



Artificial Intelligence

Emotion recognition with Convolutional neural networks
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1 Overview

This project will show the process of building a Convolutional neural network to recognize emotions on humans faces. This type of application can be use full and be applied in various system such as security cameras.

As we know nonverbal signals sometimes say more then words.

2 Introduction

3 Convolutional Neural Networks

4 Dataset description

Data that we got is in one *.csv file with two columns:

- number of emotion
in rage 0 - 6:
 - 0 - angry
 - 1 - disgust
 - 2 - fear
 - 3 - happy
 - 4 - sad
 - 5 - surprise
 - 6 - neutral
- string of pixels
Pixels are in one long string (2304 of them), they are in gray scale 0 - 255.
We need to preprocess them into array of 48x48x1 that will could be reorganised as a picture
also we will change to rage to 0 - 1 scale - by dividing via 255

#CONST

imageSize, depth = 48, 3

numberOfClasses = 7

filePath = 'data.csv'

def processPixels(pixels):

```
pixels_list = [item[0] for item in pixels.values.tolist()]
```

```
score_array = []
```

```
for index, item in enumerate(pixels_list):
```

```
    data = np.zeros((imageSize, imageSize), dtype=np.uint8)
```

```
    pixel_data = item.split()
```

```
    for i in range(0, imageSize):
```

```
        index = i * imageSize
```

```
        data[i] = pixel_data[index:index + imageSize]
```

```
    score_array.append(np.array(data))
```

```
score_array = np.array(score_array)
```

```
score_array = score_array.astype('float32') / 255.0
```

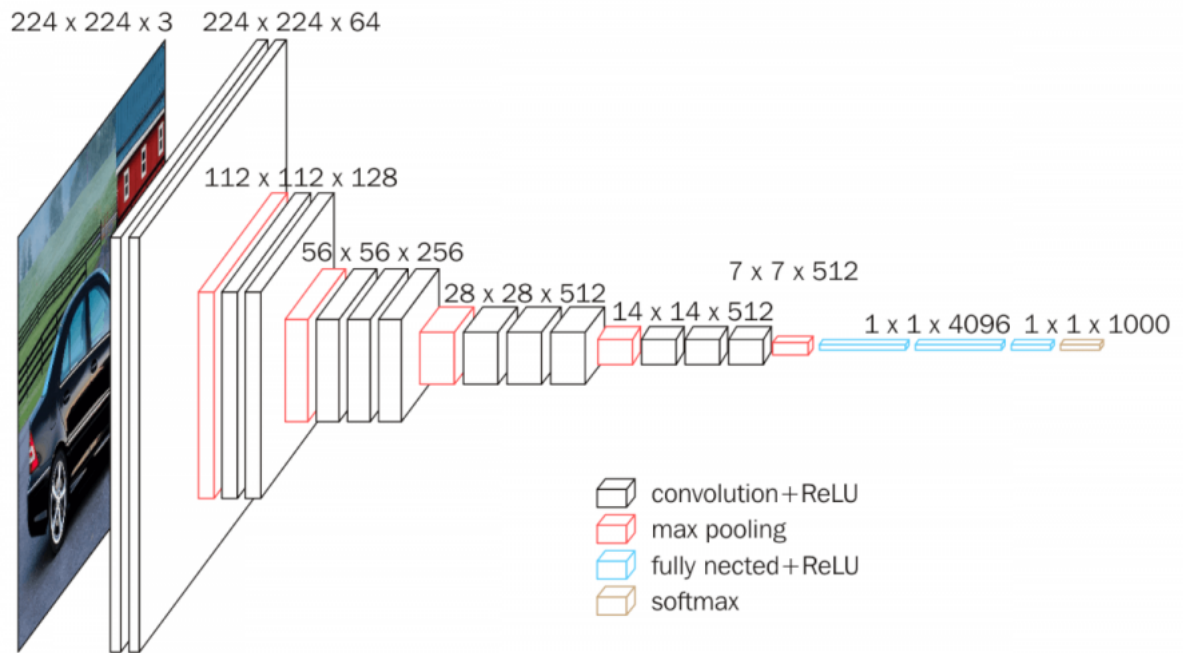
```
return score_array
```

After that we need to multiplay the layers into (48, 48, 3) becouse VGG16 CNN is prepared for RGB pictures. So basically recopy gray pixels 2 times more.

```
def makeVGG16input(array_input):
    array_input = np.expand_dims(array_input, axis=3)
    array_input = np.repeat(array_input, 3, axis=3)
    return array_input
```

5 Model building

We decided to use pre-trained VGG16 model, without its top two layers.



VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”. The model achieves 92.7 top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3 x 3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU’s.

In Keras it’s really easy to implement this model and freeze layers to non-trainable (In code in “Implementation” section) Our VGG model looks like this:

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	(None, 48, 48, 3)	0
block1_conv1 (Conv2D)	(None, 48, 48, 64)	1792
block1_conv2 (Conv2D)	(None, 48, 48, 64)	36928
block1_pool (MaxPooling2D)	(None, 24, 24, 64)	0
block2_conv1 (Conv2D)	(None, 24, 24, 128)	73856
block2_conv2 (Conv2D)	(None, 24, 24, 128)	147584
block2_pool (MaxPooling2D)	(None, 12, 12, 128)	0
block3_conv1 (Conv2D)	(None, 12, 12, 256)	295168
block3_conv2 (Conv2D)	(None, 12, 12, 256)	590080
block3_conv3 (Conv2D)	(None, 12, 12, 256)	590080
block3_pool (MaxPooling2D)	(None, 6, 6, 256)	0
block4_conv1 (Conv2D)	(None, 6, 6, 512)	1180160
block4_conv2 (Conv2D)	(None, 6, 6, 512)	2359808
block4_conv3 (Conv2D)	(None, 6, 6, 512)	2359808
block4_pool (MaxPooling2D)	(None, 3, 3, 512)	0
block5_conv1 (Conv2D)	(None, 3, 3, 512)	2359808
block5_conv2 (Conv2D)	(None, 3, 3, 512)	2359808
block5_conv3 (Conv2D)	(None, 3, 3, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0
global_average_pooling2d_2 ((None, 512)		0

Total params: 14,714,688
 Trainable params: 0
 Non-trainable params: 14,714,688

6 Implementation

7 Quantization

8 Results

9 Conclusion