Machine Learning Engineer Nanodegree

Dog Breed Classifier

Table of content

lable of content	1
Definition Project Overview	2
Project Overview	2
Problem Statement	2
Metrics	2
Analysis	3
Data Exploration and Visualization	3
Human dataset	3
Sample images with labels	4
Dog dataset	6
Sample images with labels	7
Algorithms and Techniques	7
Benchmark	8
Methodology	8
Data Pre-processing	8
Implementation	8
The classifier training stage	8
The network architecture	9
Using the trained model to classify dogs	10
Results	11
Model Evaluation and Validation	11
Conclusion	12
Reflection	12
Improvement	13

Definition

Project Overview

A dog breed classifier is a computer vision classifier that uses Convolutional Neural Networks (CNN) to build a pipeline to process real-world, user-supplied images.

Given an image of a dog, The 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.

Problem Statement

The goal is to create a dog breed classifier based on a dog or human image.

In the real world, there are a lot of different dog breeds. While Humans can detect few dog breeds, The classifier can detect more than 100 different dog breeds.

The output will be the Input Image labeled with the predicted dog class. The Input will be an RGB image of a dog or a human.

Machine learning will be used to capture the features for the Input image and use those features to predict the dog class.

The project will be developed by completing the following tasks:

- 1. Download the input data
- 2. Preprocess the data and see If the classes are imbalanced3. Create
- 3. Human Face detection using open cv library haar cascades
- 4. Create a general dog detector using a pre-trained model like VGG which is a sequence of convolution and pooling layers
- 5. Using transfer learning to create the dog breed classifier after dropping the classifier layer in the pre-trained model and attach the new one after changing the output number.
- 6. Take a raw image and return the dog breed.

Metrics

CrossEntropyLoss

It is useful when training a classification problem with C classes. This Cross-Entropy Loss is useful when you have an unbalanced training set.

$$\mathrm{loss}(x, class) = -\log\left(rac{\mathrm{exp}(x[class])}{\sum_{j}\mathrm{exp}(x[j])}
ight) = -x[class] + \log\left(\sum_{j}\mathrm{exp}(x[j])
ight)$$

The losses are averaged across observations for each minibatch.

$$loss = \frac{\sum_{i=1}^{N} loss(i, class[i])}{\sum_{i=1}^{N} weight[class[i]]}$$

Accuracy

is a common metric for binary and multi-class classifiers; it takes into account both true positives and true negatives with equal weight.

accuracy =(true positives + true negative) / size of dataset

Because we have multi-class classification precision and recall will not be a good metric as we are focus on the total number of correct prediction

We can use ROC-AUC as a metric and compare the results as the next Improvements.

Analysis

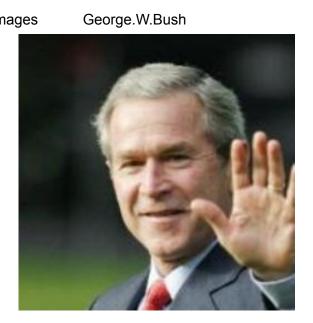
Data Exploration and Visualization

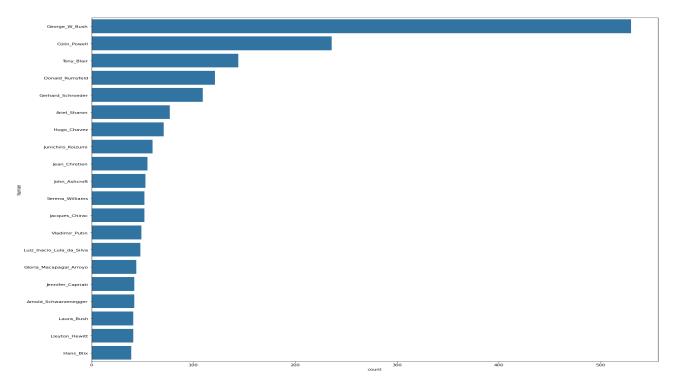
Human dataset

The human dataset has 13233 images with 5749 unique Humans. George_W_Bush has the most counts with 530 image

The top 20 Humans were:

Name	# of im
George W Bush	530
Colin Powell	236
Tony Blair	144
Donald Rumsfeld	121
Gerhard Schroeder	109
Ariel Sharon	77
Hugo Chavez	71
Junichiro Koizumi	60
Jean_Chretien	55
John Ashcroft	53
Serena_Williams	52
Jacques Chirac	52
Vladimir Putin	49
Luiz Inacio Lula da Silva	48
Gloria_Macapagal_Arroyo	44
Jennifer Capriati	42
Arnold Schwarzenegger	42
Laura Bush	41
Lleyton_Hewitt	41
Hans_Blix	39





Sample images with labels











Jamie_Cooke



Hernan_Crespo





Allison_Janney



Travis_Rudolph



Demetrius_Ferraciu





Brian_Cook





LeRoy_Millette_Jr



Eddie_Lucio



Ward_Cuff



Nia_Vardalos



Don_King





Dog dataset

The Dog dataset has 8351 images with 133 unique dog breeds. the Alaskan malamute has the most counts with 95 image

The top 20 Dogs were:

Dog breed	# cc
Alaskan malamute	96
Border collie	93
Basset hound	92
Dalmatīan	89
Bull terrier	87
Bullmastiff	86
Basenji	86
Cavalier king charles spaniel	84
Australian cattle dog	83
Australian shepherd	83
Dachshund	82
Irish terrier	82
American staffordshire terrier	82
Boston terrier	81
Briard	81
Bernese mountain dog	81
Affenpinscher	80
American eskimo dog	80
Bloodhound	80
Cane corso	80
–	





Sample images with labels











































Algorithms and Techniques

The classifier is a Convolutional Neural Network, which is the state-of-the-art algorithm for most image processing tasks, including classification. It needs a large amount of training data compared to other approaches.

The following parameters can be tuned to optimize the classifier:

- 1. Training parameters:
 - Training length (number of epochs)
 - Batch size (how many images to look at once during a single training step)
 - Learning rate (how fast to learn; this can be dynamic)
- 2. Neural network architecture:
 - Number of layers

- Layer types (convolutional, fully-connected, or pooling)
- 3. Preprocessing parameters

During training, both the training and the validation sets are loaded into the RAM. After that, random batches are selected to be loaded into the GPU memory for processing.

We could use Two Techniques:

1- Train the model from scratch:

We can build our model from scratch specifically to the problem. This Technique is when we want to build a detector for simple use cases

The problem with that Technique that we need to train the model from the beginning and need to design every layer in the model (Convolution, fully connected and pooling ...etc)

2- Use pre-trained Network by transfer learning

We can use the CNN model that has been trained and use the layers that detect the features from the input whatever the Input type or shape and replace the pre-trained Network classifier for a custom classifier.

This Technique save a lot of training time as we freeze the feature layers and train only the classifier

I have used transfer learning in the final solution using the VGG16 model as It was trained on a huge dataset.

Benchmark

I have used Two benchmarks.

the first one was training a model from scratch and test the model and record the highest score that we can get with a given dataset and try to beat this result using other techniques.

The second one was to set an accuracy threshold from the model that we can accept for the application. I targeted 75% accuracy on the test set

I have set a timing constraint for real-time classification, so the model target to classify the input image in time doesn't exceed 50 ms

Methodology

Data Pre-processing

The preprocessing has the following steps:

- 1. Make augmentation for images (RandomRotation,RandomResizedCrop and RandomHorizontalFlip)
- 2. Normalize the input images
- 3. The images are divided into training, validation, and test sets
- 4. Create the data loaders by configuring the batch size and shuffle the training data

Implementation

The implementation process can be split into two main stages:

- 1. The classifier training stage
- 2. Using the trained model to classify dogs

The classifier training stage

During the first stage, the classifier was trained on the preprocessed training data using transfer learning.

The training steps were:

- 1. load both the training and validation images into memory using the data loaders that we have created
- 2. Define the network architecture and training parameters
- 3. Define the loss function, accuracy
- 4. Train the network, logging the validation/training loss and the validation accuracy
- 5. If the accuracy is not high enough, return to step 2
- 6. Save and freeze the trained network

The network architecture

I have used transfer learning using the vgg16 model

```
(features): Sequential(
```

- (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
- (1): ReLU(inplace=True)
- (2): Conv2d(64, 64, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
- (3): ReLU(inplace=True)
- (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)

```
(5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (6): ReLU(inplace=True)
 (7): Conv2d(128, 128, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
 (8): ReLU(inplace=True)
 (9): MaxPool2d(kernel size=2, stride=2, padding=0, dilation=1, ceil mode=False)
 (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (11): ReLU(inplace=True)
 (12): Conv2d(256, 256, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
 (13): ReLU(inplace=True)
 (14): Conv2d(256, 256, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
 (15): ReLU(inplace=True)
 (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
 (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (18): ReLU(inplace=True)
 (19): Conv2d(512, 512, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
 (20): ReLU(inplace=True)
 (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (22): ReLU(inplace=True)
 (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
 (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (25): ReLU(inplace=True)
 (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
 (27): ReLU(inplace=True)
 (28): Conv2d(512, 512, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
 (29): ReLU(inplace=True)
 (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(avgpool): AdaptiveAvgPool2d(output size=(7, 7))
(classifier): Sequential(
 (fc1): Linear(in features=25088, out features=4096, bias=True)
 (relu): ReLU()
 (Dropout1): Dropout(p=0.5, inplace=False)
 (fc2): Linear(in features=4096, out features=1024, bias=True)
 (Dropout2): Dropout(p=0.5, inplace=False)
 (fc3): Linear(in_features=1024, out_features=133, bias=True)
 (output): LogSoftmax()
)
```

I have kept the features layers as It has already trained to detect shapes and patterns and replaced the classifiers layers with one that I need to classify the new 133 dog breed.

The new classifier becomes:

```
(classifier): Sequential(
  (fc1): Linear(in_features=25088, out_features=4096, bias=True)
  (relu): ReLU()
  (Dropout1): Dropout(p=0.5, inplace=False)
```

```
(fc2): Linear(in_features=4096, out_features=1024, bias=True)
(Dropout2): Dropout(p=0.5, inplace=False)
(fc3): Linear(in_features=1024, out_features=133, bias=True)
(output): LogSoftmax()
)
```

Using the trained model to classify dogs

- 1. Create the model using the given layers
- 2. Load the pre-trained weights
- 3. Process the input Images
- 4. Using open cv to detect faces in Images
- 5. Using a pre-trained VGG model to detect dogs
- 6. Predict the input Image using the model

Results

Model Evaluation and Validation

During development, a validation set was used to evaluate the model.

The final architecture and hyperparameters were chosen because they performed the best among the tried combinations.

For a complete description of the final model and the training process, refer to The network architecture section

I have trained the model after replacing the Classifier layers for 10 Epochs with the following train and Validation losses:

```
Epoch: 1 Training Loss: 1.343471 Validation Loss: 0.829716
Epoch: 2 Training Loss: 1.270921 Validation Loss: 0.739991
Epoch: 3 Training Loss: 1.208083 Validation Loss: 0.681313
Epoch: 4 Training Loss: 1.185337 Validation Loss: 0.700088
```

```
Epoch: 5 Training Loss: 1.175069 Validation Loss: 0.613085

Epoch: 6 Training Loss: 1.112700 Validation Loss: 0.649210

Epoch: 7 Training Loss: 1.109303 Validation Loss: 0.549573

Epoch: 8 Training Loss: 1.084382 Validation Loss: 0.585246

Epoch: 9 Training Loss: 1.055470 Validation Loss: 0.690492

Epoch: 10 Training Loss: 1.021630 Validation Loss: 0.687842
```

So as we can see the Validation was still decreasing so we can have better accuracy If we Increased the number of epochs but It will take a longer time.

Using the test set, the Test Accuracy was 80% (677/836)

Justification

The Test accuracy using transfer learning is 80%

- For the first benchmark, The Test accuracy using the trained model from **scratch** was **18**% using the same input data set and environment which is a significant improvement.
- For the second benchmark, the target was to exceed the 75% test accuracy and that was done using **transfer learning**.
- For the timing constraints for real-time, we were target to classify images at average 40ms/image

 It took 5.42 Second to classify 200 Image so the average was 27 ms/image

I used my local machine (6 GByte GPU" NVIDIA Corporation TU116M [GeForce GTX 1660 Ti Mobile]", 12 logical CPU "Intel® CoreTM i7-9750H CPU @ 2.60GHz \times 12") in the training and testing

The result is stronger than I expected as the model was trained for just 10 Epochs and we got 80 % accuracy.

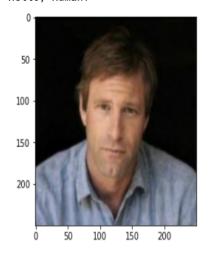
We didn't train the feature layers and use them as it with trained weights so we achieved our target with min. Training time.

The model is good enough to detect 8 images from the given 10 input images, this ratio could be increased by train the model for more Epochs

Conclusion

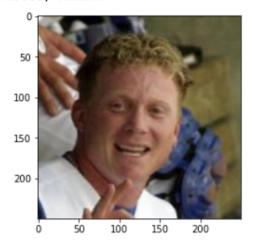
Using Convolution neural networks we can classify the dog breeds with an accuracy of more than 80 % and we can even make this classification for humans.



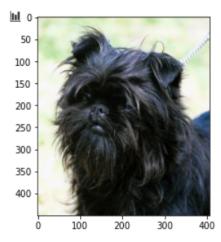


You look like a Dogue de bordeaux

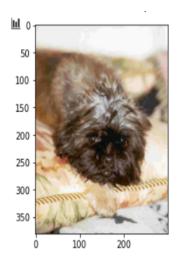
Hello, Human!



You look like a Dachshund



You look like a Affenpinscher



You look like a Brussels griffon

Reflection

The process used for this project can be summarized using the following steps:

- 1. An initial problem and relevant, public datasets were found
- 2. The data was downloaded and preprocessed (segmented)
- 3. A benchmark was created for the classifier
- 4. The classifier was trained using the data and transfer learning (multiple times, until a good set of parameters, were found)
- 5. The model was used to detect the dog breed on unseen images.

Improvement

To achieve better accuracy for the model

- 1- we can use different model features layers for our model
- 2- we can CNN to detect humans better than a face classifier
- 3- we can train for more epochs