Capstone Project
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Machine Learning Engineer Nanodegree
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Dog Breed Classifier using CNN

Project Overview

The Dog breed classifier is a notable issue in ML. The issue is to distinguish the type of canine, if a dog picture is given as information, whenever provided a picture of a human, we need to recognize the looking like canine breed. The thought is to manufacture a pipeline that can procedure real world user provided pictures and distinguish a gauge of the canine's breed. This is a multi-class classification problem where we can use supervised machine learning to take care of this issue.

The steps that were followed to work through the project were the following:

Step 0: Import Datasets

Step 1: Detect Humans

Step 2: Detect Dogs

Step 3: Create a CNN to classify Dog Breeds (from scratch)

Step 4: Use a CNN to classify Dog Breeds (using Transfer Learning)

Step 5: Create a CNN to classify Dog Breeds (using Transfer Learning)

Step 6: Write an algorithm

Step 7: Test algorithm

Problem Statement

The objective of the task is to assemble an machine learning model that can be utilized inside a web application to process a genuine world, the user provided pictures. The calculation needs to perform two errands:

Dog face detactor: Given a picture of a dog, the calculation will distinguish a gauge of the canine's breed.

Human face detactor: Whenever provided a picture of a human, the code will distinguish the looking like the canine breed.

Metrics

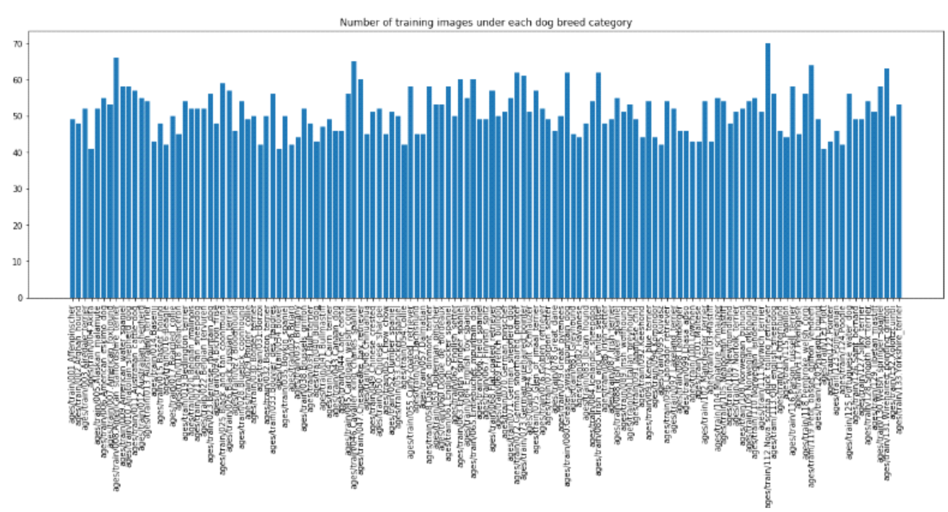
The information is part of the train, test and valid dataset. The model is trained using train dataset. We utilize the testing data to predict the performance of the model on unseen data. We will use accuracy as a measurement to assess our model on test data. Accuracy=Number of things effectively characterized/Every single ordered thing. However, it works well only if there are equal number of samples belonging to each class. In this project, there are total 133 dog breed as class labels. Based on the distribution of training/validation/testing selected, the classes were approximately evenly distributed, except a couple of classes. The number of images under each category seem to be balanced, so we can use accuaracy as our evaluation metric. Likewise, during model training, we compare the test data prediction with the validation dataset and calculate Multi-class log loss to calculate the best performing model. Log loss considers the uncertainity of prediction dependent on the amount it fluctuates from the actual label and this will help in evaluating the model.

Data Exploration

For this task, the input format must be of picture type, since we need to enter a picture and distinguish the type of the dog. The dataset has pictures of dogs and humans:

Dog pictures dataset: The canine picture dataset has 8351 complete pictures that are arranged into a train (6,680 Pictures), test (836 Pictures) and valid (835 Pictures) directories. Every one of these indexes (train, test, valid) has 133 folders corresponding to dog breeds. The pictures are of various sizes and various backgrounds, a few pictures are not full-sized.

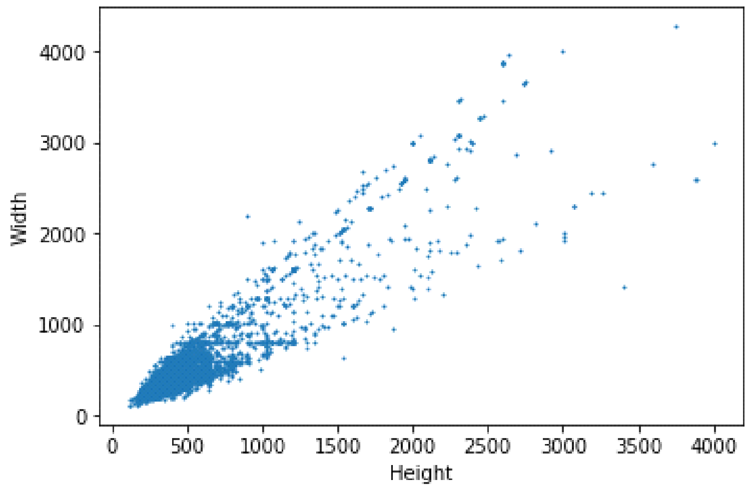
Human pictures dataset: The human dataset contains 13233 total human pictures which are arranged by names of human (5750 folders). All pictures are of size 250x250. Pictures have various backgrounds and various angles. The Humans dataset, additionally given by Udacity, contained 13233 pictures. A bar chart was drawn to figure out the balance of the classess.



As you can see above, the dataset is balanced with an average of 50 images per dog breed class. Since this is a classification problem, I chose to use accuracy as an evaluation metric. If the dataset was overly imbalanced, then precision would have been an appropriate choice.

Now, have a look at some of the dog images:

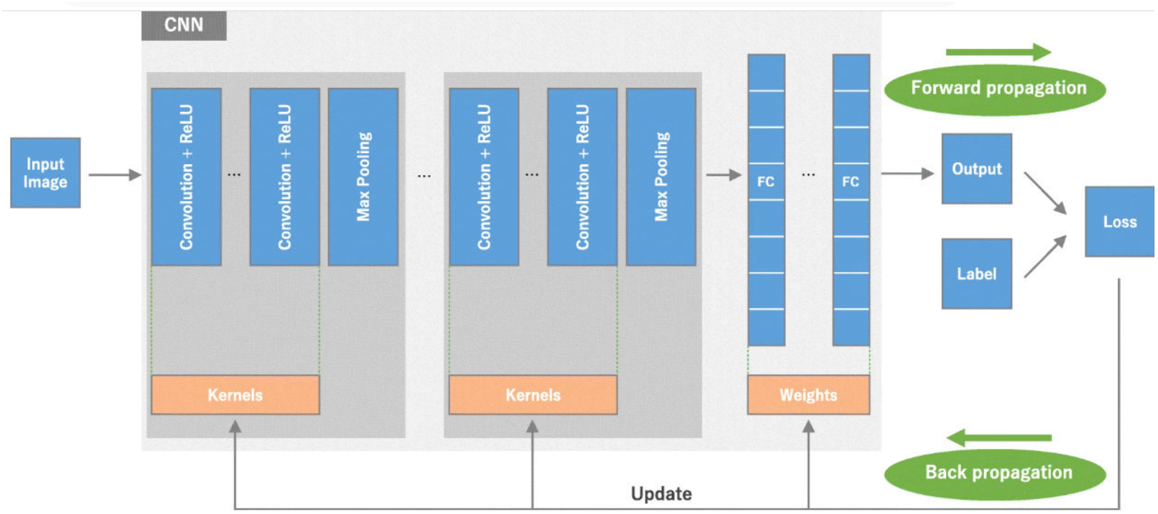
The individual images were of different sizes and orientations, but most of them were in the range of 300-500 pixels in height and width. As a part of pre-processing step these images were resized to 224x224 pixels to fit the network architecture. The distribution of height and width is shown below using scatter plot.



Algorithms and techniques

CNN

For playing out this multiclass order, we utilize the Convolutional Neural Network(CNN) to tackle the issue. CNN is a sort of deep learning model for processing information that has a grid pattern, for example, pictures, which is motivated by the association of the animal visual cortex and intended to naturally and adaptively learn spatial hierarchies of features, from low to high-level patterns. CNN is a numerical development that is normally made out of three kinds of layers (or building blocks): convolution, pooling, and fullly connected layers. The first two, convolution and pooling layers, perform feature extraction, whereas the third, a fully connected layer, map the extracted features into the final output, such as classification. A convolution layer plays a key role in CNN, which is composed of a stack of mathematical operations, such as convolution, a specialized type of linear operation. In digital images, pixel values are stored in a two-dimensional (2D) grid, i.e., an array of numbers , and a small grid of parameters called the kernel, and optimizable feature extractor is applied at each image position, which makes CNN's highly efficient for image processing, since a feature may occur anywhere in the image. As one layer feeds its output into the next layer, extracted features can hierarchically and progressively become more complex. The process of optimizing parameters such as kernels is called training, which is performed so as to minimize the difference between outputs and ground truth labels through an optimization algorithm called backpropagation and gradient descent, among others.



An overview of a convolutional neural network (CNN) architecture and the training process. A CNN is composed of a stacking of several building blocks: convolution layers, pooling layers (e.g., max pooling), and fully connected (FC) layers. A model's performance under particular kernels and weights is calculated with a loss function through forward propagation on a training dataset, and learnable parameters, i.e., kernels and weights, are updated according to the loss value through backpropagation with gradient descent optimization algorithm. ReLU, rectified linear unit

Convolution:

The main building block of CNN is the convolutional layer. Convolution is a mathematical operation to merge two sets of information.

Non-Linearity:

We again pass the result of the convolution operation through relu activation function. Every type type of convolution involves a relu operation, without that the network won't achieve its true potential.

Stride and padding:

Stride specifies how much we move the convolution filter at each step. Padding is commonly used in CNN to preserve the size of the feature maps, otherwise they would shrink at each layer, which is not desirable.

Pooling:

After a convolution operation we usually perform pooling to reduce the dimensionality. This enables us to reduce the number of parameters, which both shortens the training time and combats overfitting. Pooling layers downsample each feature map independently, reducing the height and width, keeping the depth intact.The most common type of pooling is max pooling which just takes the max value in the pooling window. Contrary to the convolution operation, pooling has no parameters. It slides a window over its input, and simply takes the max value in the window. Similar to a convolution, we specify the window size and stride.

Hyperparameters:

Let's now only consider a convolution layer ignoring pooling, and go over the hyperparameter choices we need to make. We have 4 important hyperparameters to decide on:

Filter size: we typically use 3x3 filters, but 5x5 or 7x7 are also used depending on the application. At first sight it might look strange but they have interesting applications. Remember that these filters are 3D and have a depth dimension as well, but since the depth of a filter at a given layer is equal to the depth of its input, we omit that.

Filter count: this is the most variable parameter, it's a power of two anywhere between 32 and 1024. Using more filters results in a more powerful model, but we risk overfitting due to increased parameter count. Usually we start with a small number of filters at the initial layers, and progressively increase the count as we go deeper into the network.

Stride: we keep it at the default value 1.

Padding: we usually use padding.

Fully connected :

After the convolution + pooling layers we add a couple of fully connected layers to wrap up the CNN architecture.Remember that the output of both convolution and pooling layers are 3D volumes, but a fully connected layer expects a 1D vector of numbers. So we flatten the output of the final pooling layer to a vector and that becomes the input to the fully connected layer. Flattening is simply arranging the 3D volume of numbers into a 1D vector, nothing fancy happens here.

Training:

CNN is trained with backpropagation with gradient descent. Due to the convolution operation it's more mathematically involved.

Conv2d:

This method creates a convolutional layer. The first parameter is the filter count, and the second one is the filter size. For example in the first convolution layer we create 32 filters of size 3x3. We use relu non-linearity as activation. We also enable padding.

MaxPooling2D:

It creates a maxpooling layer, the only argument is the window size 2x2 window is the most common. By default stride length is equal to the window size.

Flatten:

After the convolution + pooling layers we flatten their output to feed into the fully connected layers.

Dropout:

Dropout is by far the most popular regularization technique for deep neural networks. Even the state-of-the-art models which have 95% accuracy get a 2% accuracy boost just by adding dropout, which is a fairly substantial gain at that level.

Dropout is used to prevent overfitting and the idea is very simple. During training time, at each iteration, a neuron is temporarily "dropped" or disabled with probability p. This means all the inputs and outputs to this neuron will be disabled at the current iteration. The dropped-out neurons are resampled with probability p at every training step, so a dropped out neuron at one step can be active at the next one. The hyperparameter p is called the dropout-rate and it's typically a number around 0.5, corresponding to 50% of the neurons being dropped out.

Dropout can be applied to input or hidden layer nodes but not the output nodes. The edges in and out of the dropped out nodes are disabled. Remember that the nodes which were dropped out change at each training step. Also we don't apply dropout during test time after the network is trained, we do so only in training.

Data augmentation:

Overfitting happens because of having too few examples to train on, resulting in a model that has poor generalization performance. If we had infinite training data, we wouldn't overfit because we would see every possible instance.

The common case in most machine learning applications, especially in image classification tasks is that obtaining new training data is not easy. Therefore we need to make do with the training set at hand. Data augmentation is a way to generate more training data from our current set. It enriches or "augments" the training data by generating new examples via random transformation of existing ones. This way we artificially boost the size of the training set, reducing overfitting. So data augmentation can also be considered as a regularization technique.

My implementation of CNN

First a CNN was created from scratch that involved some steps that were taken to get to the final CNN architecture are as follows: The model has 3 convolutional layers. All convolutional layers have a kernel size of 3 and stride 1. The principal spread layer (conv1) has in_channels =3 and the last Conv layer (conv3) produces an output size of 128. The ReLU actuation work is utilized here. The pooling layer of (2,2) is utilized which will lessen the information size by 2. We have two completely associated layers that at long last produce 133-dimensional yield. A dropout of 0.25 is added to abstain from overfitting.

Then again a CNN was created, but this time using transfer learning to classify the dog breed. I have chosen to utilize the resnet101 engineering which is pre-prepared on the Imagenet dataset, The design is 101 layers deep, inside only 5 epochs, the model got 74% accuracy. In the event that we train for more epochs, the accuracy can be altogether improved.

Steps:

1) Import pre-trained resnet101 model

2) Change the out_features of a completely associated layer to 133 to solve the classification problem

3) CrossEntropy loss function is picked as the loss function.

Prepared for 5 epochs and got 74% .

Benchmark

To detect dogs in images the VGG-16 model, along with weights that have been trained on ImageNet, a very large, very popular dataset used for image classification and other vision tasks. ImageNet contains over 10 million URLs, each linking to an image containing an object from one of 1000 categories. Given an image, this pre-trained VGG-16 model returns a prediction (derived from the 1000 possible categories in ImageNet) for the object that is contained in the image. The CNN model made from scratch must have an accuracy of at least 10%. This can confirm that the model is working because a random guess will provide an answer about 1 in 133 time, which corresponds to an accuracy of under 1%. For CNN using transfer learning, I have chosen to utilize the resnet101 model which is pre-trained on the Imagenet dataset.

Data Preprocessing

All the images are resized to 224*224, then normalization is applied to all pictures (train, legitimate and test datasets). For the training data, image augmentation is done to diminish overfitting. The train data images are arbitrarily rotated and random horizontal flip is applied. At last, all the images are converted into tensor before passing into the model. A large portion of the Preprocessing models like VGG16 takes the size (224,224) as information, so I have utilized this size.

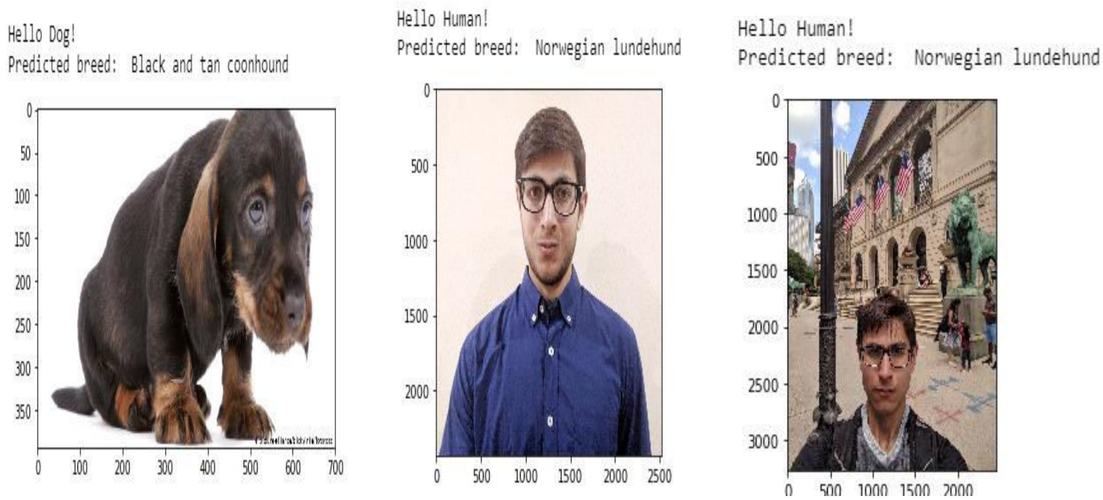
For train information, I have done picture enlargement to abstain from overfitting the model. Changes utilized: Arbitrary resize yield to 224, irregular flipping and arbitrary revolution.For approval and test information, I have done just picture resizing. I have applied standardization to each of the three datasets.

Implementation

I have assembled a CNN model from scatch to take care of the issue. The model has 3 convolutional layers. All convolutional layers have a kernel size of 3 and stride 1. The first conv layer (conv1) takes the 224*224 input image and the last conv layer (conv3) produces an output size of 128. The ReLU activation function is utilized here. The pooling layer of (2,2) is utilized which will diminish the input size by 2. We have two completely connected layers that at long last produce 133-dimensional output. A dropout of 0.25 is added to abstain from overfitting.

Refinement

The CNN made from scratch has an accuracy of 11%, though, it meets the benchmarking, the model can be essentially improved by using transfer learning. To create CNN with transfer learning, I have chosen the Resnet101 architecture which is pre-trained on the ImageNet dataset, the architecture is 101 layers profound. The last convolutional model of Resnet101 is fed as input to our model. We just need to add a completely connected layer to deliver a 133-dimensional output (one for each dog class). The model performed incredibly well when compared with CNN from scatch. With only 5 epochs, the model got 74% precision.



Sample outputs predicted using the model

Model Evaluation and Validation

Human Face detector: The human face detector function was made utilizing OpenCV's usage of Haar feature based cascade classifiers. 98% of human faces were detected in the initial 100 pictures of the human face dataset and 17% of human appearances recognized in the initial 100 pictures of the dog dataset.

Dog Face detactor: The dog detector function was made utilizing a pre-trained VGG16 model along with weights that have been trained on ImageNet dataset. 100% of dog were detected in the initial 100 pictures of the dog dataset and 1% of dog faces detected in the initial 100 pictures of the human dataset.

CNN using transfer learning: I have chosen to utilize the resnet101 model which is pre-trained on the Imagenet dataset. The CNN model made using transfer learning with ResNet101 architecture was trained for 5 epochs, and the final model produced an accuracy of 74% on test data. The model correctly predicted breeds for 621 pictures out of 836 complete pictures.

Accuracy on test data: 74% (621/836)

Justification

I think the model performance is superior to anticipated. The model made utilizing transfer learning has an accuracy of 74% compared with the CNN model made from scratch which had just 11% accuracy.

Improvement

The model can be improved by adding more training and test data, presently, the model is made created using just 133 breeds of the dog. Additionally, by performing more picture expansion, we can abstain from overfitting and improve accuracy. I have attempted uniquely with ResNet 101 architecture for feature extraction, Possibly the model can be improved utilizing the distinctive architcture.

References

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8. Sample testing images:
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