Machine Learning Engineer Nanodegree
Capstone Project Proposal

Pavlos Sakoglou
November 20, 2017

Image Classification using Deep Learning with Support Vector Machines

1 Definition

1.1 Project Overview

Convolutional Neural Networks (CNNs) are a subset of Supervised Learning class of algorithms that are very similar to regular Neural Networks and aim to find an optimal predictive model that assigns the input variable to the correct label.

In contrast to the Multilayer Perceptron Architecture (MLP) that uses fully connected network layers, a CNN does not need to provide information of the entire feature space to all hidden layer nodes, but instead it breaks the input matrix into regions and then connects each region to a single hidden node. With this regional breakdown and assignment of small local groups of features to different hidden nodes, CNNs are performing very well for image recognition tasks.

On the other hand, a Support Vector Machine classifier tries to separate the data into K classes by maximizing the distance between the differently labeled data. If the data are not linearly separable, then by using an appropriate kernel function we can map the data into a higher dimension where they happen to be linearly separable and we find the linear boundary there. Finally, we transform that linear boundary back to the original lower dimensions and we get a non-linear separator.

In this project we are going to replace the standard sigmoid activation function of the penultimate layer of the network with a linear Support Vector Machine classifier and investigate performance differences. We are going to implement the standard CNN architecture as benchmark model and see how it compares with a Deep Learning SVC so that we choose the best model to implement the final solution.

1.2 Problem Statement

With the immense usage of smart phones in developed countries, people are sharing information via various types of messenger applications in unimaginable volumes. A natural and unfortunate consequence of this is message abuse in written and visual form with written texts and images. In this project we aim to partially tackle this societal issue using deep learning with SVC.

The idea is to develop and train a smart algorithm that takes an image from a message as input and detects if the image contains nudity or not. That is, the algorithm will classify the picture as "**Nude**" or "**Safe**". The receiver of the picture will have the chance to either block or open the message; having seen the class of the newly arrived image and a warning message, thus preventing harassment and unwanted information sharing.

We view this as a supervised classification problem where we train the model with a large dataset of nude and non-nude pictures of people by providing the correct labels, and then test the model with a newly received image and learn its class.

1.3 Metrics

In order to evaluate the model's performance we will rely on three main metrics, namely Precision, F_b-Score, and Recall. Notice that this application serves as an inappropriateness filter and thus we prefer any potential errors to falsely predict an image as "**Nude**", than to falsely predict it as "**Safe**".

In other words, we want to penalize more for False Negatives, which will be described by a high Recall value. To clearly demonstrate how these evaluation metrics are eligible to determine our model's efficiency, let's take a closer look at them:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positive} + \text{False Negatives}}$$

$$F_b\text{-Score} = (1+\beta^2)\frac{\text{Precision} * \text{Recall}}{\beta^2 * \text{Precision} + \text{Recall}}$$

All metrics concern both the benchmark model and its solution, and will be used in the testing process. We will compare results between the different parameter choices and architectures, and we will pick those which maximize the Recall metric. Notice that since we value Recall more than precision here, for the F_b-Score we will choose a $\beta > 1$.

2 Analysis

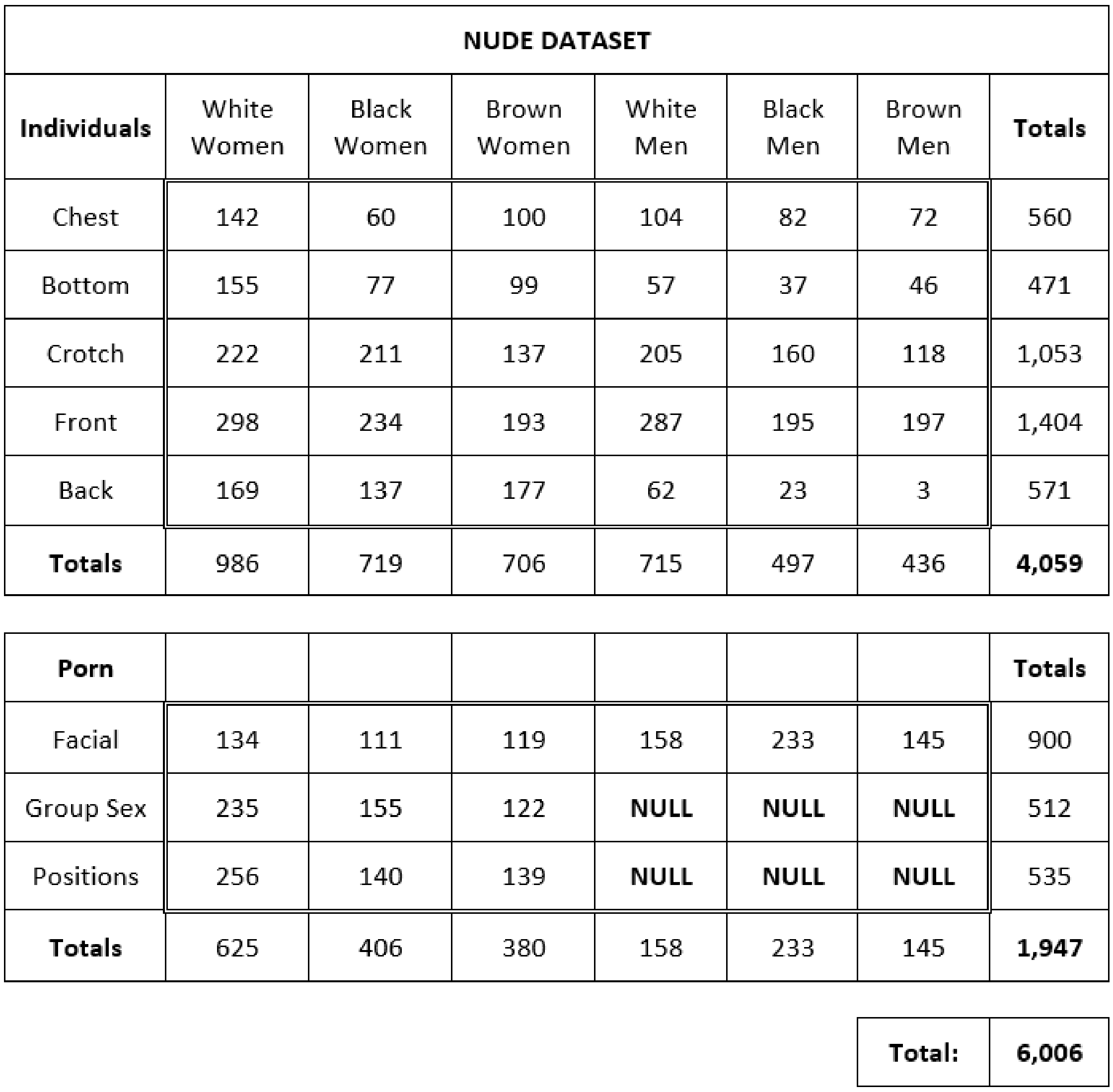
2.1 Data Exploration

In order to create a nude detector application we need to make sure that we collect data for both "**Nude**" and "**Safe**" classes that are representative of the general population's perception of nudity and non-nudity. In addition, we want to make sure that all races are represented proportionally in our dataset, thus our data must include people with different skin color and gender, namely white, black, and brown males and females. Notice that the skin color is supposed to generalize over races with similar skin color. For example, we assume that a person from India and a person from Middle East both belong in the same skin color category as a person from Cuba or Puerto Rico. The dataset for each class that we assemble will consist of about six thousand pictures overall.

In regards to the "**Nude**" dataset, we add one extra dimension: **Porn**, so that our model can look into non-standard nude picture patterns. The **Porn** dimension is also discretized in subcategories to make sure that is, too, consistent with respect with our data assumptions. It generalizes of three dominant porn categories: facial, group sex, and positions.

As a result, the feature space of "**Nude**" dataset consists of 6,006 pictures and the following features for both males and females. We also made sure that non of these features will dominate the other ones, thus as per each features' *importance*, we assembled proportionally many data for each one:

1. **Chest**: close up pictures of male and female chest of all colors. This features represents 9.32% of the dataset.
2. **Bottom**: close up pictures of male and female bottom of all colors. This features represents 7.84% of the dataset.
3. **Crotch**: close up pictures of male and female crotch area of all colors. This features represents 17.53% of the dataset.
4. **Front**: full on frontal pictures of male and female body of all colors. This features represents 23.37% of the dataset.
5. **Back**: full on back pictures of male and female body of all colors. This features represents 9.5% of the dataset.
6. **Porn**: several porn pictures between sets of males and females. This features represents 32.41% of the dataset.



NUDE DATASET							
Individuals	White Women	Black Women	Brown Women	White Men	Black Men	Brown Men	**Totals**
Chest	142	60	100	104	82	72	560
Bottom	155	77	99	57	37	46	471
Crotch	222	211	137	205	160	118	1,053
Front	298	234	193	287	195	197	1,404
Back	169	137	177	62	23	3	571
Totals	986	719	706	715	497	436	**4,059**

Porn							**Totals**
Facial	134	111	119	158	233	145	900
Group Sex	235	155	122	**NULL**	**NULL**	**NULL**	512
Positions	256	140	139	**NULL**	**NULL**	**NULL**	535
Totals	625	406	380	158	233	145	**1,947**

Total:	**6,006**

We did similar work for the "**Safe**" dataset. We want to make sure that the corresponding examples are strongly non-nude pictures for the model to generalize over them easily.

Nevertheless, in order to make our model sophisticated enough so it can discriminate against fully nude and partially nude, we would be required to employ bottleneck features for each dimension of the feature space. In fact, we would need to augment the data (rotate, shear, zoom etc.) in order to have enough for each feature to successfully train bottleneck models. Such task will only optimize the process, but the scope of this paper is mostly to investigate performance between the benchmark and the chosen model, and decide which classifies best. We can discuss additional performance boost techniques in another project.

As a result, the "**Safe**" dataset will consist of the following features for all skin colors and genders as above, proportionally assembled as per their importance, and we will assume that topless and underwear/swim suit pictures of both genders will be classified as nude.

1. **Lower Half**: close up amateur and professional pictures of lower body of males and females of all colors. It includes men and women in pants, and women in skirts and dresses. This features represents 12.41% of the dataset.
2. **Front**: frontal pictures of males and females of all colors. It includes full body and upper body professional and amateur pictures. This features represents 25.59% of the dataset.
3. **Intimate**: pictures of multiple people and families in intimate moments. It includes family dinners, couples of all colors and genders kissing, holding hands and being close to each other. This features represents 14.62% of the dataset.
4. **Faces**: face and portrait pictures of males and females of all colors and ages. This features represents 21.76% of the dataset.
5. **General**: pictures of people in different backgrounds, landscapes, animals, and objects in bright colors that do not strictly resemble the color of the skin. This features represents 25.55% of the dataset.

SAFE DATASET							
Individuals	White Women	Black Women	Brown Women	White Men	Black Men	Brown Men	**Totals**
Lower Half	139	119	152	105	129	132	776
Front	358	233	264	316	200	229	1600
Intimate	357	261	299	**NULL**	**NULL**	**NULL**	917
Faces	339	121	369	260	134	138	1361
Totals	1193	734	1084	681	463	499	**4,654**

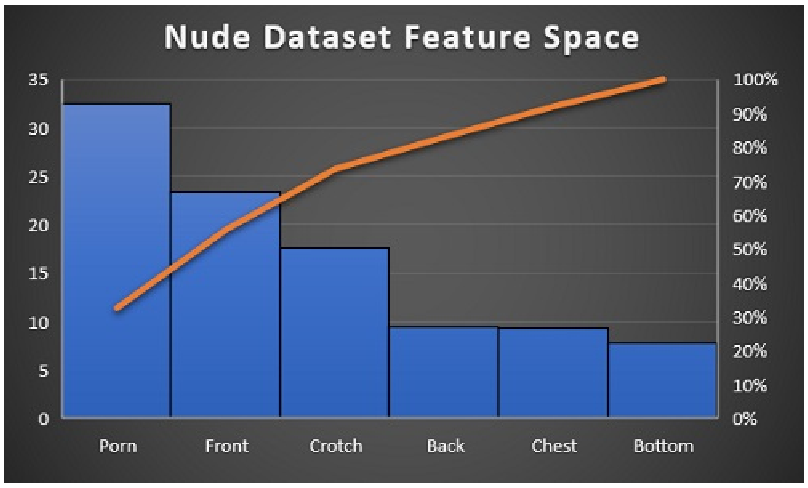
General							
People	725	**NULL**	**NULL**	**NULL**	**NULL**	**NULL**	725
Animals	201	**NULL**	**NULL**	**NULL**	**NULL**	**NULL**	201
Landscapes	98	**NULL**	**NULL**	**NULL**	**NULL**	**NULL**	98
Objects	574	**NULL**	**NULL**	**NULL**	**NULL**	**NULL**	574
Totals	1,598						**1,598**

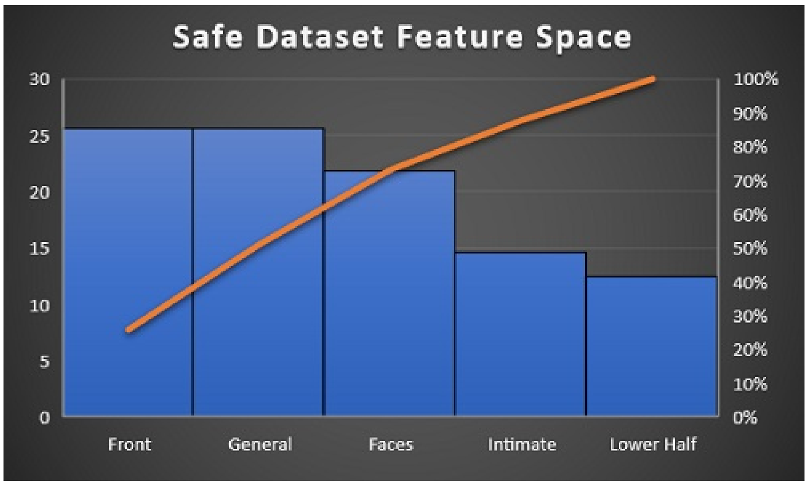
Total:		**6,252**

2.2 Exploratory Visualization

For better data comprehension, we provide the following plots that explain the feature proportionality among both datasets. Keep in mind that for the **Nude** dataset, the Porn feature implicitly includes almost all of the other features and by boosting it with more pictures proportionally is a suitable way to generalize the content of the entire class.

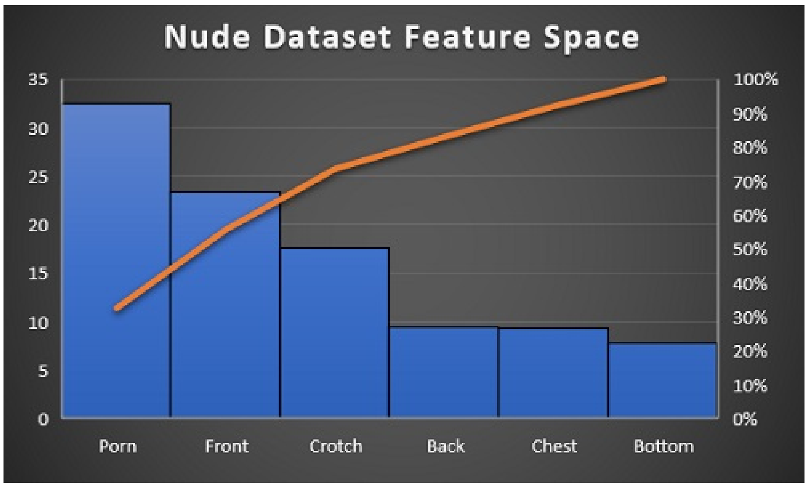
Fig. 2.2.1 The plots below show the data distributions for each dataset

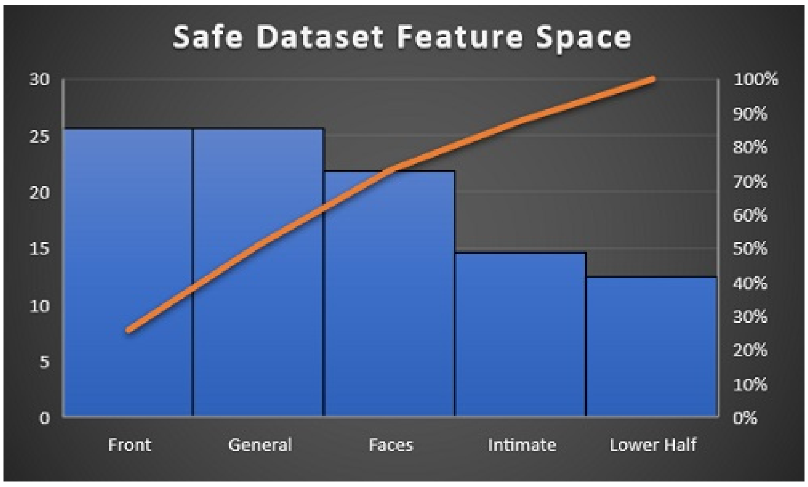




In addition, we computed the correlation of the data of each class for the training, validation, and test sets. We need to make sure that the intra-class data have high correlation, and that the inter-class data have low correlation. That way we ensure that the model will make a good job distinguishing the differences between the two underlying classes. If the inter-class data were hightly correlated, then the model would have no way knowning how to separate data of different classes, and we would end up with non-intuitive, non-meaningful classification.

Fig. 2.2.2 The plots below show the data correlations for each dataset





2.3 Algorithms and Techniques

The model we are using is a Convolutional Neural Network with a Support Vector Machine classifier. We implement this model by constructing a regular CNN using a linear activation function at the penultimate layer and by compiling the model using a hinge loss function which is also used in the SVM model. In addition we add a kernel and a bias regulizer at the final layer.

In particular, we are going to use the Sequential model from Keras framework, on which we can choose to add combinations of the following layers to define our network architecture:

1. Convolutional layers to compute the output of neurons that are connected to local regions in the input

2. Pooling layers to perform a downsampling operation along the spatial dimensions
3. Fully connected layers to compute the output of fully connected input neurons
4. Activation functions to map the dot product of the linear combination of neurons to a probability
5. Flatten operations to decrease dimensionality of layer inputs
6. Dropout operation to omit a portion of the nodes in each epoch

We will then compile the model using the aforementioned hinge loss function, which mathematically is defined as:

$$V(f(\hat{x}), y) = \text{max}(0, 1 - yf(\hat{x}))$$

and maps the input in [0, 1] which represents a probability. Correctly classified points lying outside the margin boundaries of the support vectors are not penalized, whereas points within the margin boundaries or on the wrong side of the hyperplane are penalized in a linear fashion compared to their distance from the correct boundary.

After compiling the model, we need to will pick values for the following training parameters in order to sufficiently train the model until there is no more room for performance improvement:

1. Number of epochs that represent full network forward and back propagation and parameter updates
2. Batch size that describes how many training sample we need to consider in each epoch

To keep track of the best parameter set and in order to use the optimal set of parameters later without having to retrain the network, we are going to use a check point file to store the optimal yet set of parameters. Thus, we will add another parameter when we fit the model, namely *callbacks=[checkpointer]*, where 'checkpointer' will the model's checkpoint file to record the optimal coefficients.

2.4 Benchmark

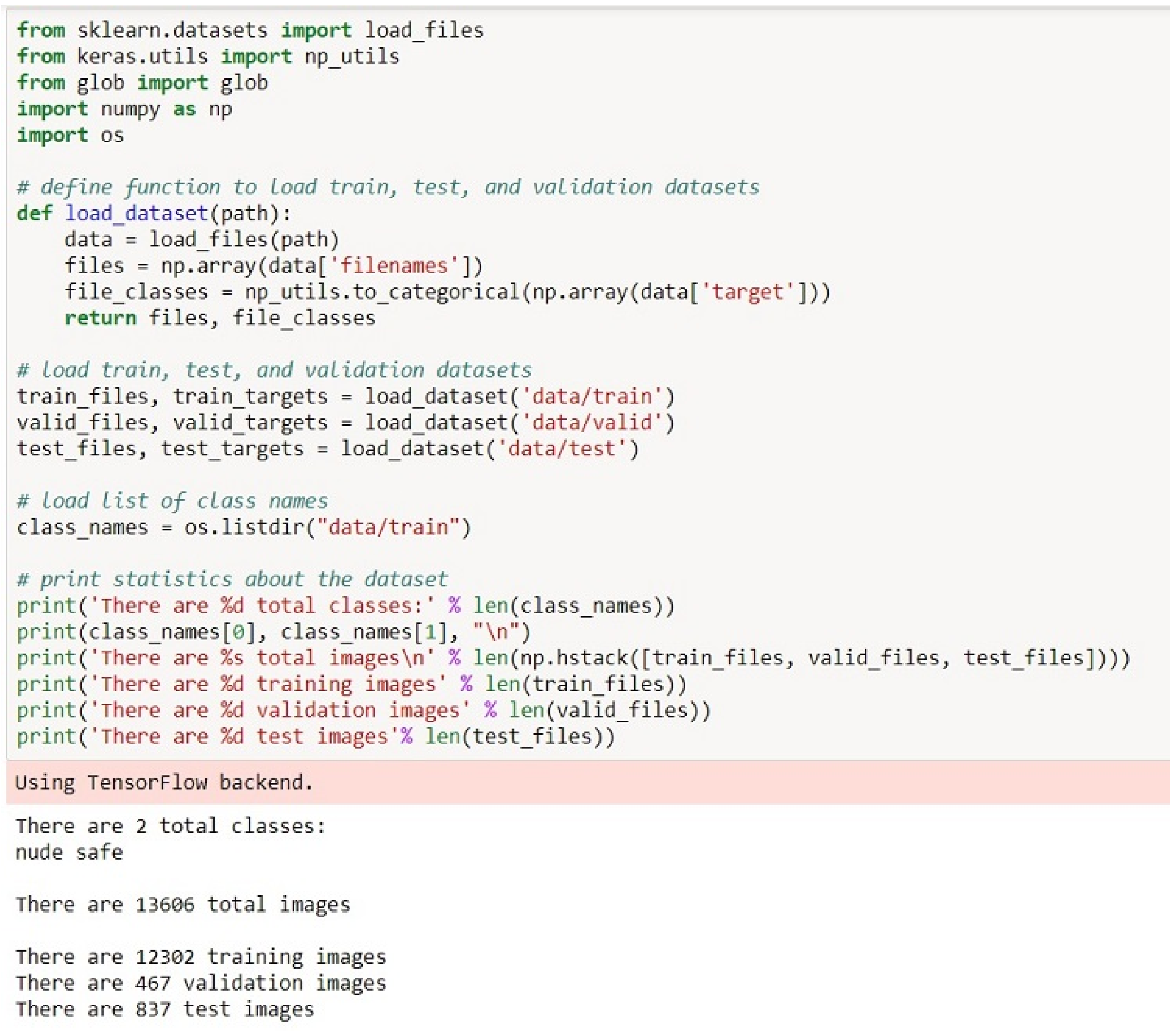
The main assumption of this project is that a CNN with a SVM classifier will perform better than a CNN with a softmax activation function. Therefore, for benchmark model we will use a CNN built with the same architecture and trained with the same set of parameters, with only difference being a sigmoid activation function in the penultimate layer instead of an SVM classifier.

We will then test both models and compare the results obtained from the CNN-SVM against the benchmark. If our assumption is correct and the network does classify images with smaller error rate than the benchmark model, then we have confirmed the correctness of our process. Otherwise, if the benchmark model performs better with the same training and optimal set of parameters, we will conclude that for our problem a standard CNN with softmax activation beats the CNN-SVM model.

3 Methodology

3.1 Loading and preparing the data

All the data we use in this project were collected from several websites, and as a result, many of the images are of different size and quality. In order to create a uniform dataset for both classes we will load the image paths from the local project directory, and then resize and covert the images into 224x224 RGB-valued tensors. Facilitating the Keras framework in Python, we proceed as follows:



```
from sklearn.datasets import load_files
from keras.utils import np_utils
from glob import glob
import numpy as np
import os

# define function to load train, test, and validation datasets
def load_dataset(path):
    data = load_files(path)
    files = np.array(data['filenames'])
    file_classes = np_utils.to_categorical(np.array(data['target']))
    return files, file_classes

# load train, test, and validation datasets
train_files, train_targets = load_dataset('data/train')
valid_files, valid_targets = load_dataset('data/valid')
test_files, test_targets = load_dataset('data/test')

# load list of class names
class_names = os.listdir("data/train")

# print statistics about the dataset
print('There are %d total classes:' % len(class_names))
print(class_names[0], class_names[1], "\n")
print('There are %s total images\n' % len(np.hstack([train_files, valid_files, test_files])))
print('There are %d training images' % len(train_files))
print('There are %d validation images' % len(valid_files))
print('There are %d test images'% len(test_files))
```

```
Using TensorFlow backend.
```

```
There are 2 total classes:
nude safe

There are 13606 total images

There are 12302 training images
There are 467 validation images
There are 837 test images
```

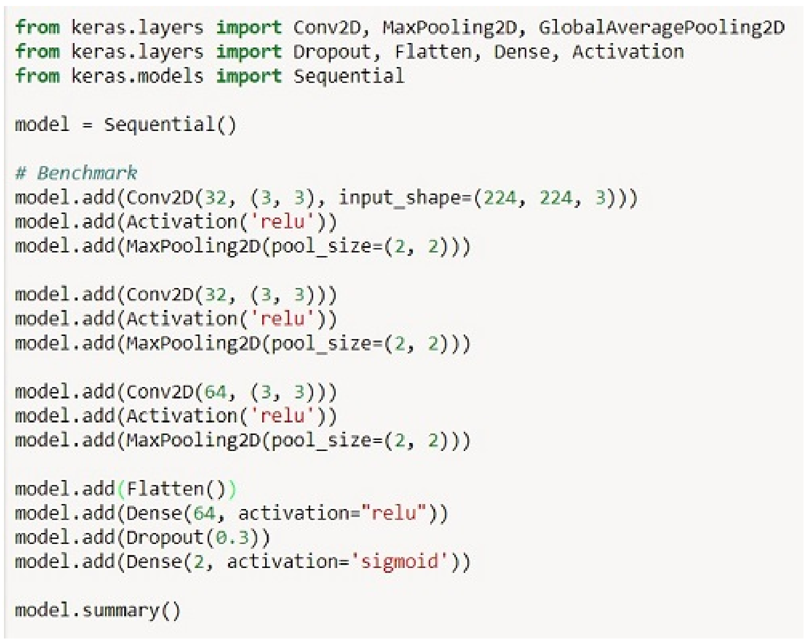
We then convert the data into 4D RGB-valued tensor with shape (1, 224, 224, 3), thereby having the data fully prepared for the network.

3.2 Implementation

3.2.1 Benchmark

The benchmark model is a regular CNN network with several layers shown below and a sigmoid activation function at the last layer, since this is a binary classification problem. In particular the model architecture is the following, implemented using Keras framework of Python:

Fig. 2.2.3 Benchmark Model Architecture

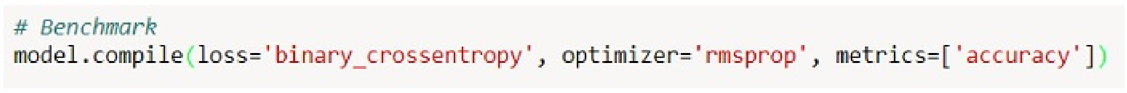


```python
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
from keras.layers import Dropout, Flatten, Dense, Activation
from keras.models import Sequential

model = Sequential()

# Benchmark
model.add(Conv2D(32, (3, 3), input_shape=(224, 224, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(64, activation="relu"))
model.add(Dropout(0.3))
model.add(Dense(2, activation='sigmoid'))

model.summary()
```

The input layer is a 3 dimensional matrix of 224x224 values, followed by a rectified linear unit activation (ReLU). Then there is max pooling layer, followed by more convolutional layers, until we eventually flatten the input to 1 dimension to use in a dense layer. Then we dropout 30% of the values to avoid overfitting, and finally we use the sigmoid for the binary classification.

We compile the model using the standard 'rmsprop' optimizer and a cross entropy loss function.

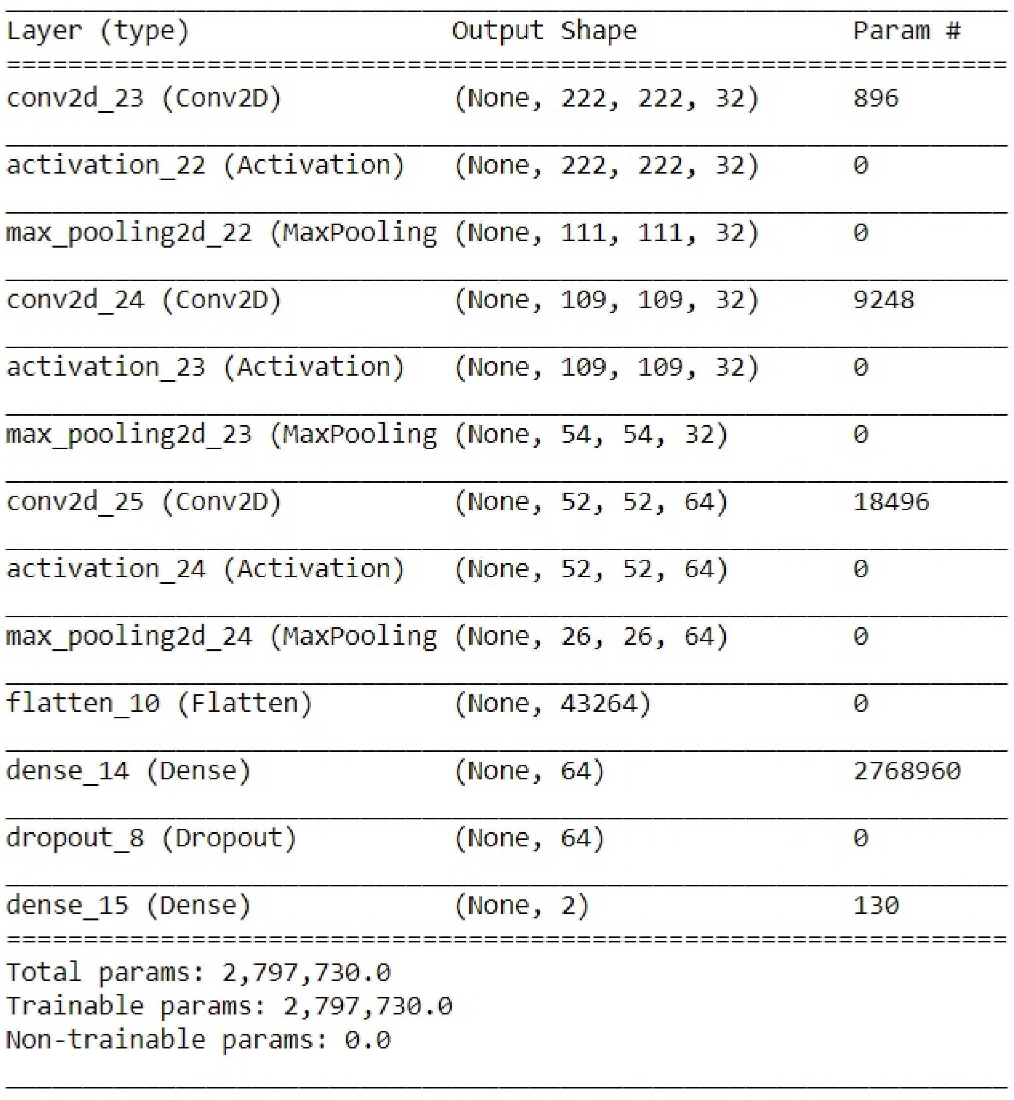
Fig. 2.2.5 Compiling Benchmark Model



```python
# Benchmark
model.compile(loss='binary_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

The model's summary is below. As you can see there are 2,797,730 parameters to be trained, 30% of them will be dropped randomly to avoid certain features to dominate others.

Fig. 2.2.4 Benchmark Model Summary



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_23 (Conv2D)           (None, 222, 222, 32)      896
_________________________________________________________________
activation_22 (Activation)   (None, 222, 222, 32)      0
_________________________________________________________________
max_pooling2d_22 (MaxPooling (None, 111, 111, 32)      0
_________________________________________________________________
conv2d_24 (Conv2D)           (None, 109, 109, 32)      9248
_________________________________________________________________
activation_23 (Activation)   (None, 109, 109, 32)      0
_________________________________________________________________
max_pooling2d_23 (MaxPooling (None, 54, 54, 32)        0
_________________________________________________________________
conv2d_25 (Conv2D)           (None, 52, 52, 64)        18496
_________________________________________________________________
activation_24 (Activation)   (None, 52, 52, 64)        0
_________________________________________________________________
max_pooling2d_24 (MaxPooling (None, 26, 26, 64)        0
_________________________________________________________________
flatten_10 (Flatten)         (None, 43264)             0
_________________________________________________________________
dense_14 (Dense)             (None, 64)                2768960
_________________________________________________________________
dropout_8 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_15 (Dense)             (None, 2)                 130
=================================================================
Total params: 2,797,730.0
Trainable params: 2,797,730.0
Non-trainable params: 0.0
_________________________________________________________________
```

All is left now is to train the benchmark model and evaluate the results. According to the output, we can go back and change the parameters of the model as well as the model's architecture so that we can derive an optimal classifier for our problem.

3.2.2 Target Model

We follow a similar process for the target model. The input to our model will be the same as with the benchmark, and the architecture will be almost identical except with the penultimate layer where instead of the standard sigmoid function, we now emulate an SVM classifier.

That being said, the penultimate layer of the model will look like:

3.3 Refinement

4 Results

4.1 Model Evaluation and Validation

4.2 Justification

5 Conclusion

5.1 Free form visualization

5.2 Reflection

5.3 Improvement