Capstone Project

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Data Scientist Nanodegree

December 9th, 2021

Introduction

This project uses Convolutional Neural Networks (CNNs)! Given an image of a dog, my 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. The goal is to classify images of dogs according to their breed. The algorithm that detects humans in an image is different from the CNN that infers dog breed.

CNNs are used for image classification and recognition because of its high accuracy. It is currently the best algorithm for the automated processing of images.

Data Exploration

The dataset contains following information:

1. There are 133 total dog categories.
2. There are 8351 total dog images.
3. From total dog images, 6680 are used as training dog images.
4. From total dog images, 835 are used as validation dog images.
5. From total dog images, 836 are used as test dog images.

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

The task of assigning breed to dogs from images is considered exceptionally challenging. For example, by looking at following images, even a human would have great difficulty in distinguishing between a Brittany and a Welsh Springer Spaniel.

Another example, labradors come in yellow, chocolate, and black. Algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.

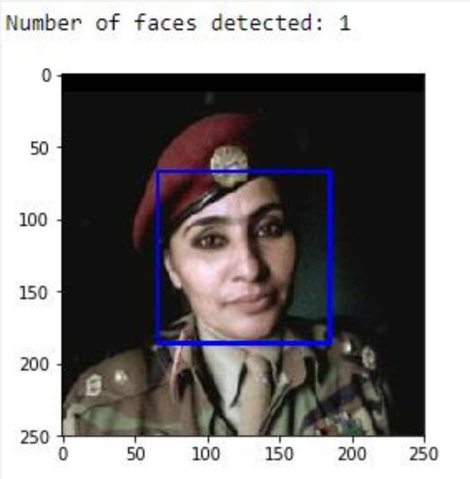
Pre-process the Data

Keras CNNs require a 4D array as input, with shape (nb_samples, rows, columns, channels), where nb_samples corresponds to the total number of images (or samples) and rows, columns, and channels correspond to the number of rows, columns, and channels for each image, respectively.

Our function takes a string-valued file path to a color image as input and returns a 4D tensor suitable for supplying to a Keras CNN. It first loads the image and resizes it to a square image that is 224 * 224 pixels. Next, the image is converted to an array, which is then resized to a 4D tensor. In this case, since we are working with color images, each image has three channels. Likewise, since we are processing a single image (or sample), the returned tensor will always have shape (1, 224, 224, 3). We rescale the images by dividing every pixel in every image by 255 before being fed to the model.

Functions

Human Face Detector: OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images. Returns True if a human face is detected in an image and False otherwise.



Dog Detector: pre-trained ResNet-50 model to detect dogs in images. Returns true if a dog is detected in an image (and false if not).

Implementation

Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. We will create a CNN that classifies dog breeds. We will be doing in two different ways:

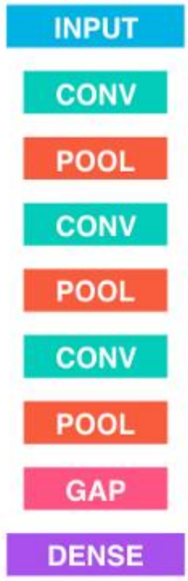
1. From Scratch.

2. Using Transfer Learning.

Practice is far ahead of the theory in deep learning. Experiment with many different architectures, and trust your intuition.

Create a CNN (from Scratch)

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 223, 223, 16)      208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 111, 111, 16)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 110, 110, 32)      2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 55, 55, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 54, 54, 64)        8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 27, 27, 64)        0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 133)               8645
=================================================================
Total params: 19,189.0
Trainable params: 19,189.0
Non-trainable params: 0.0
_________________________________________________________________
```



We can experiment with different Keras basic models. The main idea is to increase/decrease the number of channels throughout layers and at the same time increase/reduce the layer length and width.

After experimenting with some architectures, my model architecture contains:

- 3 convolutional layers with 50, 75, and 125 feature respectively maps with size 3×3 and with a rectifier function.
- After each convolutional layer, there is a pooling layer that takes the maximum value called MaxPooling2D, it is configured as a 2×2 pool size.
- After second and third pooling layer, there is a dropout layer for regularization. It is set to randomly exclude 25% of the neurons in the layer to avoid overfitting.

- After that there is the flattened layer that converts the 2D matrix data into a vector called Flatten. It allows the output to be fully processed by a standard fully connected layer.
- After above, there is the fully connected layer with 1024 neurons and rectifier activation function.
- Finally, the output layer has 133 neurons for the 133 dog categories and a softmax activation function to output probability-like predictions for each class.

```
Test accuracy: 9.4498%
```

Create a CNN (using Transfer Learning)

I have used pre-trained model ResNet-50 model. The bottleneck features are available in Keras and can be easily extracted from there. After extracting the bottleneck features, model architecture is extended as follows:

- GlobalAveragePooling2D as pooling layer takes input.
- After that, there is the fully connected layer with 1024 neurons and rectifier activation function.
- Finally, the output layer has 133 neurons and a softmax activation function.

```
Test accuracy: 78.4689%
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
global_average_pooling2d_2 ( (None, 2048)              0
_________________________________________________________________
dense_4 (Dense)              (None, 1024)              2098176
_________________________________________________________________
dropout_4 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_5 (Dense)              (None, 133)               136325
=================================================================
Total params: 2,234,501
Trainable params: 2,234,501
Non-trainable params: 0
_________________________________________________________________
```

Evaluation and Validation

Both the models have been compiled with loss=*categorical_crossentropy*, optimizer=*rmsprop*, metrics=*accuracy*.

Both the models have been trained with 20 epochs and 20 batch size.

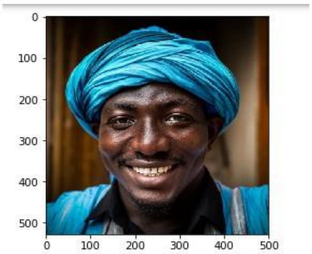
A validation set is used to evaluate the model and checks whether validation loss decreases. If this is the case, the model weights are saved with a check pointer (Keras function *ModelCheckpoint)* and will be loaded later for testing.

Since the pre-trained Resnet50 model and customized architecture (using Transfer Learning) has highest accuracy, it has been used to write a function that takes an image path as input and returns the dog breed (Affenpinscher, Afghan hound, etc.) that is predicted by model.

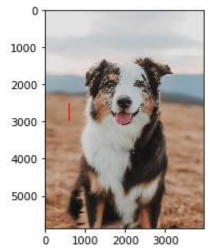
Model Testing

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.

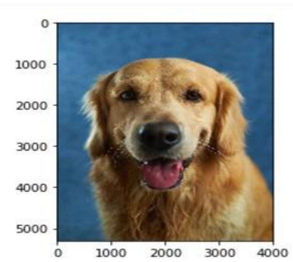


This photo looks like : Dachshund



This photo looks like : Australian_shepherd

This photo looks like : Poodle



This photo looks like : Golden_retriever

Conclusion

The model from scratch and then model from transfer learning shows that pre-trained model is very better for improving model accuracy but to reach acceptable and productive performance, it also needs to be fine-tuned.

To improve the model performance, following can be considered:

1. The dataset is quite small with imbalanced classes. Additional images can be collected to increase the training and validation data.
2. If model building from scratch is to be used then, more fully-connected layers (dense layers) can be used to see if accuracy would be improved.
3. Data augmentation can also be performed.

The findings here are observational, not the result of a formal study.