Capstone Project

Machine Learning Engineer Nanodegree

Yisakor Weldegebriel
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Definition

Overview

Extracting meaning from images and classifying them has been an area of interest for decades. The first major breakthrough came about with the use of Convolutional Neural Networks (CNNs) in the early 1990s[1].
A famous benchmark is the MNIST dataset used to classify handwritten digits.

In this project I worked on the classification of dog breeds using a CNN.

There are two main classification models in this project:

- The first one is a CNN architecture I built from scratch
- The second is built off of the VGG model using transfer learning

The program will take an image or an array of images as input and display:

- The breed in the case of a dog input
- The closest dog breed in the case of a human input
- An "I don't recognize this object." message if the input is neither

[1] Most of the information on the history of CNNs were taken from the following website: https://hackernoon.com/a-brief-history-of-computer-vision-and-convolutional-neural-networks-8fe8aacc79f3

Problem Statement

The objective is to create a program that predicts dog breeds. The steps taken to do so were:

1. Download and preprocess data
2. Build human face and dog detectors based on pretrained models
3. Build a dog breed classifying model from scratch
4. Build a dog breed classifying model with Transfer Learning
5. Code a final function that outputs predictions

Metrics

Accuracy is the metric used for this project and it's calculated as follows:

$$accuracy = \frac{true\ predictions}{total\ predictions}$$

Analysis

Data Exploration

The dataset used for this project was provided by Udacity.
It contains training, validation and testing data for 133 dog breeds as well as a human face dataset.

Basic Statistics:

Total number of images: 8351
Training images: 6680
Validation images: 835
Number of breeds (classes): 133

Percentage of training data: 80%
Percentage of validation data: 10%
Percentage of test data: 10%

Figure 1- Images from the dataset

There are no particular outliers in the dataset that was used.

Exploratory Visualization

We have an image-based dataset.
There is a total of 6680 images for training and you will find below their distribution for each class of dog breed.

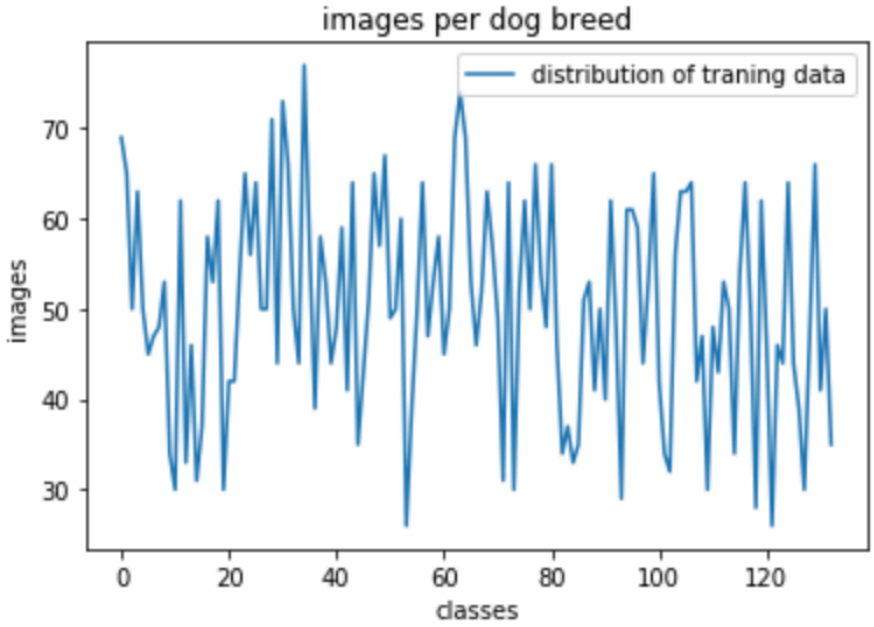


Figure 2 - Distribution of images for each class

It is worth noting that there isn't an even distribution of training data for each class, possibly leading to biases in the model. Some classes have as high as 70 images or more for training and others as low as 30.

Algorithms and Techniques

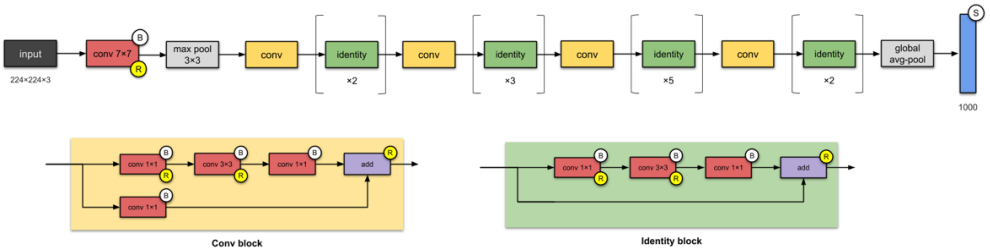
The main component to creating a classification model is a Convolutional Neural Network. We have an ample amount of data to train the CNN on, and its performance as seen in pretrained models is remarkable.
There are 133 possible predictions for each image, so the algorithm assigns a probability for each breed and outputs the breed with the maximum amount.

An accurate CNN model takes a lot of time and parameter tuning so in addition to creating a model from scratch, I used transfer learning to obtain a more accurate model on the back of an existing model.

A CNN will be composed of the following parameters that can be tuned for optimal accuracy:

- Layer types (convolutional, fully connected, maxpool)
- Number of Layers
- Batch size
- Epochs

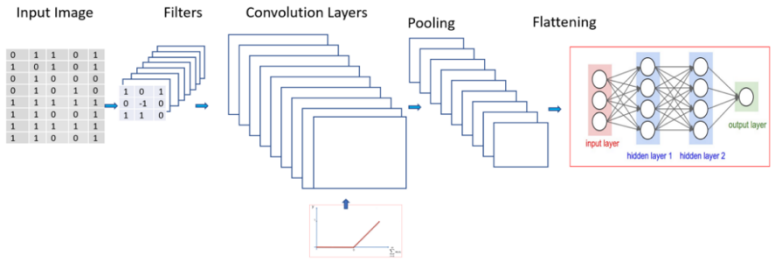
- Learning rate
- Dropout rate



[2]

Figure 3 - Example of CNN architecture

INPUT FEATURES: Since the task at hand is image classification, there are a lot of features and data included in every image.
But we want the CNN to be able to extract relevant features so that it's able to correctly predict and classify test inputs.
For that we apply filters to generate feature maps using the Relu activation function. Then we apply pooling for translation invariance[3].



Benchmark

The benchmark for the model built from scratch is an accuracy rate of 10%.
For the Transfer Learning model, the bar is set at 60%.

[2] The example image of a CNN architecture was taken from: https://towardsdatascience.com/illustrated-10-cnn-architectures-95d78ace614d

[3] Information on how CNNs extract features and map them was taken from udacity's course and the following website: https://towardsdatascience.com/convolutional-neural-network-feature-map-and-filter-visualization-f75012a5a49c

Methodology

Data Preprocessing

For the human face detection method, the downloaded dataset is loaded into arrays. For the rest of the detection methods data is preprocessed through transforms and separated into training, validation and testing data before being fed to the CNN.

The transform consists of:

1. Resizing images into squares
2. Randomly rotating images 10°
3. Randomly flipping images horizontally
4. Turning them into Tensors and normalizing

Then the data is shuffled in the loaders.

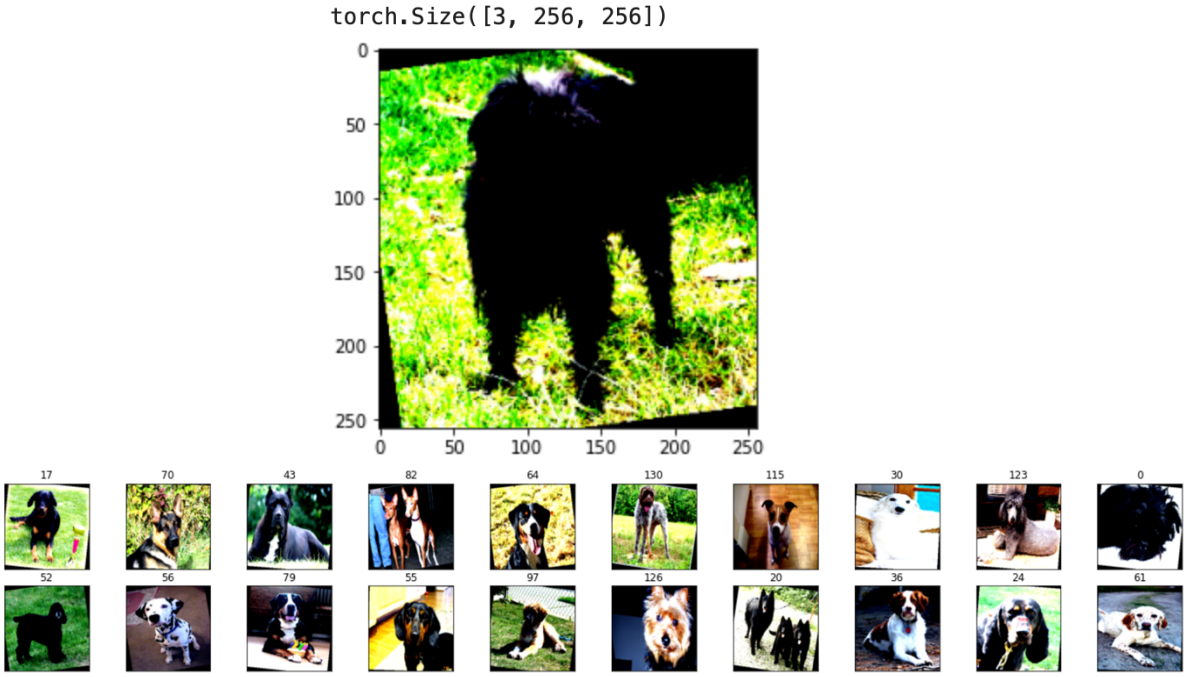


Figure 4 - Data after preprocessing

Implementation

The first model architecture I used contains 6 layers:

- 3 Convolutional layers
- 1 Max Pooling layer
- 2 Fully Connected layers
- Dropout rate of 0.25

```
(classifier): Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace)
  (2): Dropout(p=0.5)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace)
  (5): Dropout(p=0.5)
  (6): Linear(in_features=4096, out_features=133, bias=True)
)
```

Figure 5 - Recap of CNN architecture

After a bit of research on Pytorch, I opted for a CrossEntropyLoss function because it is best suited for multi-class classification.
I also picked an SGD optimizer with a learning rate of 0.01

For the Transfer Learning portion, the existing model I chose to adapt to my project is VGG16. This model is already optimized to classify 1000 different objects including different types of dogs so repurposing it as a dog breed classifier should work out well.

```
(classifier): Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace)
  (2): Dropout(p=0.5)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace)
  (5): Dropout(p=0.5)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```

Figure 6 - Recap Transfer Learning CNN

Improvement/Iterations

In order to achieve better results on the model built from scratch, I decided to experiment with the number of convolutional layers. I increased it from 3 to 6 and added one more fully connected layer. But it did not yield better results.

Results

Model Evaluation and validation

The final architecture of the CNN is the best performing out of the iterations I tried.

I defined training and testing methods and I was able to observe that for the model built from scratch, validation loss is at a minimum after about the 10^{th} epoch, after which the model starts over-fitting.
Depending on the training cycle, accuracy varies from 10% to 11% on the test data.
This result meets the threshold set in the benchmark.

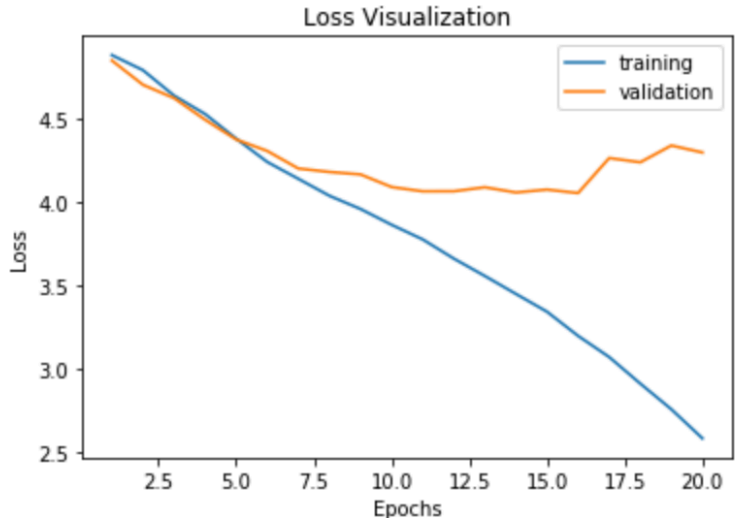


Figure 7 - Model_Scratch

The transfer Learning model outperforms the models built from scratch by a lot so that is what I used for the final prediction methods at the end of the notebook. Sensitivity analysis is performed at the end of the notebook.

I was able to reach an accuracy rate of about 85% using transfer learning after about 15 epochs.
The speed of convergence is impressive, especially in comparison to the previous model. The accuracy is above the benchmark that was set and it exceeded my expectations

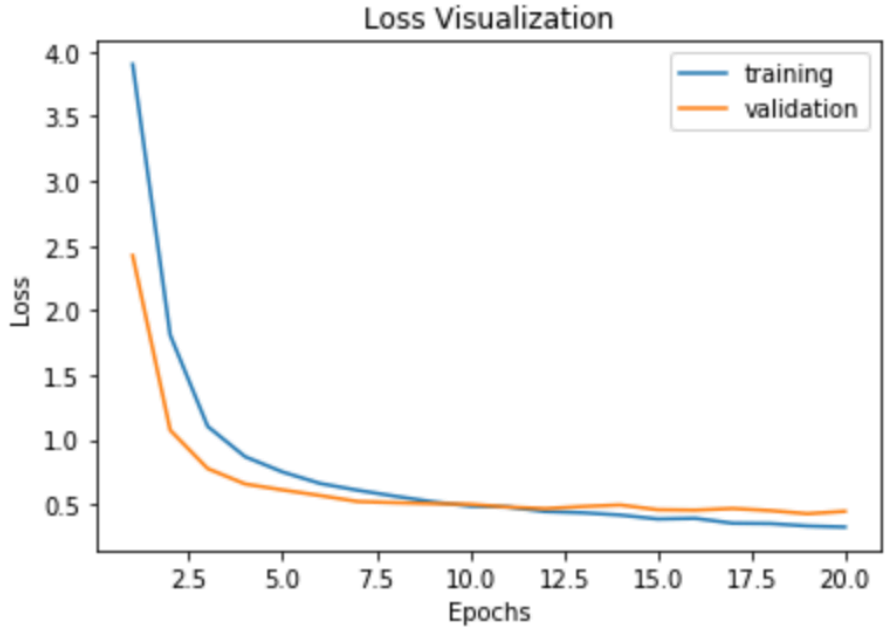


Figure 8- Transfer_Model

Conclusion

Thus, if there's a choice to be made, clearly the model to choose is the one built with transfer learning.
You will find below a sample predictions made during testing.

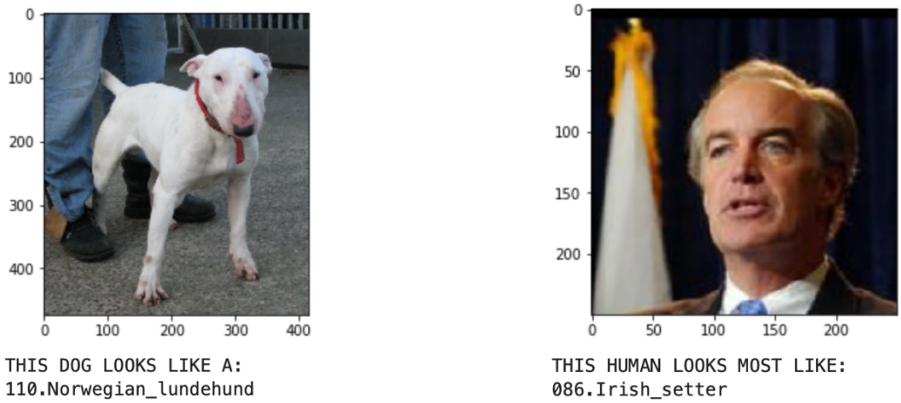


Figure 9 – Sample predictions made from the model

Justification

The transfer learning model has an accuracy score of 85%, surpassing the 60% threshold set as the benchmark by 15%.

At the end of the notebook, sensitivity analysis is performed.
The model is tested with different types of images of dogs, humans, as well as an image with both humans and dogs (as seen in figure 9).

Given that the accuracy score is above 80%, this model can be qualified as robust, in my opinion. It will give correct predictions most of the time.
Although compared to the dog detector with VGG16 and face detector from CV2 it still has some ways to go. These models have accuracy rates of about 98% - 99%.

I believe the trustworthiness of the transfer model will depend on the application domain. If the model is to be used in a medical/veterinarian context for instance or any field where you would need very high precision models, then I wouldn't recommend this one because 15% is not negligeable.
But for a less demanding application area, this model is more than capable of getting the job done.

The model built from scratch meets just about the threshold for accuracy and cannot be considered robust nor reliable.

Perhaps to land a better model built from scratch I would need more layers, and just overall more finely tuned hyperparameters and training time (with more epochs).

Summary

In summary I was able to implement code that for an input image handled 3 cases:

- If the input is a dog image, it will predict what the dog's breed is.
- If it's a human face, it will predict the dog breed closest to that face.
- If it's neither, it returns an error messaging stating that it does not recognize the object.