Capstone Project Report

Dog Breed Detection using Convolutional Neural Networks

Guilherme Baldo Carlos, January 20th, 2022

I. Definition

Project Overview

There are hundreds of dog breeds all around the world. The current project aims to develop convolutional neural networks (CNNs) to identify dog breeds with input images. The algorithm produced is composed of a pipeline of image classifiers. This algorithm works by identifying if an image provided by the user contains a person, a dog or neither. In the case of a dog, the algorithm responds with the dog breed. In the case of a person the algorithm responds with the dog breed the person in the picture most resembles. Finally in the case of neither a dog nor a person in the image the algorithm will respond with invalid input.

To develop the solution two datasets are used. First, to evaluate the face detector the LFW (Labeled Faces in the Wild) public dataset is used. This dataset contains 13 thousand images of people. The second dataset is provided by Udacity and corresponds in a dataset with 133 dog breeds and 8351 dog images with varying image size. Those dog images are splitted in train set (6680 images), validation set (835 images) and test set (836 images). One third dataset is indirectly used and it is the ImageNet which contains 1000 classes and it is used to perform transfer learning, so we use CNNs that are pretrained on those models.

Problem Statement

To address the challenge proposed, three image classifiers needed to be used.

- face detector: used to identify faces in images in order to classify an input image as a human or not.
- dog detector: a CNN responsible for performing classification and used for telling if the input image corresponds to a dog or not.
- dog breed classifier: a CNN developed and trained to perform dog breed classification and telling the dog breed the dog in the input image is or the dog breed the person in the input image most resembles.

The project was developed using a base jupyter notebook which breaks down the project in the following steps:

1. Import datasets: two links are provided and the datasets must be download the datasets and extracted it in the predefined location
2. Detect humans: in this step the Haar Cascade face detector provided by OpenCV is used to perform face detection. A function to wrap the face detector should be developed.
3. Detect dogs: a pretrained VGG-16 which is a state-of-the-art CNN classifier must be used to perform dog detection. Since this model was trained to perform 1000-class classification, a function to wrap this model and filter dog and non-dog detections should be developed.
4. Create a CNN to classify dog breeds from scratch: in this step it is necessary to develop and train a CNN model from scratch.
5. Create a CNN to classify dog breeds using transfer learning: in this step an existing CNN provided by pytorch must be chosen to perform dog breed classification. Transfer learning must be used.
6. Write your algorithm: the final algorithm is built using the face detector to identify if the input image corresponds to a person, the dog detector to identify if the input image corresponds to a dog and the dog breed classifier to tell what is the dog breed or what dog breed most resembles the person in the input image.
7. Test your algorithm: in this final step the algorithm must be tested with different dog and human images externally provided.

Evaluation Metrics

Since we are talking about classification, we want to measure how many of the human images the face detector is able to detect. How many dog images the dog detector is able to correctly predict. And finally how many dog breeds the dog breed classifier is able to predict correctly.
The metric used for that is the accuracy and for classification purposes it is calculated as below:

$$accuracy\ =\ \#\ of\ correct\ predictions\ /\ \#\ of\ predictions$$

The accuracy requirement for the dog breed classifier built from scratch is minimum 10% and the accuracy for the dog breed classifier using transfer learning is 60%.

The accuracy works really well for balanced datasets. But as it will be shown in the next section. The dataset of dog images provided is not balanced. The reason accuracy is not reliable for imbalanced datasets is that a model may perform very well for the major class in the dataset and very poorly in the minor class in the dataset and still achieve a high accuracy. Therefore the other metrics, such as precision, recall and F1-score are used to complement model evaluation. However the threshold for acceptance of the solution is still accuracy as required by the project description.
The recall answers the question of what portion of that specific class the model is able to predict as that class. As shown below:

$recall \ = \ \# \, of \ correct \, predict \ example \ of \ the \ class \ A \ / \ \# \, of \ examples \ of \ class \ A$
or
$recall \ = \ true \, positives \ / \ (true \, positives \ + \ false \, negatives)$

So from all of the class A present in the dataset, how many of them were predicted by the model as class A. And that is calculated for each class in the dataset.
On the other hand, the precision answers the question of what portion of the examples predicted as class A are actually from class A. As shown below:

$precision \ = \ \# \, of \ correct \, predict \ example \ of \ the \ class \ A \ / \ \# \, of \ examples \, predicted \ as \ class \ A$
or
$precision \ = true \, positives \ / \ (true \, positives \ + \ false \, positives)$

The F1-score aims to aggregate the recall and the precision and produce a metric that can be easily used to compare different models even if the dataset is imbalanced. The F1-score is calculated as below:

$F1 \, score \ = 2 \, x \, (precision \, x \, recall)/(precision \ + \ recall)$

II. Analysis

Data Exploration

In this project we train and evaluate the dog breed classifier in a dataset provided by Udacity. This dataset contains 133 dog breeds and 8351 dog images with varying image size. Those dog images are splitted in train set (6680 images), validation set (835 images) and test set (836 images). We see below (Figure 1) some examples of images from the dataset with its labels.

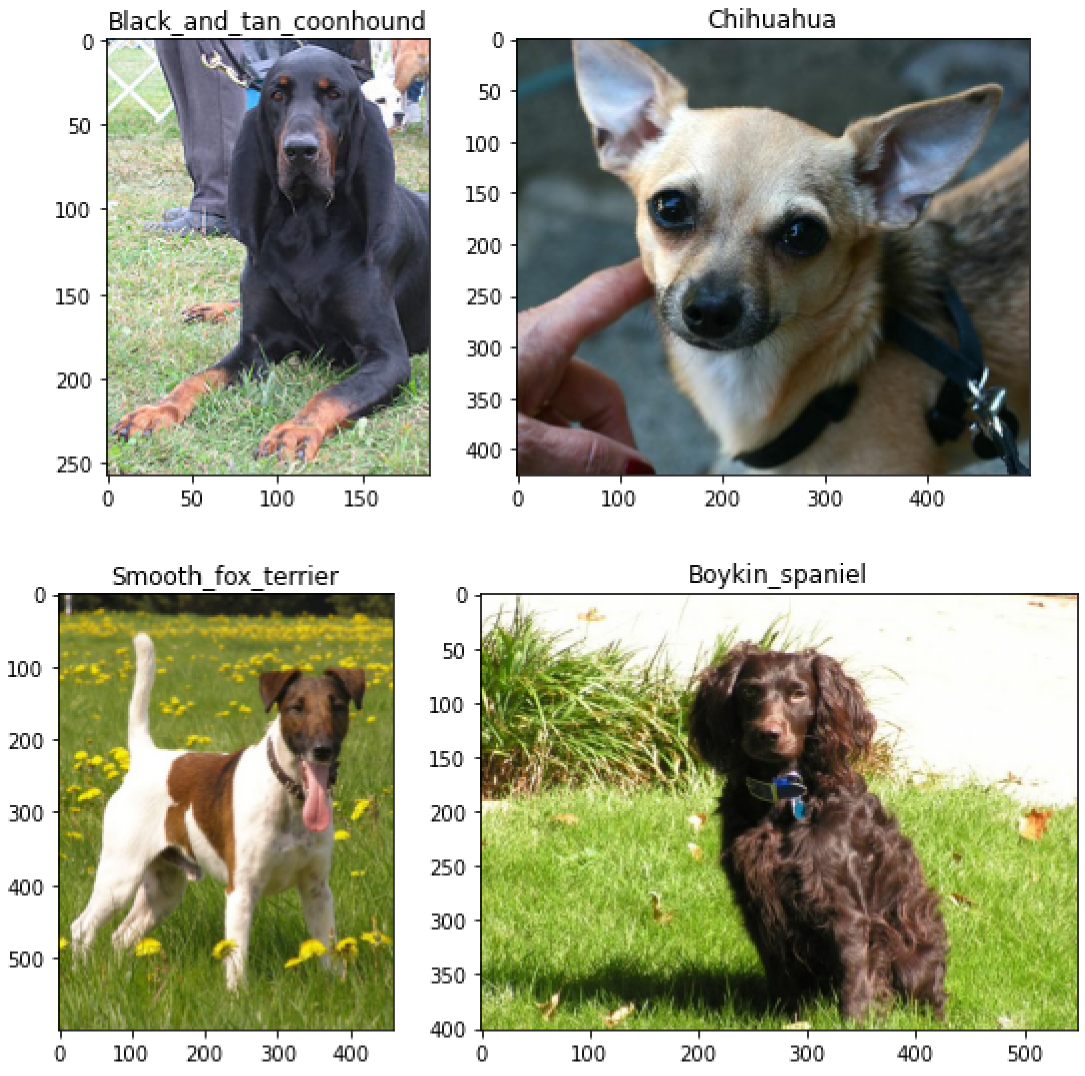


Figure 1 - Examples of images in the dog images dataset.

As we note, the images come in different sizes. That is explored further in the exploratory visualization section.

Exploratory Visualization

Some visualizations are used to further understand the dataset. Regarding the aforementioned difference in image dimensions from the dataset, the plots below show how these dimensions are distributed. The width, height and aspect ratio (height/width) distributions are shown below (Figure 2).

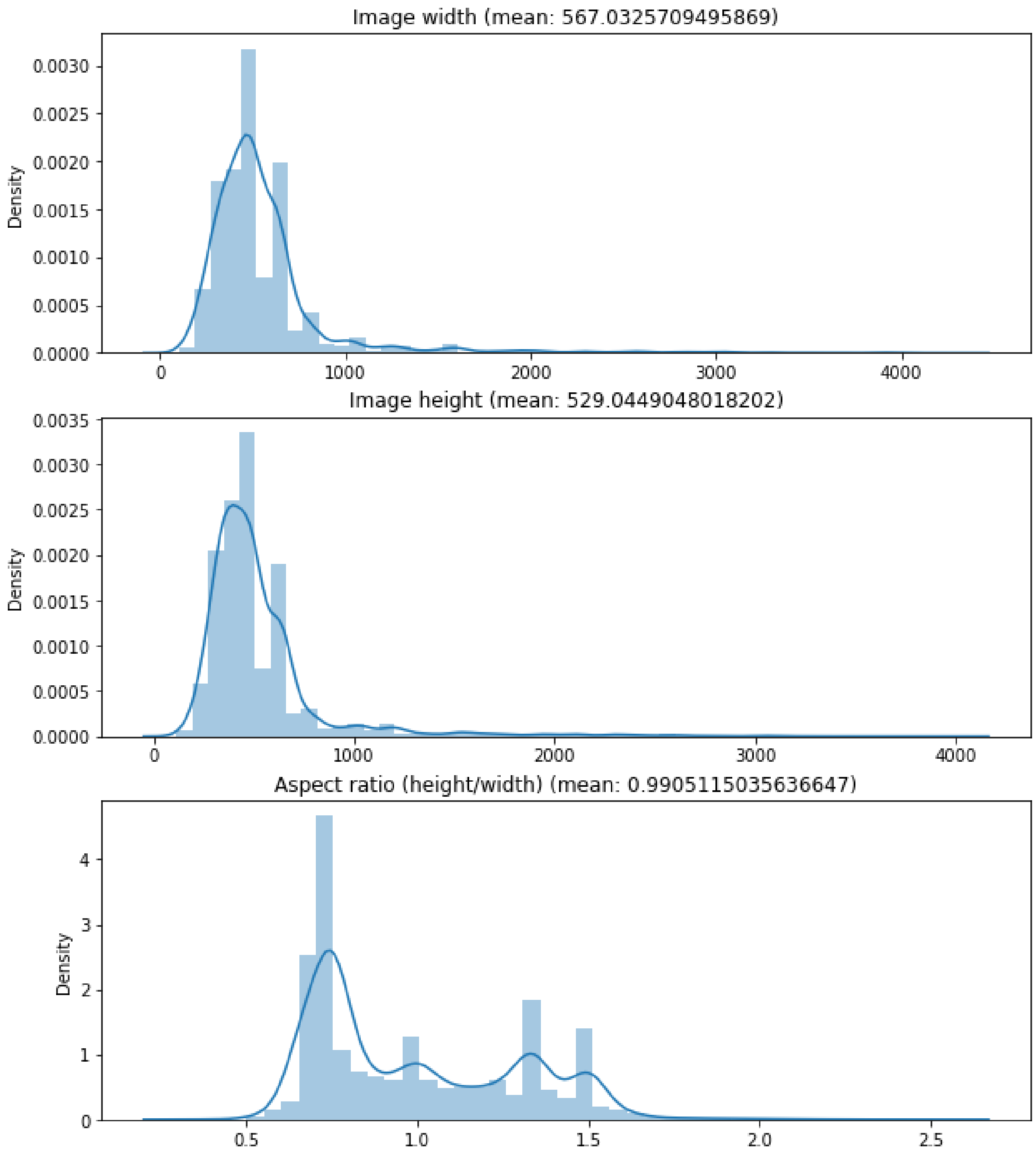


Figure 2 - Histogram of image dimensions and aspect ratios in the dog images dataset.

It is possible to notice that for the image width and height there is a high frequency of images with dimensions around 550 pixels. As for the aspect ratio, the majority of images present an aspect ratio that goes from 0.5 to 1.5 (1 indicates a square image). That said, the images range from a landscape aspect image with width twice the height to portrait aspect images with height 50% greater than width.

As stated before there are 133 dog breeds (classes) in the dataset. It is important for training that the dataset is not far from balanced. Therefore, the visualization below (Figure 3) shows the frequency distribution for each class in the training dataset.

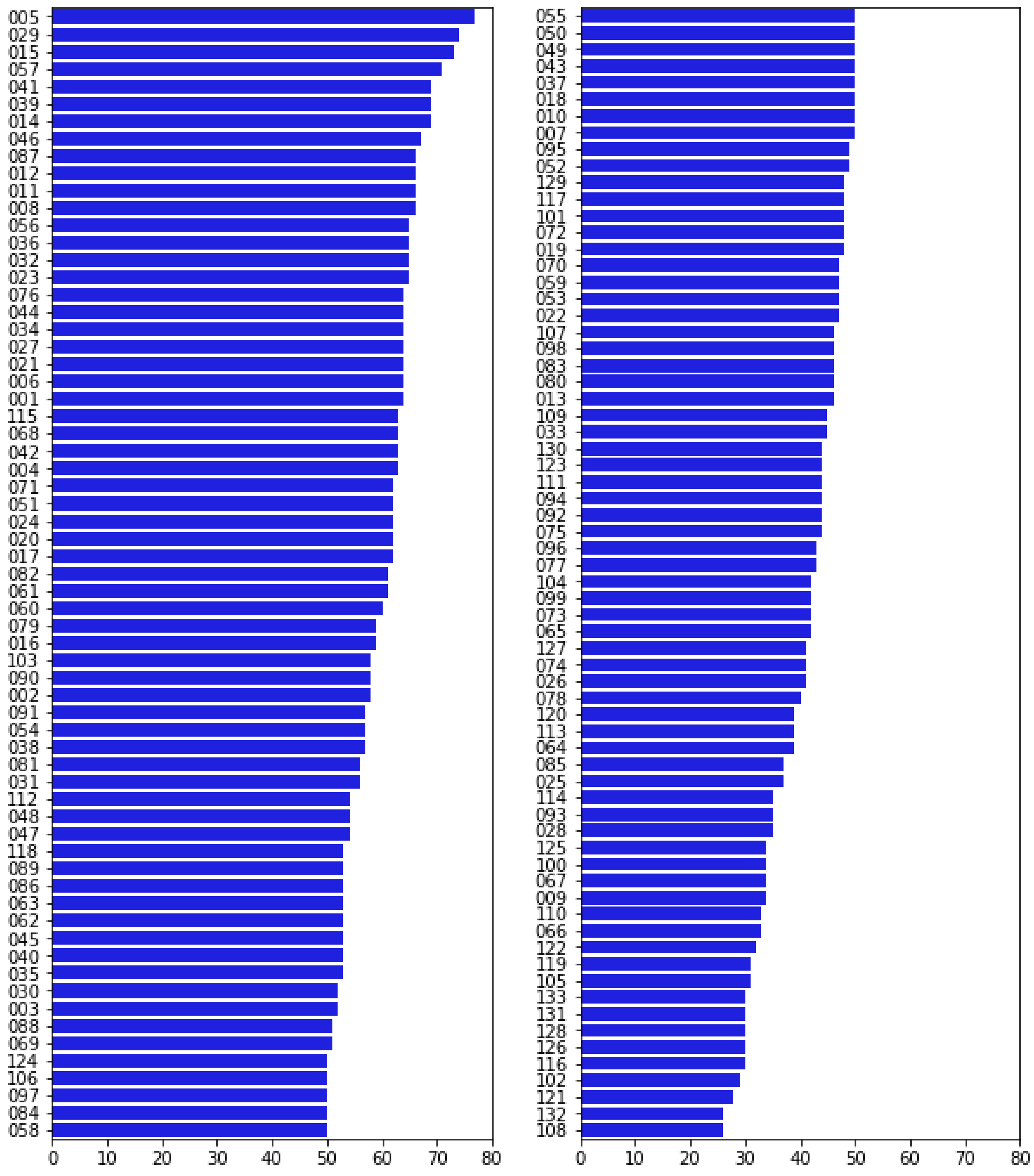


Figure 3 - Frequency of class labels in the dog images dataset.

It is possible to see that there is a difference in distribution between different dog breeds. Ranging from dog breeds with 26 images to dog breeds with 77 examples. So the most frequent class in the dataset has around triple the frequency of the less frequent. That is not addressed in this project but may be an improvement point.

Algorithms and techniques

To solve the problem of human detection the face detector Haar Cascades provided in OpenCV is used. Haar Cascades face detector is a lightweight face detector that on the downside is prone to false positives and on the upside it provides a fast inference with low memory usage and disk space usage. In our project it demonstrated a sampled accuracy of 96% on the images for which we know there was a face, so 4% false negatives. And using it in the dog images it yielded a 18% false positives rate. For our application that is sufficient since it is not critical that we achieve a perfect result here, specially because the dog breed classifier that will be used after this step in the pipeline is used regardless if there is a person or dog in the image.
To solve the problem of dog detection the VGG-16 model pretrained on ImageNet was used as instructed by the project description. This model is already able to detect a 1000 classes, so a function was built to binarize the output of this model from dog (class 151 to 278) and non dog (0 to 150 and 279 to 999). The VGG-16 (Figure 4) is a CNN classifier composed by a feature extractor with sequential convolutions and pooling operations that aim to hierarchically extract from small simple features to more and more complex and large features from the input image. That is achieved by the reduction in width and height dimensions promoted by the pooling operations and the increasing number of filters in deeper layers.

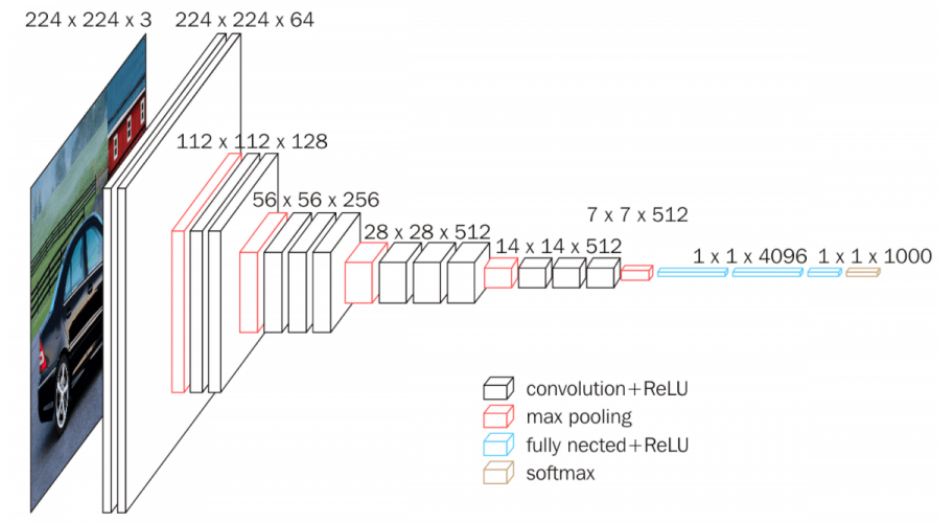
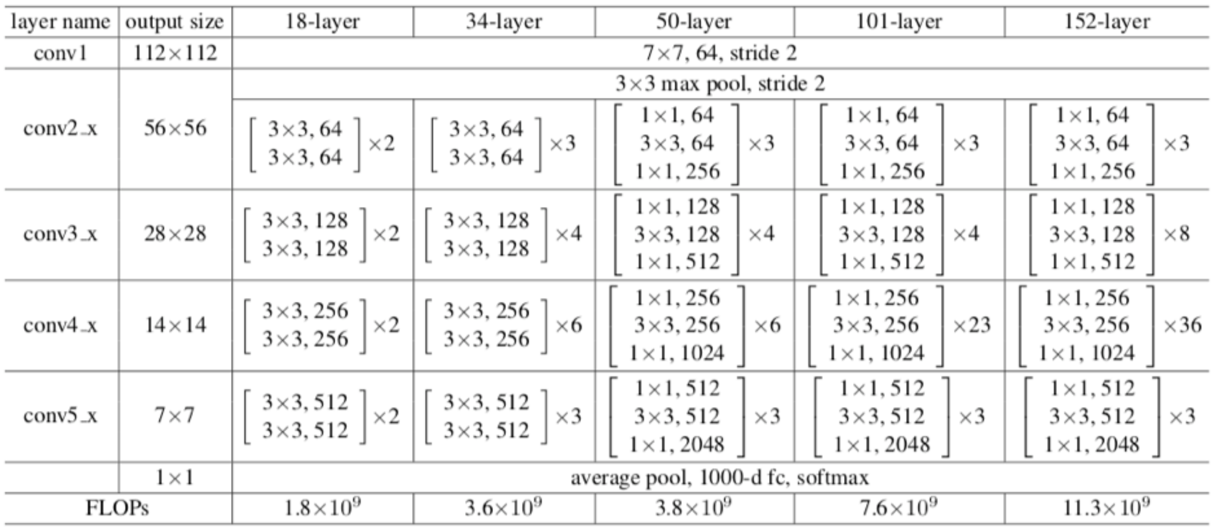


Figure 4 - VGG-16 architecture.

And finally the features extracted are fed to a fully connected multi layer perceptron network.
As for the dog breed classification two solutions are explored. The first solution consists of a model built and trained from scratch on the dog breed dataset following CNN design guidelines. That solution was built with inspiration in the VGG-16 architecture by reducing the number of convolutions, exploring different numbers of filters by layers and number of neurons in the fully connected network.
The other solution was based on the selection of a state of the art model pretrained on ImageNet and fine tuned on the dog breed dataset. Namely the models explored for this solution are from the ResNet family of models. The ResNet family of models is composed of the ResNet18, ResNet34, ResNet50, ResNet101 and ResNet152. The number in the end of the architecture name corresponds to the number of layers in the architecture. The table (Table 1) below shows the architecture of each of the models in the ResNet family.



layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Table 1 - ResNet family of models.

The particularity in this family is the use of residual blocks. Residual blocks (Figure 5) contain the skip connection that performs the identity operation. That skip connection allows the training of depper networks and therefore convolutional networks that are able to extract hierarchical more complex features of a wider range of dimensions and combine them more effectively.

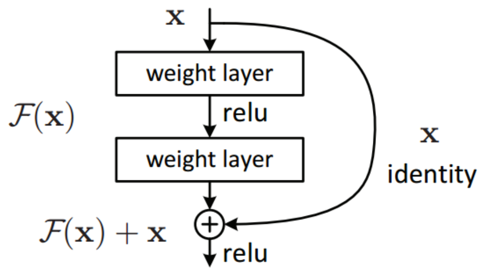


Figure 5 - Residual Block.

Benchmark Model

The benchmark model that will be used to compare the solution built using transfer learning was the solution built from scratch. It is expected that the results achieved with transfer learning require fewer epochs for training and achieve better metrics.
There are imposed requirements for the accuracy of the models. The model built from scratch must achieve at least 10% accuracy and the model built with transfer learning must achieve at least 60% accuracy.

III. Methodology

Data preprocessing

The preprocessing pipeline used for the dog detector (pretrained VGG-16) was composed by the following transformations:

1. Resize the input image to 256x256.
2. Cropping 224x224 from the center of the image.
3. Converting the image to tensor.
4. Normalizing the tensor.

For the dog breed classifier two other data preprocessing pipelines were defined. One for the training dataset and the other for both the validation and test.
The data preprocessing pipeline define for training includes some data augmentation and is described below:

1. Randomly flipping the image horizontally.
2. Randomly rotating the image 10 degrees.
3. Cropping 224x224 from a random position of the image.
4. Converting the image to tensor.
5. Normalizing the tensor.

And for the validation and testing (no data augmentation for inference):

1. Resize the input image to 256x256.
2. Cropping 224x224 from the center of the image.
3. Converting the image to tensor.
4. Normalizing the tensor.

As for the dog detector.

Refinement

The starting point to design the dog breed detector from scratch was to take inspiration in the previously used model VGG-16 (used for the dog detector). The VGG-16 architecture in Figure 4. However the number of convolutions between the pooling operations was reduced to 1 convolution layer. In the Figure 6 we see the modified VGG-16 and the parameters we are going to experiment, namely conv1, conv2, conv3, conv4, conv5 indicating the number of filters for each convolutional layer and fc1 and fc2 for the number of processors in the fully connected layers.

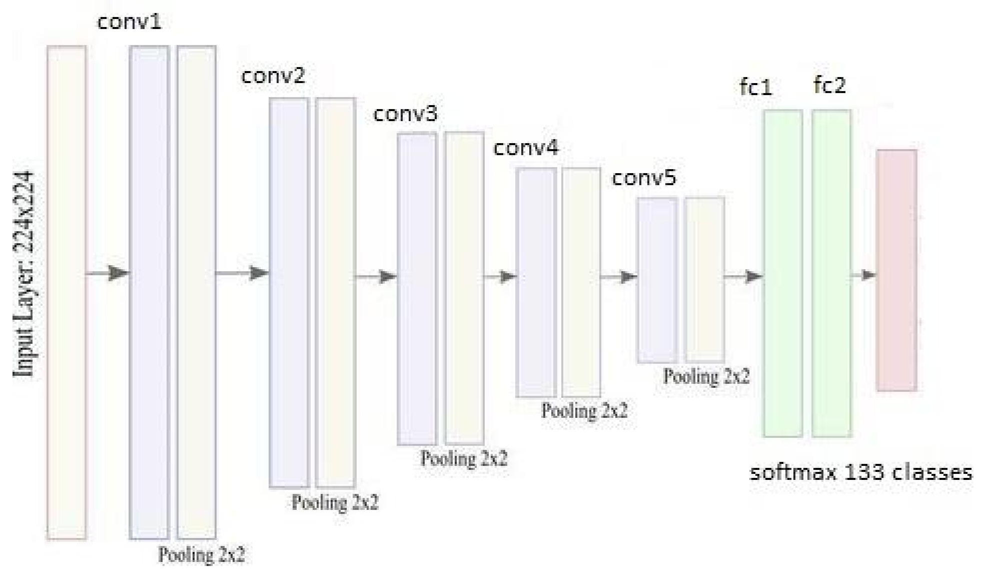


Figure 6 - Modified VGG-16 with parameters conv1, conv2, conv3, conv4, conv5, fc1 and fc2.

In table 2 we see the values explored for the parameters.

experiment	conv1	conv2	conv3	conv4	conv5	fc1	fc2
1	64	128	256	512	512	512	512
2	32	64	128	256	512	512	512
3	16	32	64	128	256	512	512
4	32	64	128	256	512	1024	1024
5	32	64	128	256	512	256	256

Table 2 - Model from scratch experiments.

The results obtained with the experiments are shown in table 3. The experiment 1 with the number of filters equal to the original VGG-16 was not possible because of memory limitations. So for experiment 2 with a reduced number of filters the model achieved an accuracy of 35% which is greater than the threshold 10% and F1-score of 29.9%. Reducing the number of filters even further led to a decrease in accuracy (30.1%) and F1-score (24.9%). So for the experiments changing the number of processors from the fully connected layers we will stick to the model from experiments 2 as baseline.

Increasing the number of processor in the fully connected layer from 512 to 1024 (experiment 4) led to a decrease in accuracy (28.9%) and F1-score (26.4%) and similarly in the experiment 5 the reduction from 512 to 256 of the number of processors in the fully connected layers also led to a relative decrease in accuracy (28%) and F1-score (26.3%). So we select the model from experiment 2 for our model from scratch (accuracy: 35% and F1-score: 29.9%).

experiment	accuracy	precision	recall	F1-score	comments
1	-	-	-	-	not enough memory
2	0.350	0.315	0.329	0.299	reduced number of filters from experiment 1
3	0.301	0.258	0.280	0.249	reduced number of filters from experiment 2
4	0.289	0.292	0.284	0.264	increased number of processors in fully connected layers from experiment 2
5	0.280	0.280	0.299	0.263	reduced number of processors in fully connected layers from experiment 2

Table 3 - Experiment results for model from scratch

In the next step of the project a model using transfer learning was used. And the ResNet family of models was chosen (Table 1). Table 4 shows the results of the training experiments.

model	accuracy	precision	recall	F1-score
ResNet18	0.733	0.752	0.718	0.707
ResNet34	0.722	0.767	0.713	0.710
ResNet50	-	-	-	-
ResNet101	-	-	-	-
ResNet152	-	-	-	-

Table 4 - Results for the model training with transfer learning using the ResNet family of models.

It is possible to notice that ResNet34 yielded a smaller value for accuracy but a greater value for F1-score, indicating that maybe ResNet34 deals better with class imbalance and yields a

better prediction considering this issue. The experiments for ResNet50, ResNet101 and ResNet 152 were not possible because of memory limitations.
Both ResNet18 and ResNet34 achieved accuracy above the 60% threshold. So we selected ResNet34 for its higher F1-score.

Implementation

The models were implemented with the PyTorch framework and trained with SGD, cross entropy loss and adam optimizator. As stated before, accuracy was the metric used. The model trained from scratch was trained for 50 epochs with learning rate 0.001 and the model trained with transfer learning was trained for 20 epochs with learning rate 0.001.
The following graph shows the evolution of the training and validation loss during the training epochs for the model trained from scratch.

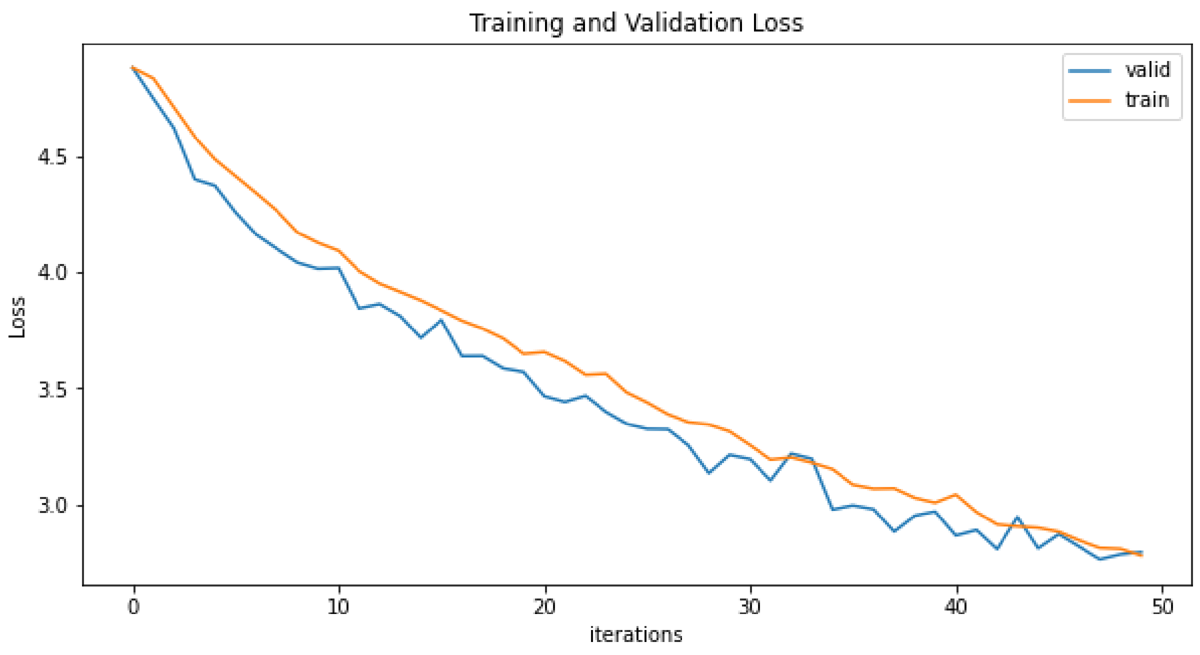


Figure 7 - Training and validation loss curve for the model from scratch.
And the following graph shows the evolution of the training and validation loss during the training epochs for the model trained with transfer learning.

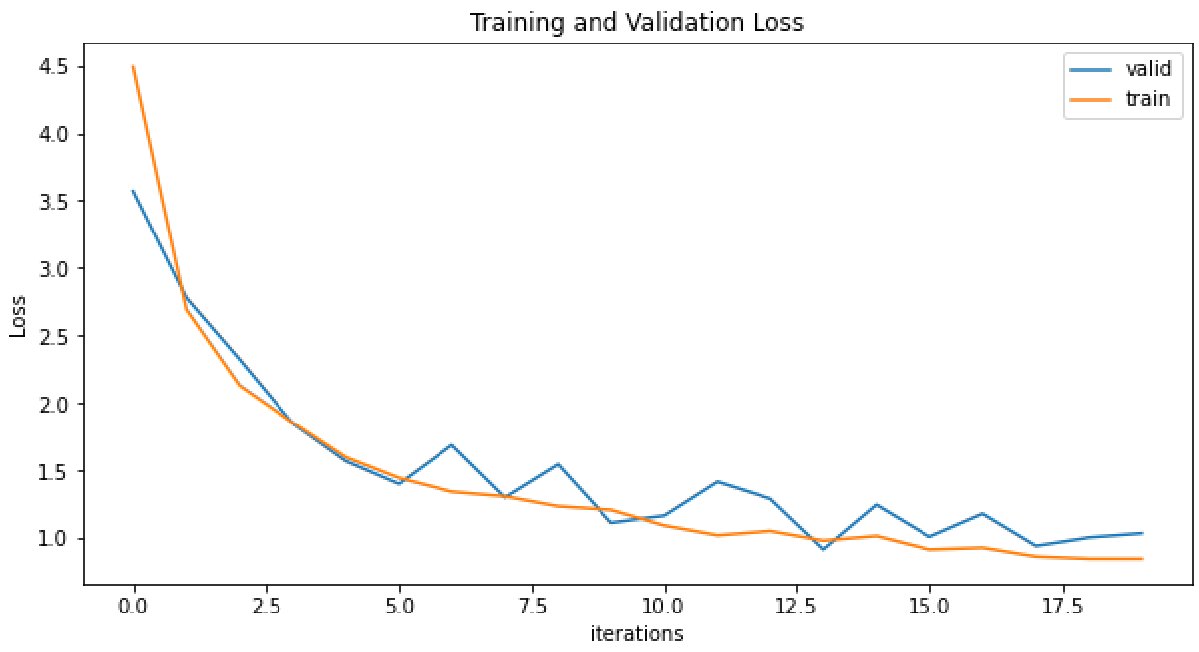


Figure 8 - Training and validation loss curve for the model using transfer learning.

The next diagram shows the whole algorithm fluxogram.

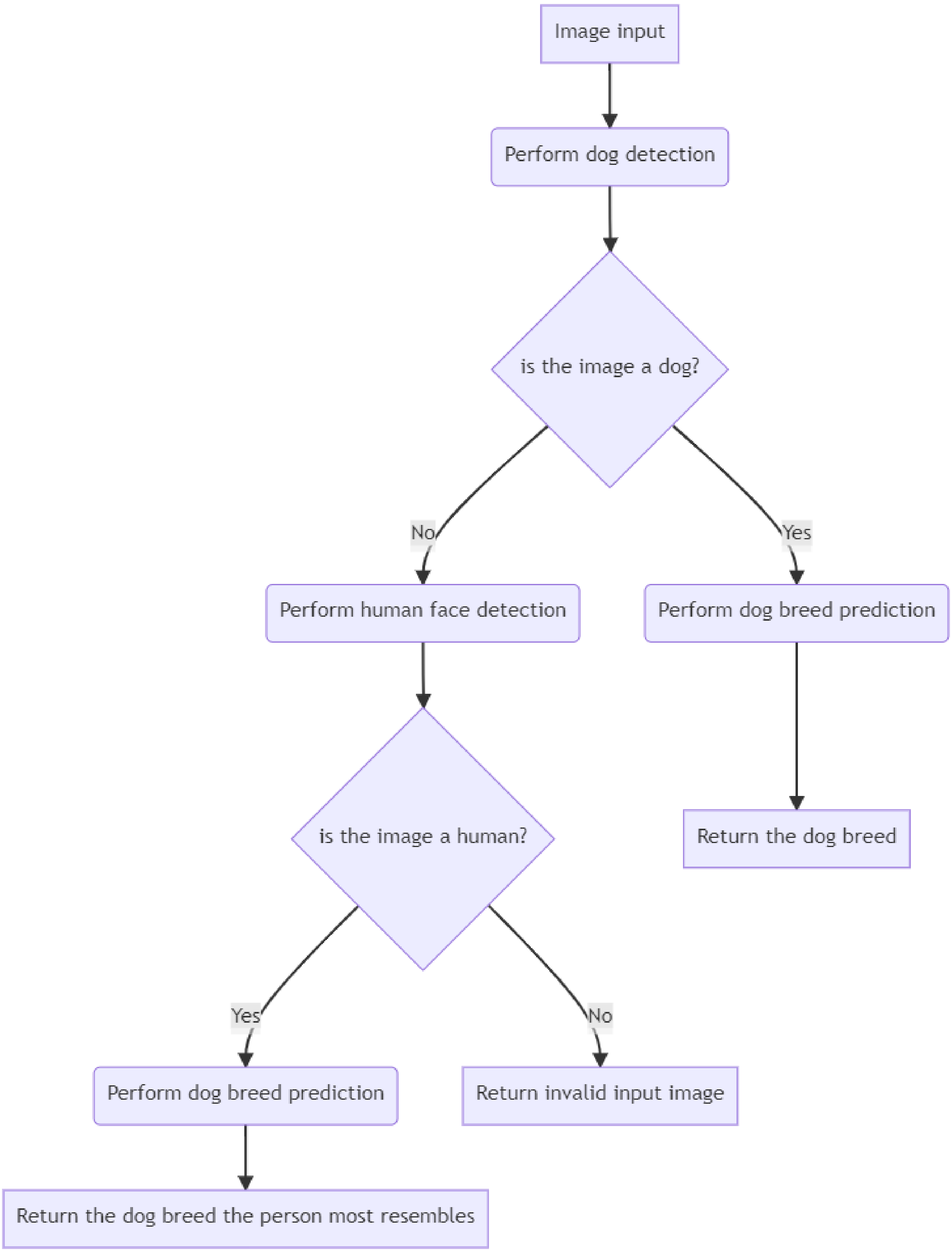


Image input
Perform dog detection
is the image a dog?
No
Yes
Perform human face detection
Perform dog breed prediction
is the image a human?
Return the dog breed
Yes
No
Perform dog breed prediction
Return invalid input image
Return the dog breed the person most resembles

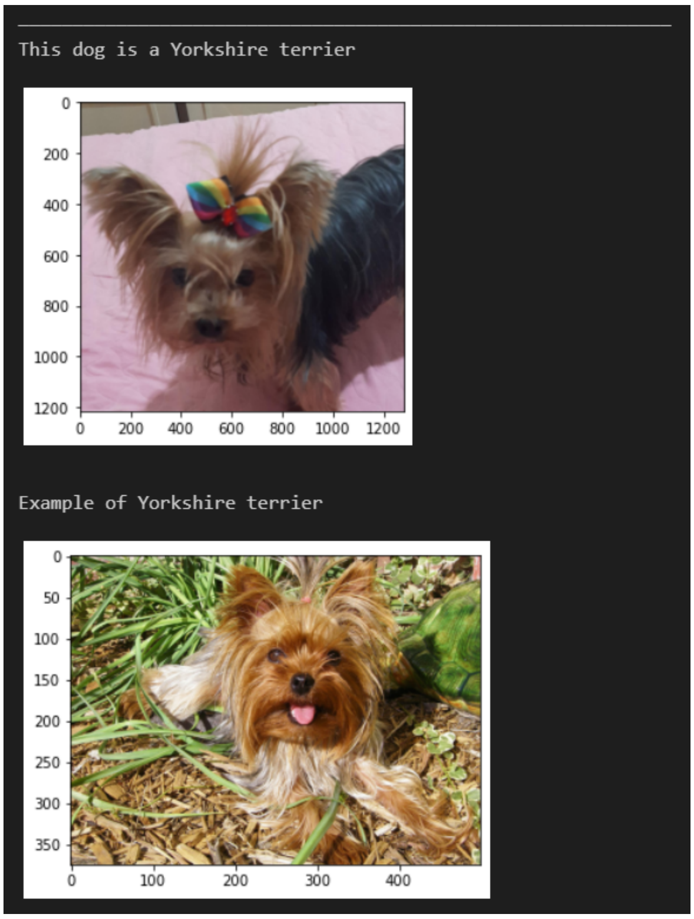
IV. Results

Justification

For the dog breed detector, both the model trained from scratch and the model trained with transfer learning were able to achieve an accuracy above the threshold required. Namely, the model trained from scratch achieved a 35% accuracy when 10% was required and the model trained with transfer learning (ResNet34) achieved a 72.2% accuracy when 60% was required.
The final algorithm used the model trained with transfer learning to perform the dog breed detection. For the dog detector teh VGG-19 was used and the HaarCascades face detector provided by OpenCV was used as a face detector.

Model evaluation and validation

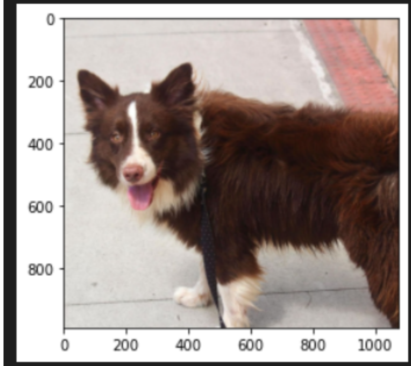
Running the algorithm for some dog images from outside the dataset we get the following results



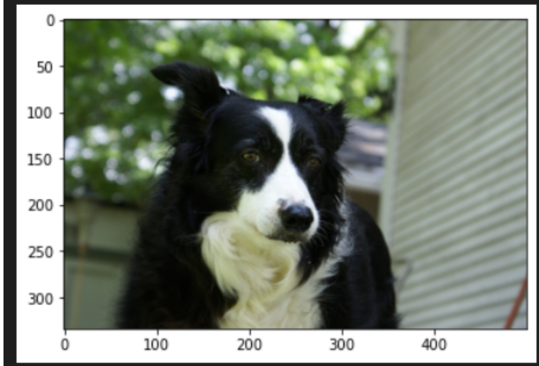
```
This dog is a Yorkshire terrier
```

```
Example of Yorkshire terrier
```

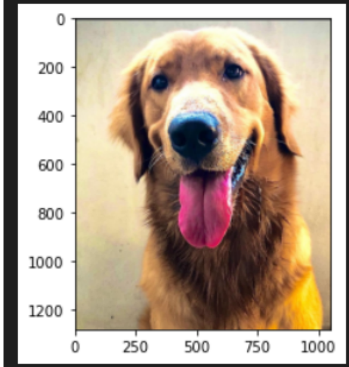
```
This dog is a Border collie
```



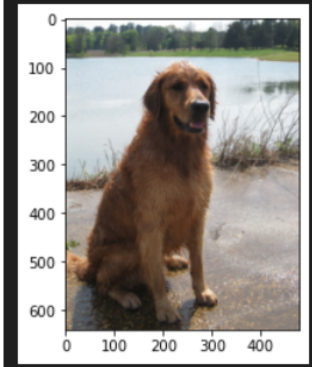
```
Example of Border collie
```



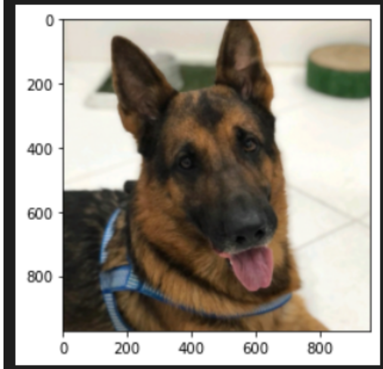
```
This dog is a Golden retriever
```



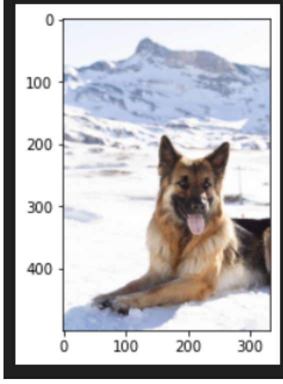
```
Example of Golden retriever
```



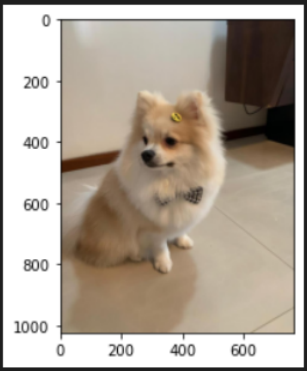
```
This dog is a German shepherd dog
```



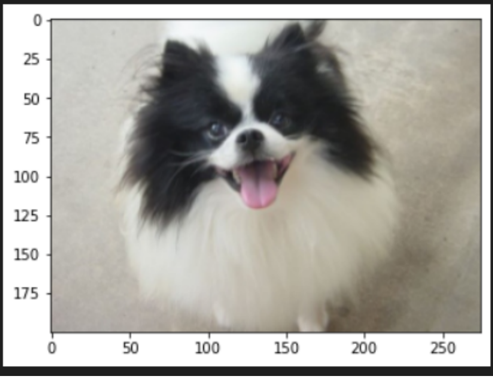
```
Example of German shepherd dog
```



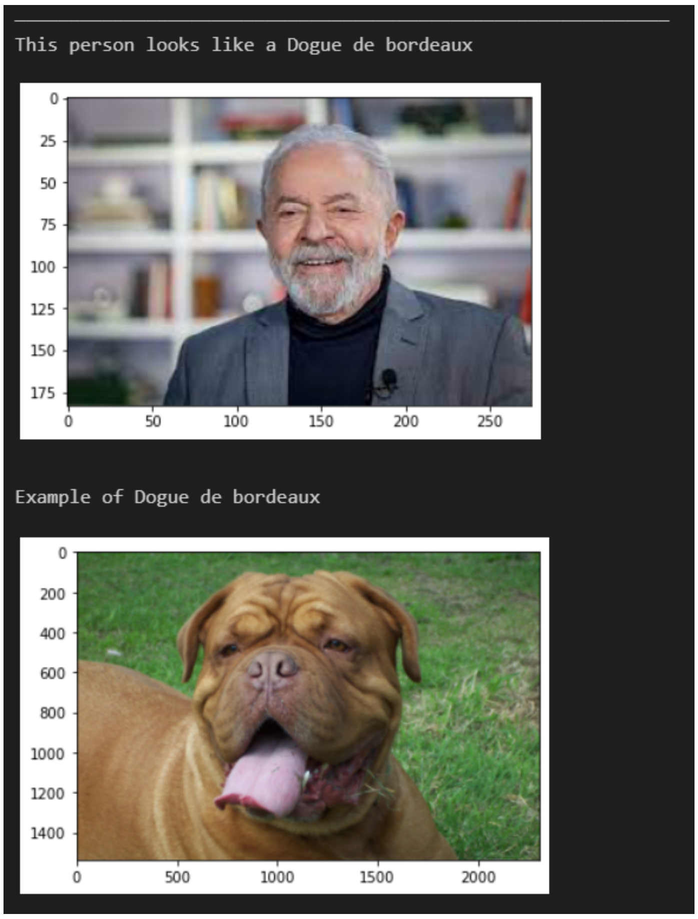
```
This dog is a Pomeranian
```



```
Example of Pomeranian
```



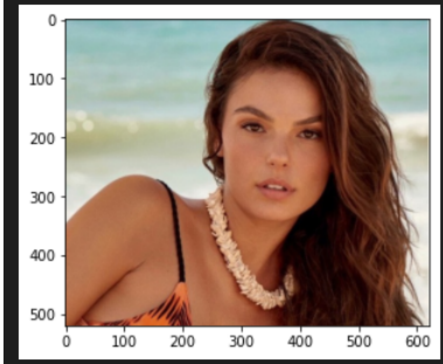
So it is possible to see that the model is succeeding in identifying the dog breed as at least in the examples provided it was able to guess correctly the dog breed. The examples below the input image are from the dog images dataset provided by Udacity.
When we apply the same algorithm to people we get the following example results.



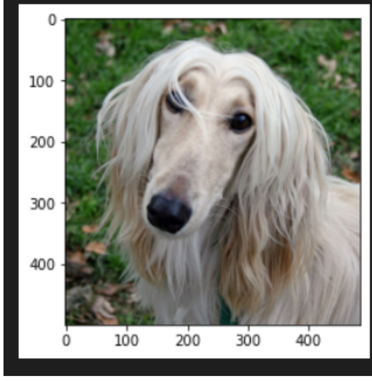
```
This person looks like a Dogue de bordeaux
```

```
Example of Dogue de bordeaux
```

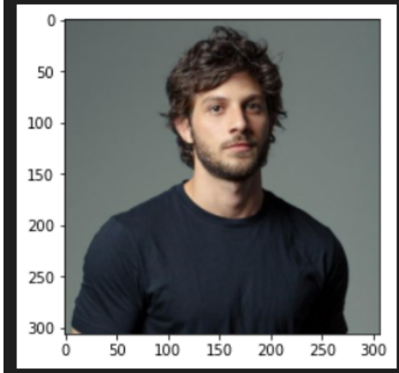
```
This person looks like a Afghan hound
```



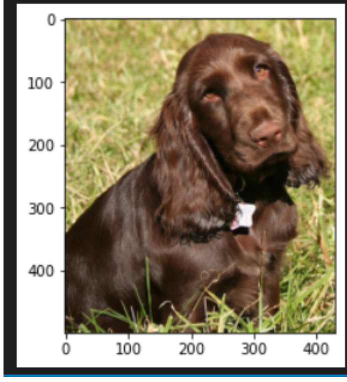
```
Example of Afghan hound
```



```
This person looks like a Field spaniel
```

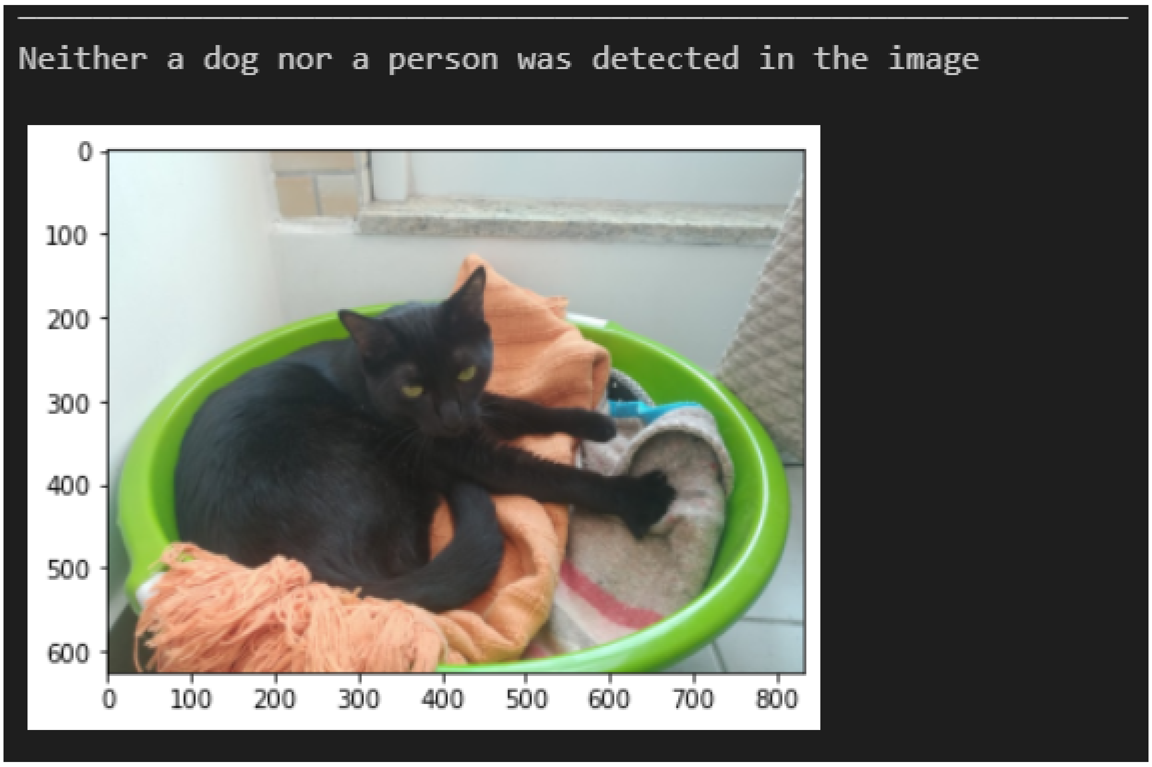


```
Example of Field spaniel
```



Despite being funny to experiment with, it is possible to notice that the output of the algorithm really resembles the human images.

And finally when we present the algorithm with a non-dog and non-human image it responds adequately.



```
Neither a dog nor a person was detected in the image
```