Real Time Bare Skinned Images Filtering Using CNN

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Introduction

Skin colour detection has been used in numerous computer vision applications like face detection, nudity recognition, hand gesture detection and person identification.Skin colour detection is a challenging task as the skin colour in an image is sensitive to various factors like illumination, camera characteristics, ethnicity, individual characteristics such as age, sex and body parts and other factors like makeup, hairstyle and glasses.All these factors affect appearance of skin colour. Another problem is that there is a significant overlap between the skin and non-skin pixels.However when these techniques are used in real-time, it is crucial to follow time deadlines and memory constraints. Sometimes, accuracy may need to be sacrificed when the skin detection strategy is used only as a preprocessing step to face detection, particularly in real time applications. In this study we have focused on the problem of developing an accurate and robust model for the human skin.

Objective

The model will offer child proof surfing on the internet without parent intervention. So that parents do not have to worry about their children coming across nude images at such an early age without knowing the actual meaning of it. That is it will monitor every page and filter all the images, hiding their details from the children and disabling their activation upon any click. Even if the people in the image is not completely nude, may it be just the upper or lower half of the person’s body; the model will still blur that image once it reaches the minimum percentage of human pixel colour set by the classifier, thus ensuring guaranteed protection.

Neural Networks

Neural Networks is a machine learning algorithm, which is built on the principle of the organization and functioning of biological neural networks. Neural networks consist of individual units called neurons. Neurons are located in a series of groups — layers.Neurons in each layer are connected to neurons of the next layer. Data comes from the input layer to the output layer along these compounds. Each individual node performs a simple mathematical calculation. Then it transmits its data to all the nodes it is connected to.

Different types of neural network architecture are as follows:

1)Perceptrons

2)Convolutional Neural Networks

3)Recurrent Neural Networks

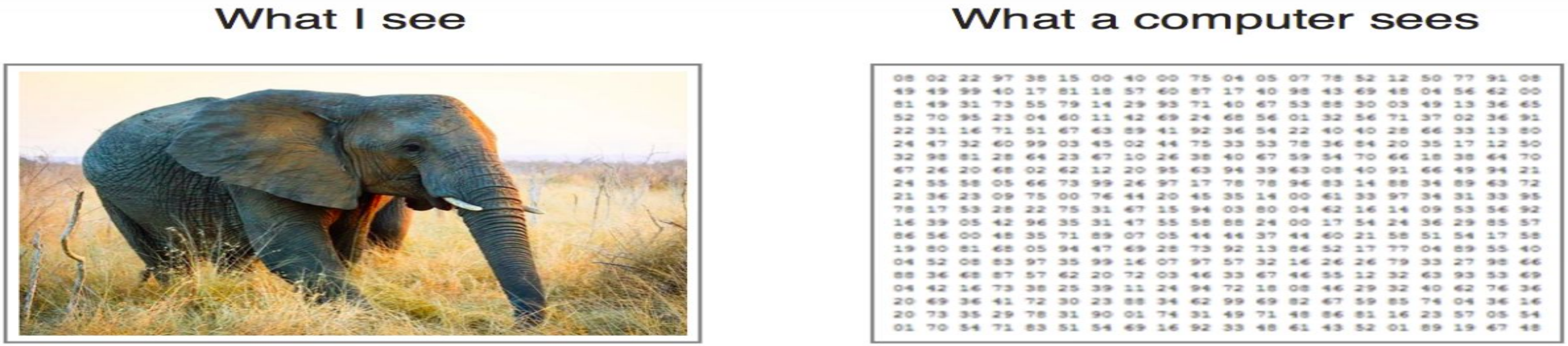
4)Long / Short Term Memory

5)Gated Recurrent Unit

6)Hopfield Network

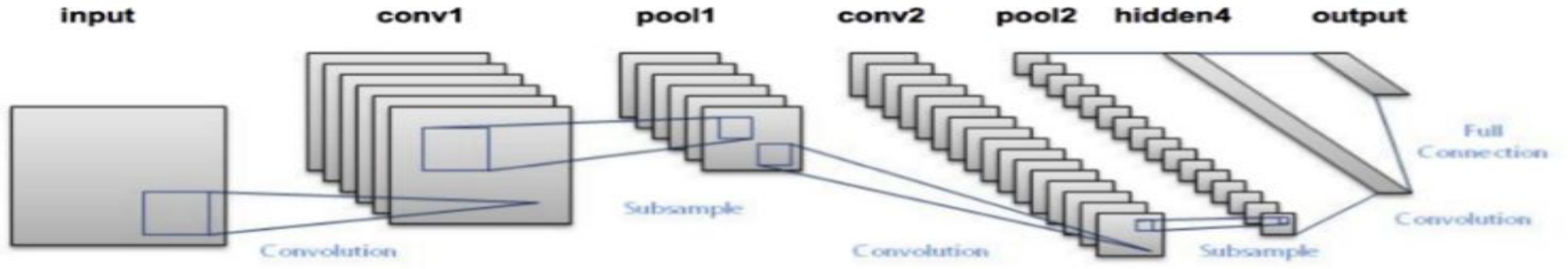
Why Convolution Neural Networks

Convolutional neural networks (CNN) is a special architecture of artificial neural networks, proposed by Yann LeCun in 1988. CNN uses some features of the visual cortex. One of the most popular uses of this architecture is image classification. For example Facebook uses CNN for automatic tagging algorithms, Amazon — for generating product recommendations and Google — for search through among users' photos.The main task of image classification is acceptance of the input image and the following definition of its class. This is a skill that people learn from their birth and are able to easily determine that the image in the picture is an elephant. But the computer sees the pictures quite differently:



Convolution Neural Network cont.....

Instead of the image, the computer sees an array of pixels. For example, if image size is 300 x 300. In this case, the size of the array will be 300x300x3. Where 300 is width, next 300 is height and 3 is RGB channel values. The computer is assigned a value from 0 to 255 to each of these numbers. This value describes the intensity of the pixel at each point.To solve this problem the computer looks for the characteristics of the base level. In human understanding such characteristics are for example the trunk or large ears. For the computer, these characteristics are boundaries or curvatures. And then through the groups of convolutional layers the computer constructs more abstract concepts.In more detail: the image is passed through a series of convolutional, nonlinear, pooling layers and fully connected layers, and then generates the output.



Output of Cat and Dog Tutorial with 4 Layers

```
Epoch 11/20
32/32 [==============================] - 229s 7s/step - loss: 0.6069 - acc: 0.6576 - val_loss: 0.6123 - val_acc: 0.6475
Epoch 12/20
32/32 [==============================] - 228s 7s/step - loss: 0.6024 - acc: 0.6834 - val_loss: 0.6115 - val_acc: 0.6625
Epoch 13/20
32/32 [==============================] - 227s 7s/step - loss: 0.6050 - acc: 0.6580 - val_loss: 0.6072 - val_acc: 0.6600
Epoch 14/20
32/32 [==============================] - 226s 7s/step - loss: 0.6050 - acc: 0.6761 - val_loss: 0.5730 - val_acc: 0.7000
Epoch 15/20
32/32 [==============================] - 230s 7s/step - loss: 0.6051 - acc: 0.6700 - val_loss: 0.6301 - val_acc: 0.6250
Epoch 16/20
32/32 [==============================] - 230s 7s/step - loss: 0.5850 - acc: 0.6917 - val_loss: 0.6203 - val_acc: 0.6450
Epoch 17/20
32/32 [==============================] - 227s 7s/step - loss: 0.6045 - acc: 0.6427 - val_loss: 0.5674 - val_acc: 0.7250
Epoch 18/20
32/32 [==============================] - 230s 7s/step - loss: 0.5942 - acc: 0.6790 - val_loss: 0.5915 - val_acc: 0.6575
Epoch 19/20
32/32 [==============================] - 230s 7s/step - loss: 0.5915 - acc: 0.6861 - val_loss: 0.5500 - val_acc: 0.7575
Epoch 20/20
32/32 [==============================] - 225s 7s/step - loss: 0.5653 - acc: 0.7142 - val_loss: 0.5567 - val_acc: 0.7275
>72.750
```

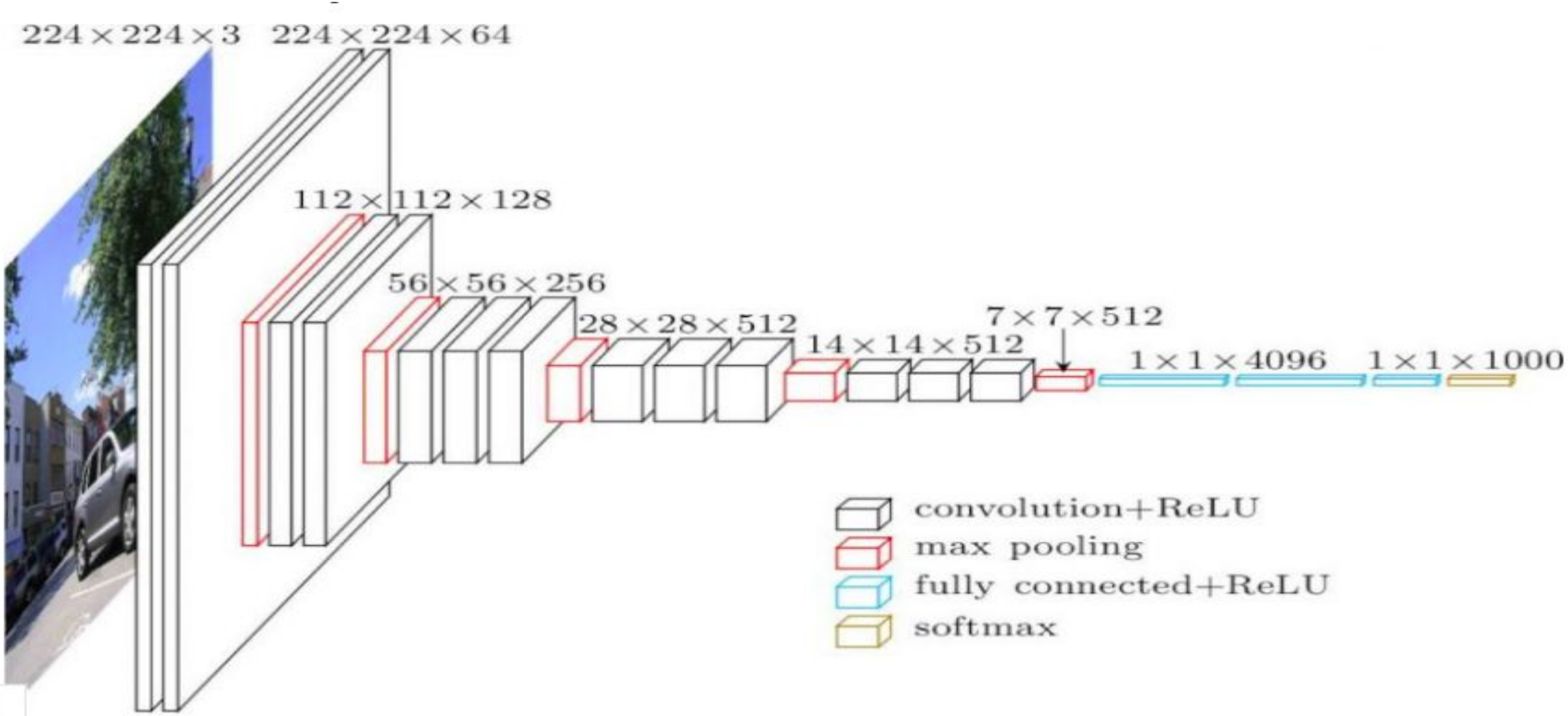
Using VGG16 model

```
Epoch 1/10
32/32 [==============================] - 1192s 37s/step - loss: 0.9444 - acc: 0.9191 - val_loss: 0.5645 - val_acc: 0.9500
Epoch 2/10
32/32 [==============================] - 1181s 37s/step - loss: 0.3874 - acc: 0.9700 - val_loss: 0.3456 - val_acc: 0.9750
Epoch 3/10
32/32 [==============================] - 1187s 37s/step - loss: 0.3833 - acc: 0.9719 - val_loss: 0.6194 - val_acc: 0.9525
Epoch 4/10
32/32 [==============================] - 1192s 37s/step - loss: 0.3094 - acc: 0.9751 - val_loss: 0.5087 - val_acc: 0.9600
Epoch 5/10
32/32 [==============================] - 1185s 37s/step - loss: 0.1624 - acc: 0.9858 - val_loss: 0.2661 - val_acc: 0.9750
Epoch 6/10
32/32 [==============================] - 1189s 37s/step - loss: 0.1257 - acc: 0.9902 - val_loss: 0.2903 - val_acc: 0.9750
Epoch 7/10
32/32 [==============================] - 1200s 37s/step - loss: 0.1794 - acc: 0.9873 - val_loss: 0.6117 - val_acc: 0.9525
Epoch 8/10
32/32 [==============================] - 1205s 38s/step - loss: 0.1362 - acc: 0.9902 - val_loss: 0.4027 - val_acc: 0.9725
Epoch 9/10
32/32 [==============================] - 1207s 38s/step - loss: 0.1283 - acc: 0.9902 - val_loss: 0.2983 - val_acc: 0.9800
Epoch 10/10
32/32 [==============================] - 1190s 37s/step - loss: 0.1441 - acc: 0.9897 - val_loss: 0.3136 - val_acc: 0.9800
>98.000
```

Predictions

```
/content/drive/My Drive/major projects/cat and dog/test/dog.4024.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4134.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4025.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4183.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4166.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4138.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4040.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4162.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4102.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4134.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/cat.4014.jpg
[0.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4014.jpg
[1.]
/content/drive/My Drive/major projects/cat and dog/test/dog.4033.jpg
[1.]
```

VGG16 Architecture



VGG16

The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2. Three Fully-Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.

VGG16 Layers

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 224, 224, 3)       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
```

VGG16 Layers

```
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
fc1 (Dense)                  (None, 4096)              102764544
_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312
_________________________________________________________________
predictions (Dense)          (None, 1000)              4097000
=================================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
_________________________________________________________________
```

Bare Image Classification

```
Found 806 images belonging to 2 classes.
Found 200 images belonging to 2 classes.
Epoch 1/10
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:716: UserWarning: This ImageDataGenerator speci
  warnings.warn('This ImageDataGenerator specifies '
13/13 [==============================] - 652s 50s/step - loss: 1.8829 - acc: 0.8087 - val_loss: 8.7702 - val_acc: 0.4250
Epoch 2/10
13/13 [==============================] - 642s 49s/step - loss: 0.9601 - acc: 0.9238 - val_loss: 8.8420 - val_acc: 0.4250
Epoch 3/10
13/13 [==============================] - 639s 49s/step - loss: 0.8273 - acc: 0.9382 - val_loss: 6.0052 - val_acc: 0.5900
Epoch 4/10
13/13 [==============================] - 640s 49s/step - loss: 0.8191 - acc: 0.9387 - val_loss: 9.9569 - val_acc: 0.3550
Epoch 5/10
13/13 [==============================] - 635s 49s/step - loss: 0.5197 - acc: 0.9616 - val_loss: 8.3309 - val_acc: 0.4600
Epoch 6/10
13/13 [==============================] - 634s 49s/step - loss: 0.4111 - acc: 0.9684 - val_loss: 7.1673 - val_acc: 0.5250
Epoch 7/10
13/13 [==============================] - 635s 49s/step - loss: 0.4449 - acc: 0.9703 - val_loss: 6.7312 - val_acc: 0.5450
Epoch 8/10
13/13 [==============================] - 636s 49s/step - loss: 0.4037 - acc: 0.9739 - val_loss: 7.6236 - val_acc: 0.4850
Epoch 9/10
13/13 [==============================] - 637s 49s/step - loss: 0.3788 - acc: 0.9747 - val_loss: 8.5476 - val_acc: 0.4500
Epoch 10/10
13/13 [==============================] - 639s 49s/step - loss: 0.3963 - acc: 0.9711 - val_loss: 9.2629 - val_acc: 0.4100
>41.000
```

Bare Image Classification

```
Epoch 8/20
13/13 [==============================] - 643s 49s/step - loss: 0.6071 - acc: 0.9559 - val_loss: 8.4083 - val_acc: 0.4550
Epoch 9/20
13/13 [==============================] - 642s 49s/step - loss: 0.3916 - acc: 0.9723 - val_loss: 8.7273 - val_acc: 0.4300
Epoch 10/20
13/13 [==============================] - 641s 49s/step - loss: 0.3892 - acc: 0.9735 - val_loss: 8.6571 - val_acc: 0.4400
Epoch 11/20
13/13 [==============================] - 639s 49s/step - loss: 0.4021 - acc: 0.9727 - val_loss: 8.9160 - val_acc: 0.4250
Epoch 12/20
13/13 [==============================] - 642s 49s/step - loss: 0.4010 - acc: 0.9739 - val_loss: 8.8522 - val_acc: 0.4150
Epoch 13/20
13/13 [==============================] - 639s 49s/step - loss: 0.4105 - acc: 0.9744 - val_loss: 8.4253 - val_acc: 0.4500
Epoch 14/20
13/13 [==============================] - 643s 49s/step - loss: 0.3911 - acc: 0.9756 - val_loss: 8.3093 - val_acc: 0.4550
Epoch 15/20
13/13 [==============================] - 658s 51s/step - loss: 0.3911 - acc: 0.9756 - val_loss: 8.2767 - val_acc: 0.4550
Epoch 16/20
13/13 [==============================] - 672s 52s/step - loss: 0.3666 - acc: 0.9771 - val_loss: 8.2689 - val_acc: 0.4550
Epoch 17/20
13/13 [==============================] - 659s 51s/step - loss: 0.3666 - acc: 0.9771 - val_loss: 8.2671 - val_acc: 0.4550
Epoch 18/20
13/13 [==============================] - 647s 50s/step - loss: 0.3788 - acc: 0.9763 - val_loss: 8.2677 - val_acc: 0.4550
Epoch 19/20
13/13 [==============================] - 653s 50s/step - loss: 0.3666 - acc: 0.9771 - val_loss: 8.2671 - val_acc: 0.4550
Epoch 20/20
13/13 [==============================] - 650s 50s/step - loss: 0.3788 - acc: 0.9763 - val_loss: 8.2689 - val_acc: 0.4550
>45.500
```

Creation Of Our Own Model

```
model = Sequential()
model.add(Conv2D(input_shape=(200,200,3),filters=64,kernel_size=(3,3),padding="same", activation="relu"))
model.add(Conv2D(filters=64,kernel_size=(3,3),padding="same", activation="relu"))
model.add(MaxPooling2D(pool_size=(3,3),strides=(2,2)))

model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPooling2D(pool_size=(3,3),strides=(2,2)))

model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPooling2D(pool_size=(3,3),strides=(2,2)))

model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512,kernel_size=(3,3),padding="same", activation="relu"))
model.add(MaxPooling2D(pool_size=(3,3),strides=(2,2)))

model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512,kernel_size=(3,3),padding="same", activation="relu"))
model.add(MaxPooling2D(pool_size=(3,3),strides=(2,2)))

model.add(Flatten())

model.add(Dense(units=1024,activation="relu"))
model.add(Dense(units=1000,activation="relu"))
model.add(Dense(units=500,activation="relu"))
model.add(Dense(units=128,activation="relu"))
model.add(Dense(units=128,activation="relu"))
model.add(Dense(units=64,activation="relu"))
model.add(Dense(units=1, activation="sigmoid"))
```

VGG19 Model With Some Additional Dense Layers

```python
import sys
from matplotlib import pyplot
from keras.utils import to_categorical
from keras.applications.vgg19 import VGG19
from keras.models import Model
from keras.layers import Dense
from keras.layers import Flatten
from keras.optimizers import SGD

model=VGG19(include_top=False,input_shape=(200,200,3))
for layer in model.layers:
  layer.trainable=False
flat1=Flatten()(model.layers[-1].output)
class1=Dense(500,activation='relu',kernel_initializer="he_uniform")(flat1)
class2=Dense(500,activation='relu',kernel_initializer="he_uniform")(class1)
class3=Dense(500,activation='relu',kernel_initializer="he_uniform")(class2)
class4=Dense(500,activation='relu',kernel_initializer="he_uniform")(class3)
output=Dense(1,activation='sigmoid')(class4)
model=Model(inputs=model.inputs,outputs=output)
```

Dataset

One of the most tedious parts of training an image classifier or working on any computer vision project is actually gathering the images that you'll be training your model on. So for our model there were no dataset available which were greater than 100- 200 images. So to train our model we had to collect a lot of images to get the desired accuracy. In the search of that we started scrapping images from the internet. We wrote our own code to scrap these images from individual list of links that we found on a github account. As of now we have trained our model with five thousand images giving us an accuracy of 87.29%. But we have collected a dataset of 25 thousand images and are going to train our model on that dataset. Hoping to get a better accuracy and more efficient model. This data collection was random so we also had to sort the images into nude and non-nude manually. We have animated images as well as real human images in order to cover all the bases possible.

Output of Our Model With 5604 training images

```
[ ]
opt=SGD(lr=0.001,momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train,Y_train,validation_data=(X_test,Y_test),batch_size=128,epochs=15,verbose=1)
#model.save_weights("weights.h5")
#model.save("final.h5")
```

```
Train on 5604 samples, validate on 999 samples
Epoch 1/15
5604/5604 [==============================] - 40s 7ms/step - loss: 0.6825 - acc: 0.5803 - val_loss: 0.6212 - val_acc: 0.7518
Epoch 2/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.6601 - acc: 0.6089 - val_loss: 0.7298 - val_acc: 0.3233
Epoch 3/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.6681 - acc: 0.5805 - val_loss: 0.7753 - val_acc: 0.3293
Epoch 4/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.6332 - acc: 0.6363 - val_loss: 0.5746 - val_acc: 0.6937
Epoch 5/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5637 - acc: 0.7136 - val_loss: 0.4926 - val_acc: 0.7898
Epoch 6/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5376 - acc: 0.7404 - val_loss: 0.4925 - val_acc: 0.7848
Epoch 7/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5592 - acc: 0.7243 - val_loss: 0.5506 - val_acc: 0.7317
Epoch 8/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5184 - acc: 0.7575 - val_loss: 0.4492 - val_acc: 0.8318
Epoch 9/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5239 - acc: 0.7514 - val_loss: 0.5181 - val_acc: 0.7708
Epoch 10/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5199 - acc: 0.7521 - val_loss: 0.4678 - val_acc: 0.8078
Epoch 11/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.5038 - acc: 0.7630 - val_loss: 0.4547 - val_acc: 0.8438
Epoch 12/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.4857 - acc: 0.7741 - val_loss: 0.3581 - val_acc: 0.8629
Epoch 13/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.4804 - acc: 0.7741 - val_loss: 0.3733 - val_acc: 0.8539
Epoch 14/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.4822 - acc: 0.7703 - val_loss: 0.5174 - val_acc: 0.7808
Epoch 15/15
5604/5604 [==============================] - 38s 7ms/step - loss: 0.4780 - acc: 0.7784 - val_loss: 0.3424 - val_acc: 0.8729
<keras.callbacks.History at 0x7f4ce2324860>
```

Output of VGG19 with 5604 training images

```
opt=SGD(lr=0.001,momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train,Y_train,validation_data=(X_test,Y_test),batch_size=128,epochs=15,verbose=1)
#model.save_weights("weights.h5")
model.save("final.h5")
```

```
Train on 5604 samples, validate on 999 samples
Epoch 1/15
5604/5604 [==============================] - 21s 4ms/step - loss: 0.0065 - acc: 0.9995 - val_loss: 0.7341 - val_acc: 0.8368
Epoch 2/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0065 - acc: 0.9995 - val_loss: 0.6669 - val_acc: 0.8589
Epoch 3/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0067 - acc: 0.9993 - val_loss: 0.6752 - val_acc: 0.8559
Epoch 4/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0065 - acc: 0.9995 - val_loss: 0.7129 - val_acc: 0.8478
Epoch 5/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0066 - acc: 0.9995 - val_loss: 0.6376 - val_acc: 0.8669
Epoch 6/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0069 - acc: 0.9993 - val_loss: 0.6841 - val_acc: 0.8539
Epoch 7/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9993 - val_loss: 0.6529 - val_acc: 0.8609
Epoch 8/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0065 - acc: 0.9995 - val_loss: 0.7065 - val_acc: 0.8478
Epoch 9/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0065 - acc: 0.9993 - val_loss: 0.6958 - val_acc: 0.8529
Epoch 10/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9995 - val_loss: 0.6650 - val_acc: 0.8599
Epoch 11/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9995 - val_loss: 0.7135 - val_acc: 0.8478
Epoch 12/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9995 - val_loss: 0.6784 - val_acc: 0.8579
Epoch 13/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9995 - val_loss: 0.7408 - val_acc: 0.8438
Epoch 14/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0064 - acc: 0.9995 - val_loss: 0.6634 - val_acc: 0.8619
Epoch 15/15
5604/5604 [==============================] - 16s 3ms/step - loss: 0.0065 - acc: 0.9993 - val_loss: 0.7027 - val_acc: 0.8539
```

Comparison

OWN MODEL	VGG19 MODEL
1] It has 15 Convlotion Layers with 5 blocks	1]It has 16 Convolution Layers with 5 blocks.
2] It has 5 MaxPooling Layers with pool size (3,3) and strides(2,2).	2] It has 5 MaxPooling Layers.
3] It has 7 Fully Connected Layers having : 1024 units in 1st layer,1000 units in 2nd layer,500 units in 3rd layer,128 units in 4th and 5th layer, 64 units in 6th layer and 1 unit in 7th i.e output layer.	3] It has 5 Fully Connected Layers having: 500 units in all the 4 layers and 1 unit in 5th i.e output layer.
4] Accuracy of Model with 15 epoches:87.29	4]Accuracy of Model with 15 .epoches :85.39

Few of the Common Parameters

- Optimizer Used : Stochastic Gradient Descent(SGD)
- Activation Function : Sigmoid
- Learning Rate : 0.001
- Momentum : 0.9
- Batch Size : 128
- Loss : Binary Crossentropy
- Training Imgaes : 5604
- Testing Images :999
- No. of Epoches : 15

Analysis of model with different Optimizers and Activation Function

ACTIVATION FUNCTION	tahn	elu	sigmoid	hard_sigmoid	selu	softsign	softmax	softplus	relu	exponential	linear
OPTIMIZER											
SGD	81.48	67.47	87.29	79.98	79.98	43.04	20.02	79.68	79.98	60.16	79.98
RMSprop	79.98	79.98	79.98	20.02	79.98	20.02	20.02	79.98	79.98	79.98	79.98
Adagrad	20.02	79.98	20.02	79.98	79.98	79.98	20.02	79.98	79.98	20.02	79.98
Adadelta	80.68	57.26	60.96	78.18	82.98	80.48	20.02	60.76	82.08	47.65	74.17
Adam	79.98	79.98	79.98	79.98	79.98	79.98	20.02	79.98	79.98	20.02	79.98
Adamax	20.02	79.98	20.02	20.02	79.98	79.98	20.02	79.98	79.98	79.98	79.98
Nadam	79.98	79.98	79.98	79.98	79.98	79.98	20.02	79.98	79.98	79.98	79.98

Predictions

```
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Future Scope

To Create Google Chrome Extension Using the Trained model which will blur the Bare Skinned Images on the Webpage At RunTime as soon as the page gets loaded .

Also the hyperlink will be disabled if any with such type of images.

Thank You