

PROJECT NTDS

Face Emotion Recognition



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DATA CLEANING



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EXPLORING THE
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OUR NEURAL NETWORK



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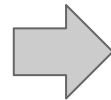
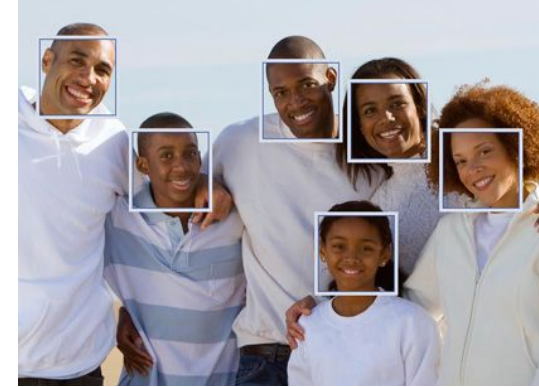
PERFORMANCES



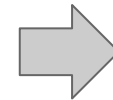
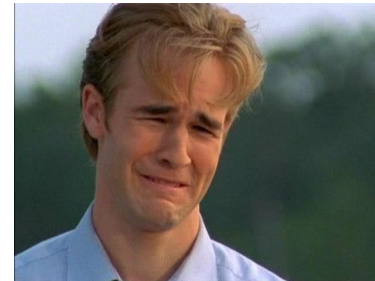
INTRODUCTION - DATABASE

Aim of the project:

- Detect faces in an image
- Recognize and detect generic features of a human face
- Classify faces in discrete human emotions



Surprised



Sad



INTRODUCTION - DATABASE

Database

- Kaggle competition
- 48x48 pixel grayscale images of labeled faces
- 35 000 face pictures

Classes:

0. Angry
1. Disgust
2. Fear
3. Happy
4. Sad
5. Surprise
6. Neutral

Images from the database:



Sad



Angry



Happy



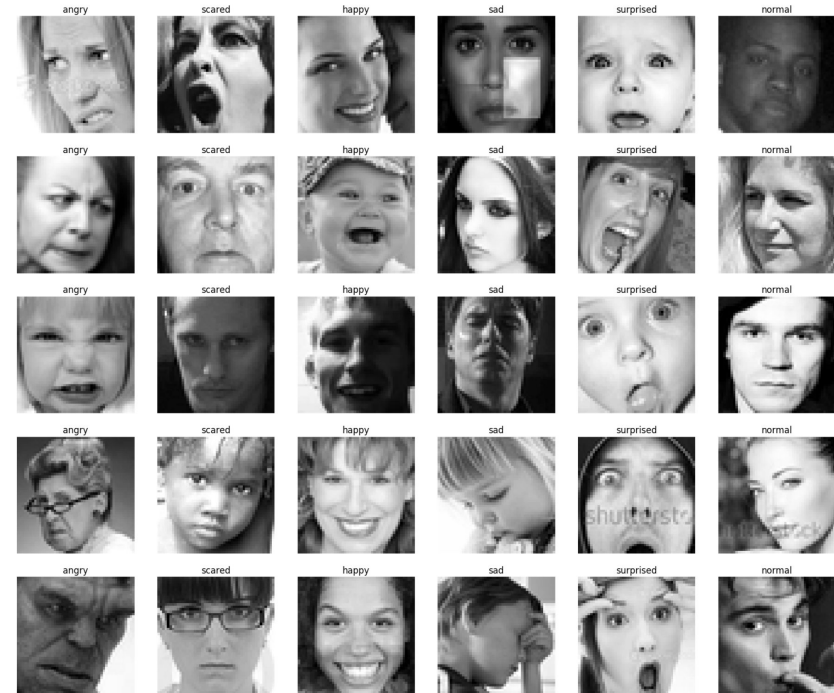
Surprised



DATABASE - Data

Database

- Looks like taken from google images..
- Different facial perspective
- Some images corrupted



1

Data cleaning

1

Data cleaning

- Remove strange data
 - Pixelated images
 - Animation images
 - Black images

Looking at the image intensity histogram.



Important information removed as well.

- Merge class 0 and 1 (Angry and Disgust)
 - Very similar classes
 - Class “disgust” had a small amount of images.



Number of classes reduced to 6.
(Class “Angry” and “Disgust” merged)

1

Data cleaning

Image filtering – $\max(\text{histogram}) > 350$ (discarded images example):



1

Data cleaning

Reduce the amount of “Happy” images

To have similar amount of data for each class, eliminated 3k “happy” images.

Number of 0 (angry) images	5 134	
Number of 1 (scared) images	4 829	
Number of 2 (happy) images	5 789	(was 9k -> reduced)
Number of 3 (sad) images	5 765	
Number of 4 (surprised) images	3 739	
Number of 5 (normal) images	5 876	

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Exploring the models

2

Exploring the models

Model chosen: CONVOLUTIONAL NEURAL NETWORK

- Very good performances in image classification tasks
- Allows to extract many and very complicated features
- Models what do we(humans) do.

What we tried:

- 2 to 10 convolutional layers
- 1 to 4 fully connected layer in different positions
- Different size of patches (2 to 16)
- Different number of filters (10 to 64)
- Regularization and other techniques

2

Exploring the models - Techniques

- Hyperparameters
 - Size and number of filters
 - Number of layers
- Pooling layers
 - Reduce the dimensionality and thus the computational cost
- Dropout
 - Random deactivation of some unit in the NN with a defined probability

3

Our neural network

3

Our convolutional neural network

Our network consists of 6 convolutional layers and a final fully connected

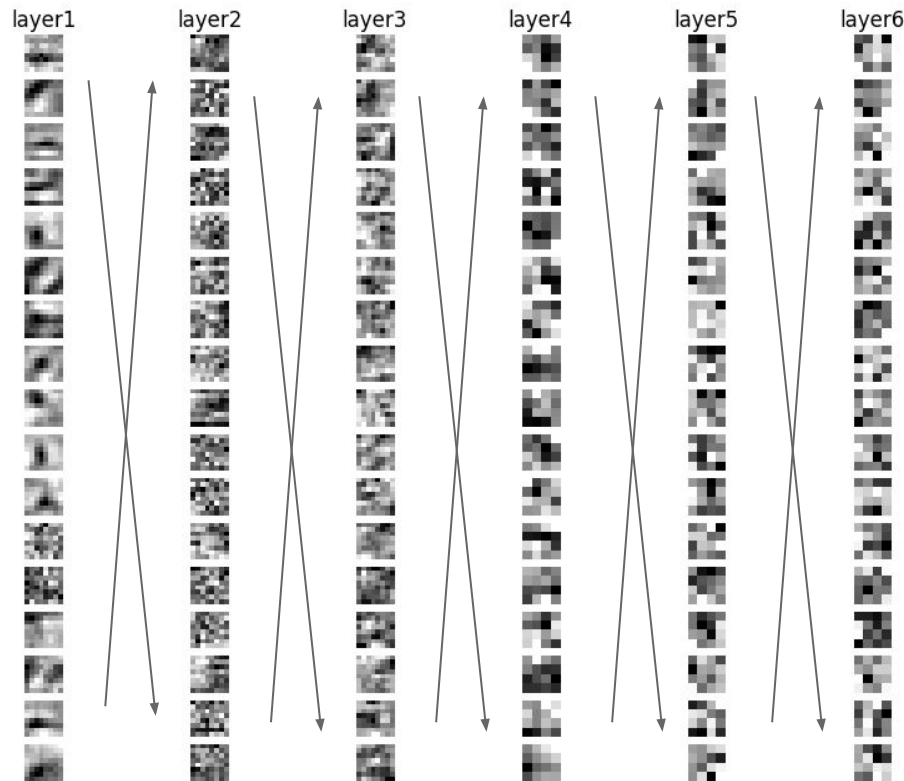
1. Convolutional layer
 - a. Filter number: 22
 - b. Filter size: 8x8
 - c. ReLU activation
2. Convolutional layer
 - a. Filter number: 22
 - b. Filter size: 8x8
 - c. Pool size: 2
 - d. ReLU activation
3. Convolutional layer
 - a. Filter number: 22
 - b. Filter size: 8x8
 - c. ReLU activation
4. Convolutional layer
 - a. Filter number: 22
 - b. Filter size: 4x4
 - c. Pool size: 4
 - d. ReLU activation

3

Our convolutional neural network

5. Conv. layer
 - a. Filter size: 4×4 - 22 filters
 - b. ReLU activation
6. Conv. layer
 - a. Filter size: 4×4 - 22 filters
 - b. Dropout
 - c. ReLU activation
7. Fully connected
 - a. Size: (792, 6)
 - b. Softmax

Adam Optimizer: learning rate 0.001



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Performances and results

4

Performances and results

- Test accuracy: 56%
- Iterations: 20k
- Loss: 0.38
- Train accuracy: 84%

```
Iteration i= 19400 , train accuracy= 0.875 , loss= 0.398623  
test accuracy= 0.4375
```

```
Iteration i= 19500 , train accuracy= 0.875 , loss= 0.293031  
test accuracy= 0.4375
```

```
Iteration i= 19600 , train accuracy= 0.875 , loss= 0.39247  
test accuracy= 0.484375
```

```
Iteration i= 19700 , train accuracy= 0.875 , loss= 0.430336  
test accuracy= 0.453125
```

```
Iteration i= 19800 , train accuracy= 0.8125 , loss= 0.450704  
test accuracy= 0.53125
```

```
Iteration i= 19900 , train accuracy= 0.84375 , loss= 0.373512  
test accuracy= 0.4375
```

```
Iteration i= 20000 , train accuracy= 0.84375 , loss= 0.388213  
test accuracy= 0.5625
```

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Performances and results

20k Iterations to train the model

- Train accuracy= 84.4%
- Loss= 0.38
- Test accuracy= 56.25%

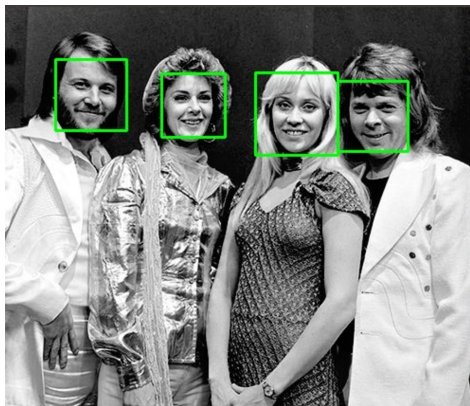
- Accuracy for each class

- Angry: 69.6%
- Scared: 57.1%
- Happy: 57.1%
- Sad: 31.6%
- Surprised: 72.7%
- Normal: 45.5%

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Face Extraction from an image OpenCV + examples

- Used OpenCV 3.0
- Face model and extraction based on the online tutorial:
<https://realpython.com/blog/python/face-recognition-with-python/>



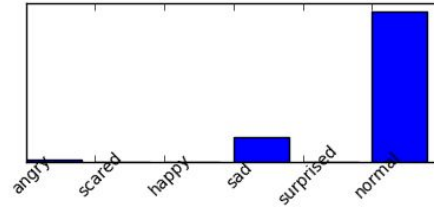
```
faces = faceCascade.detectMultiScale(  
    image,  
    scaleFactor=1.1,  
    minNeighbors=5,  
    minSize=(30, 30),  
    flags = cv2.cv.CV_HAAR_SCALE_IMAGE  
)
```

4

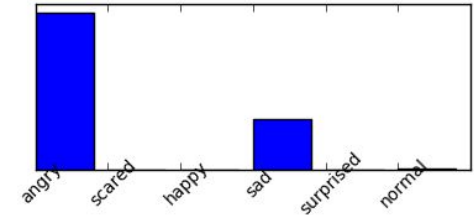
Feeding new (unlabeled) data

E.G. From the camera, file -->>

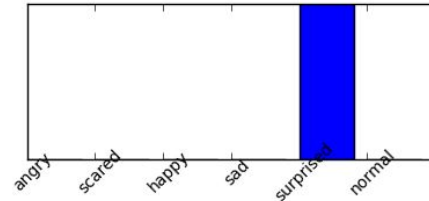
normal



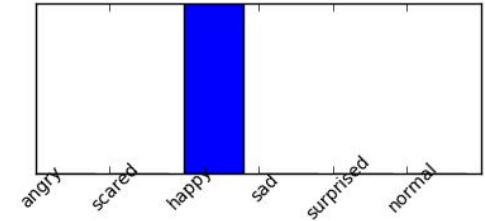
angry



surprised



happy



Conclusions and comment

- High computational power to train the network (~20h)
- Overall accuracy of about 56%
- Very good accuracy for "happy" and "surprised" class
- Noise due to images labeled wrong or not centered in the picture
- Complicated features to extract in face emotions

Possible improvements:

- Randomly flip the images
- Deeper neural network to extract more features
- More sophisticated image pre-processing (e.g. straighten faces).
- Run CNN on GPU / s.

THANKS!

Questions?

Time for a demo ! →

