3.655233144760132
Validation loss decreased from 3.7740135192871094 to 3.655233144760132.  Saving model ...
Epoch: 12         Training Loss: 3.048314094543457         Validation Loss: 3.608815908432007
```

```
Validation loss decreased from 3.655233144760132 to 3.608815908432007.  Saving model ...
Epoch: 13        Training Loss: 2.8813416957855225        Validation Loss: 3.6870274543762207
Epoch: 14        Training Loss: 2.6841163635253906        Validation Loss: 3.6635513305664062
Epoch: 15        Training Loss: 2.509587287902832        Validation Loss: 3.6883246898651123
Epoch: 16        Training Loss: 2.3309102058410645        Validation Loss: 3.7347073554992676
Epoch: 17        Training Loss: 2.117274045944214        Validation Loss: 3.779330015182495
Epoch: 18        Training Loss: 1.9411699771881104        Validation Loss: 3.8848206996917725
Epoch: 19        Training Loss: 1.7652369737625122        Validation Loss: 4.0814595222473145
Epoch: 20        Training Loss: 1.6439415216445923        Validation Loss: 3.872816562652588
```

In [16]:
```
# 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 [17]:
```
def test(data_loader_test, 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(data_loader_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(data_loader_test, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.668148


Test Accuracy: 15% (128/836)
```

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 [18]:
```
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes

from torch.utils.data import DataLoader
from torchvision import datasets
from skimage import io

#not sure what the next two lines are doing but they help to avoid error in model...
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

transformation_train = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_validate = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_test = transforms.Compose([
```

```
            transforms.Resize(224),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
            ])

        dataset_train = datasets.ImageFolder(root='/data/dog_images/train/',transform=transform
        dataset_validate = datasets.ImageFolder(root='/data/dog_images/valid/',transform=transf
        dataset_test = datasets.ImageFolder(root='/data/dog_images/test/',transform=transformat

        data_loader_train = DataLoader(dataset_train,batch_size = 20,shuffle=True)
        data_loader_validate = DataLoader(dataset_validate,batch_size = 20)
        data_loader_test = DataLoader(dataset_test,batch_size = 20)
```

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 [19]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         # vgg16
         # resnet18
         model_transfer = models.densenet121(pretrained=True)

         #print(model_transfer)

         #DENSENET121
         print(model_transfer.classifier.in_features)
         print(model_transfer.classifier.out_features)

         #RASNSNET18
         #print(model_transfer.fc.in_features)
         #print(model_transfer.fc.out_features)


         #VGG16
         #print(model_transfer.classifier[6].in_features)
         #print(model_transfer.classifier[6].out_features)

         #for param in model_transfer.features.parameters():
         #    param.requires_grad = False
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/models/densenet.p
Downloading: "https://download.pytorch.org/models/densenet121-a639ec97.pth" to /root/.torch/mode
100%|| 32342954/32342954 [00:00<00:00, 77975287.78it/s]
```

```
1024
1000
```

```
In [20]: print(model_transfer)
```

```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True)
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition1): _Transition(
    (norm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer5): _DenseLayer(
  (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer10): _DenseLayer(
  (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
    )
    (transition2): _Transition(
      (norm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer10): _DenseLayer(
      (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer13): _DenseLayer(
      (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer14): _DenseLayer(
      (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer16): _DenseLayer(
    (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer17): _DenseLayer(
    (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer18): _DenseLayer(
    (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer19): _DenseLayer(
    (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer20): _DenseLayer(
    (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer21): _DenseLayer(
    (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer22): _DenseLayer(
      (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer23): _DenseLayer(
      (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer24): _DenseLayer(
      (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition3): _Transition(
    (norm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer3): _DenseLayer(
    (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer10): _DenseLayer(
    (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer11): _DenseLayer(
    (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer12): _DenseLayer(
    (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer13): _DenseLayer(
    (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer14): _DenseLayer(
    (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer15): _DenseLayer(
        (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
    )
    (norm5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (classifier): Linear(in_features=1024, out_features=1000, bias=True)
)
```

In [21]:
```
#densenet
model_transfer.classifier = nn.Linear(1024, 133)
for param in model_transfer.features.parameters():
    param.requires_grad = False


#vgg
#model_transfer.classifier[6] = nn.Linear(512, 133)


use_cuda = torch.cuda.is_available()
if use_cuda:
    model_transfer = model_transfer.cuda()

print(model_transfer)
```

```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
(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_stats=True)
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer2): _DenseLayer(
    (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer3): _DenseLayer(
    (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition1): _Transition(
    (norm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer5): _DenseLayer(
      (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer10): _DenseLayer(
    (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer11): _DenseLayer(
    (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition2): _Transition(
    (norm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer10): _DenseLayer(
    (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer13): _DenseLayer(
      (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer14): _DenseLayer(
      (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer16): _DenseLayer(
      (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer17): _DenseLayer(
  (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer18): _DenseLayer(
  (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer19): _DenseLayer(
  (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer20): _DenseLayer(
  (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer21): _DenseLayer(
  (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
  (relu2): ReLU(inplace)
  (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
)
(denselayer22): _DenseLayer(
  (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer23): _DenseLayer(
      (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer24): _DenseLayer(
      (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition3): _Transition(
    (norm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer5): _DenseLayer(
      (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer7): _DenseLayer(
      (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer8): _DenseLayer(
      (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer9): _DenseLayer(
      (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer10): _DenseLayer(
      (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer13): _DenseLayer(
      (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer14): _DenseLayer(
      (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
```

```
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
    )
    (norm5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (classifier): Linear(in_features=1024, 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:

I tried around with different pretrained models like vgg, rasnet a but finally ended up with densenet, which acctually performs quite good. I replaced the fully connected layer which initially sorts the data in 1000 classes by a new one that sorts only in 133 classes which represent our dog brews.

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()

#DENSENET121
optimizer_transfer = torch.optim.Adam(model_transfer.classifier.parameters(),lr=0.001)

#RESNET18
#optimizer_transfer = torch.optim.Adam(model_transfer.fc.parameters(),lr=0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

In [23]:
```
# train the model

# NOTE, I increased the epochs step by step to get a feeling how the model precision de
# model was trained in 40 epochs.
```

```python
def train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer, criterion_tra

    for epoch in range(1, n_epochs+1):

        # keep track of training and validation loss
        train_loss = 0.0

        for batch_i, (data, target) in enumerate(loaders_transfer):
            # move tensors to GPU if CUDA is available
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            # clear the gradients of all optimized variables
            optimizer_transfer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to the model
            output = model_transfer(data)
            # calculate the batch loss
            loss = criterion_transfer(output, target)
            # backward pass: compute gradient of the loss with respect to model paramet
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer_transfer.step()
            # update training loss
            train_loss += loss.item()

        print('Epoch: {} \tBatch: {:.6f} \tTaining Loss: {:.6f}'.format(epoch, batch_i+

    torch.save(model_transfer.state_dict(),save_path)
    return model_transfer

model_transfer = train(20, data_loader_train, model_transfer, optimizer_transfer, crite


# 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        Batch: 334.000000        Taining Loss: 804.057902
Epoch: 2        Batch: 334.000000        Taining Loss: 291.956455
Epoch: 3        Batch: 334.000000        Taining Loss: 201.683991
Epoch: 4        Batch: 334.000000        Taining Loss: 161.135798
Epoch: 5        Batch: 334.000000        Taining Loss: 135.153041
Epoch: 6        Batch: 334.000000        Taining Loss: 115.626069
Epoch: 7        Batch: 334.000000        Taining Loss: 104.294168
Epoch: 8        Batch: 334.000000        Taining Loss: 94.320725
Epoch: 9        Batch: 334.000000        Taining Loss: 83.498996
Epoch: 10         Batch: 334.000000         Taining Loss: 77.592903
Epoch: 11         Batch: 334.000000         Taining Loss: 73.679458
Epoch: 12         Batch: 334.000000         Taining Loss: 71.044848
Epoch: 13         Batch: 334.000000         Taining Loss: 62.051627
```

```
Epoch: 14        Batch: 334.000000        Taining Loss: 60.868579
Epoch: 15        Batch: 334.000000        Taining Loss: 54.389125
Epoch: 16        Batch: 334.000000        Taining Loss: 54.809484
Epoch: 17        Batch: 334.000000        Taining Loss: 48.736322
Epoch: 18        Batch: 334.000000        Taining Loss: 47.382500
Epoch: 19        Batch: 334.000000        Taining Loss: 43.793496
Epoch: 20        Batch: 334.000000        Taining Loss: 44.380720
```

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 [24]:
```
model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

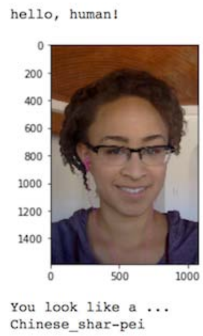
In [25]:
```
test(data_loader_test, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.627575


Test Accuracy: 83% (695/836)
```

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 [26]:
```
### TODO: Write a function that takes a path to an image as input
### and returns the dog breed that is predicted by the model.

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

import tensorflow as tf

from PIL import Image

def predict_breed_transfer(img_path, model_transfer=model_transfer):
    image = Image.open(img_path)

    transformation = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
```



Sample Human Output

```
        image = transformation(image)
        image = image[:3,:,:].unsqueeze(0)
        image = image.cuda()

        output = model_transfer(image)

        return class_names[output.cpu().data.numpy().argmax()]


    predict_breed_transfer('images/Brittany_02625.jpg', model_transfer)
```

Out[26]: 'Brittany'

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 [27]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.

def run_app(img_path):
    img = Image.open(img_path)
    display(img)
    dog = dog_detector(img_path)
    human = face_detector(img_path)
```

```
        if dog:
            dog_breed = predict_breed_transfer(img_path)
            print(f'We found a dog here, it is a {dog_breed}')
        elif human:
            human_breed = predict_breed_transfer(img_path)
            print(f'This human looks like a {human_breed}')
        else:
            print('Sorry, we could not detect a dog or human on the image...')

        return None

        ## handle cases for a human face, dog, and neither

    #run_app('images/Brittany_02625.jpg')
```

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: The output is better than I expected when I starten this project. In general there are several ways to improve the final app:

- test and train different classifiers for dogs and humans to get better resulsts on the initial classification
- increase the number of epochs in the transferred brew detection to improve the result quality
- test different pretrained models and compare its results
- increase the variaty of input data

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

## suggested code, below

run_app('own_pics/3.jpg')
run_app('own_pics/4.jpg')
run_app('own_pics/5.jpg')

for file in np.hstack((human_files[:3], dog_files[:3])):
```

```
    run_app(file)

run_app('own_pics/1.jpg')
run_app('own_pics/2.jpg')
```

```
We found a dog here, it is a Pomeranian
```

This human looks like a Affenpinscher

This human looks like a Afghan hound

This human looks like a Welsh springer spaniel

This human looks like a Dachshund

This human looks like a Irish water spaniel

We found a dog here, it is a Mastiff

We found a dog here, it is a Mastiff

We found a dog here, it is a Mastiff

```
In [ ]:
```

This human looks like a American staffordshire terrier