

Data Scientist Nanodegree

Project: Write an Algorithm for a Dog Identification App

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Introduction:

In this report, I'll go through the deep learning techniques that provide the system to detect human face and dog breed as well determine which dog breeds look like to be a specific human, we have two processes first, the human face detection and dog detection, second, the classification of human based dog breed's model. The best performance technique that using transfer learning and haar-cascade.

Project Overview:

In this project, you will learn how to build a pipeline that can be used within a web or mobile app to process real-world, user-supplied images. Given an image of a dog, your algorithm will identify an estimate of the canine's breed. If supplied an image of a human, the code will identify the resembling dog breed.

Along with exploring state-of-the-art CNN models for classification and localization, you will make important design decisions about the user experience for your app. Our goal is that by completing this lab, you understand the challenges involved in piecing together a series of models designed to perform various tasks in a data processing pipeline. Each model has its strengths and weaknesses, and engineering a real-world application often involves solving many problems without a perfect answer. Your imperfect solution will nonetheless create a fun user experience!

Method:

1. Import Datasets

A. dog dataset : (<https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip>).

B. human dataset : (<https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip>).

2. Detection Techniques

- A. We use for face detection OpenCV's implementation of [Haar feature-based cascade classifiers](#) to detect human faces in images.
- B. We use for dogs detection the VGG-16 model (Pre-train model) , along with weights that have been trained on [ImageNet](#).

3. Model Design

- A. CNN from scratch (Model Scratch):

```
Net(  
    (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (fc1): Linear(in_features=50176, out_features=1000, bias=True)  
    (fc2): Linear(in_features=1000, out_features=1000, bias=True)  
    (fc3): Linear(in_features=1000, out_features=133, bias=True)  
    (dropout): Dropout(p=0.2)  
)
```

- B. Transfer Learning Model:

```
import torchvision.models as models  
import torch.nn as nn  
  
## TODO: Specify model architecture  
model_transfer = models.vgg16(pretrained=True)  
  
# Freeze parameters so we don't backprop through them  
for param in model_transfer.parameters():  
    param.requires_grad = False  
  
from collections import OrderedDict  
classifier = nn.Sequential(OrderedDict([  
    ('fc1', nn.Linear(25088, 500)),  
    ('relu', nn.ReLU()),  
    ('fc2', nn.Linear(500, 133)),  
    ('output', nn.LogSoftmax(dim=1))  
]))  
  
model_transfer.classifier = classifier  
  
if use_cuda:  
    model_transfer = model_transfer.cuda()  
  
model_transfer
```

4. Analysis

As showcased in the jupyter notebook, I have below analysis results of the input dataset:

1. There are 133 total dog categories.
2. There are 8351 total dog images.
3. There are 6680 training dog images.
4. There are 835 validation dog images.
5. There are 836 test dog images.
6. There are 13233 total human images.

Results:

In summary, the performance of the pre-trained model I built far exceeded the hand made CNN model. The accuracy of the model reached 80% while my scratch model CNN was about 13%. This improved performance can be attributed to the vast dataset on which the pre-trained model was built. In particular, the pre-trained model was also exposed to many dog images, making it particularly ready to classify dog breeds.

Link to Medium story here: <https://medium.com/@mukhtar.rad/dog-vs-human-detectability-and-similarity-40c5a68d9575>