

Plan of the presentation

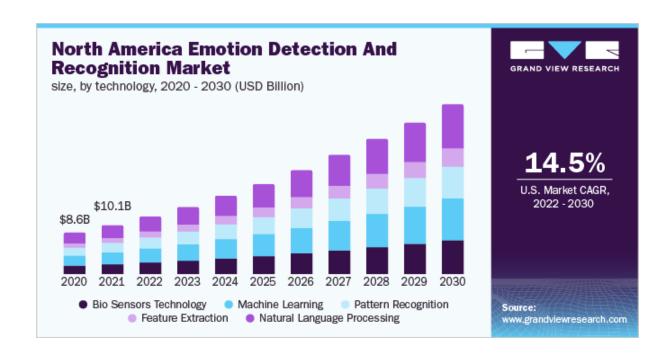
- Introduction and goals of the project
- Data collection and cleaning
 - Data sources
 - Data cleaning
 - Creating SQL database
 - Exposing data with API
- Exploratory Data analysis (EDA)
 - Emotions in everyday life
- Used models
 - Deep Learning
 - Convolution Neural Networks (CNN)
 - Pre-trained CNN model
- Summary

Introduction

Emotions are what make us human.

Emotion recognition software uses artificial intelligence (AI) and machine learning to interpret human emotions from text, voice, facial expressions, and other non-verbal cues.

The global Emotion AI market generated **\$1.8 billion in 2022** and is projected to reach **\$13.8 billion by 2032.**



Introduction

Facial Emotion recognition

Entertainment

- Face filters
- Virtual make up
- Emotion-aware Gaming

Healthcare

- Telemedicine
- Patient Monitoring
- Autism Spectrum Therapy

Automotive

- Real-time driver monitoring
- In-car personalization

Marketing

- Test emotions in ads for targeted marketing
- Evaluate user experience with digital interfaces

On-line meetings

- Track people engagement
- Analyse emotions during hiring interviews





How good is AI facial emotion recognition?

What are used models? How do they work?

What factors affect the model? How does the quality and quantity of data impact the results?

What emotions can be detected?



Data Sources

Kaggle (flat file)

FER-2013 (flat file)

API to gather more images

Emotions in everyday life (csvm file)

Web scrapping

CSV file

Emotions in Everyday Life, D. Trampe, J. Quoidbach, M. Taguet, 10.1371/journal.pone.0145450

id	Hours	Day	Pride	Love	Норе	Gratitude	Joy	Satisfaction	Awe	 Alertness	Anxiety	Disdain	Ofense	Guilt	Disgust	Fear	Embarassment	Sadness	Anger
1	1.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	14.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	14.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
1	14.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
1	15.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0

Change data types to numeric

Remove rows with missing values (1233 rows)

Shape

(69544, 21)



(68311, 21)

Number of unique values for "id"

12211



12108

Web scrapping

facs_single_units

Example	Facial Muscle	Description	Action Unit
https://imotions.com/wp-content/uploads/2022/1	Frontalis, pars medialis	Inner Brow Raiser	1
https://imotions.com/wp-content/uploads/2022/1	Frontalis, pars lateralis	Outer Brow Raiser (unilateral, right side)	2
https://imotions.com/wp-content/uploads/2022/1	Depressor Glabellae, Depressor Supercilli, Cur	Brow Lowerer	4
https://imotions.com/wp-content/uploads/2022/1	Levator palpebrae superioris	Upper Lid Raiser	5



facs_emotions_units

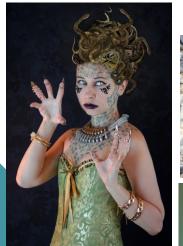
Description	Action Units	Emotion
Cheek Raiser, Lip Corner Puller	6 + 12	Happiness / Joy
Inner Brow Raiser, Brow Lowerer, Lip Corner De	1 + 4 + 15	Sadness
Inner Brow Raiser, Outer Brow Raiser, Upper Li	1 + 2 + 5 + 26	Surprise
Inner Brow Raiser, Outer Brow Raiser, Brow Low	1 + 2 + 4 + 5 + 7 + 20 + 26	Fear
Brow Lowerer, Upper Lid Raiser, Lid Tightener,	4 + 5 + 7 + 23	Anger
Nose Wrinkler, Lip Corner Depressor, Lower Lip	9 + 15 + 16	Disgust
Lip Corner Puller, Dimpler	12 + 14 (on one side of the face)	Contempt

- Cleaning values in column Action Units
- Exploding the table with emotion units to connect with table containing single units

API images

Removing some picturess, or moving them to different categories

"Anger"









"Fear"









API images

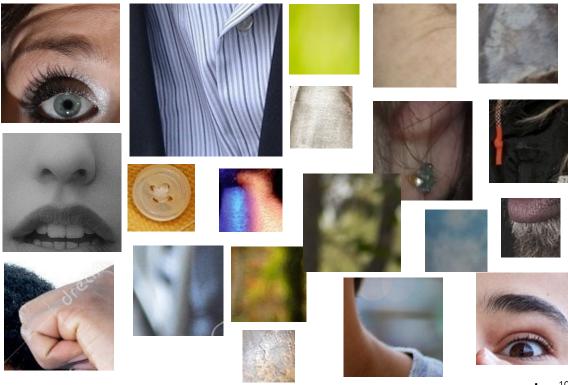
Haarcascade classifier from OpenCV for face detection

face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + 'haarcascade_frontalface_default.xml')

Face not detected



Detected as "face"



API images

PixaBay	Anger	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	Total
Initial	47	7	56	50	50	50	51	311
First selection	26	5	7	36	33	17	23	147
Face detection	18	3	4	26	25	15	18	109

DuckDuckGo	Anger	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	Total
Initial	84	99	95	97	92	93	94	654
First selection	73	71	70	89	59	71	88	521
Face detection	62	63	55	79	58	51	80	448

Images from flat files(data base)

	Anger	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	Total
Kaggle	890	439	570	1406	524	746	775	5350
FER-2013	3995	436	4097	7215	4965	4830	3171	28709

- Not balanced data, Disgusted' face is in minority
- Fer-2013 almost 6 time larger than Kaggle data set
- Randomly picked 200 images from each category

Images into Data Frames

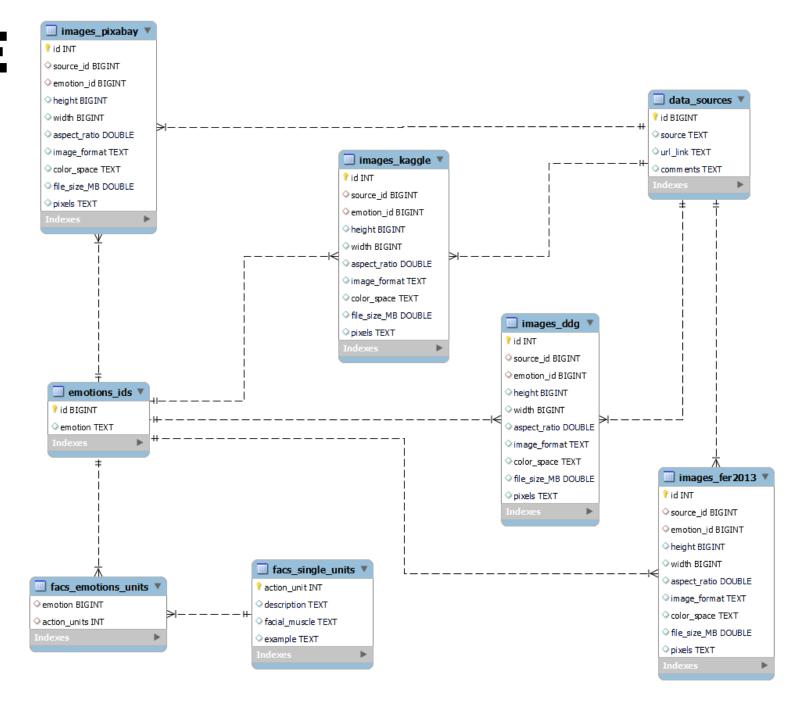
```
emotions = ['Anger', 'Disgust', 'Fear', 'Happiness', 'Neutral', 'Sadness', 'Surprise']
pixabay path = '1 pixabay images/1 Face Extraction/'
pixabay = images_to_tables(pixabay_path, categories=emotions, source=1)
pixabay
      source_id emotion_id height width aspect_ratio image_format color_space_file_size_MB
                                                                                                                                    pixels
                                302
                                       302
                                                1.000000
                                                                   JPG
                                                                                RGB
   0
                                                                                                  [[[255, 255, 255], [255, 255, 255], [255, 255,...
                                                1.050903
  1
                               1218
                                      1280
                                                                   JPG
                                                                                RGB
                                                                                         0.439991
                                                                                                      [[[68, 68, 68], [73, 73, 73], [63, 63, 63], [8...
                                                1.000000
                                                                   JPG
                                                                                         0.136570 [[[231, 231, 231], [232, 232, 232], [233, 233,...
   2
                          0
                                620
                                       620
                                                                                RGB
   3
                                410
                                       410
                                                1.000000
                                                                   JPG
                                                                                RGB
                                                                                         0.041554
                                                                                                      [[[36, 36, 36], [36, 36, 36], [36, 36, 36], [3...
                                                1.000000
                                                                   JPG
                          0
                                320
                                       320
                                                                                RGB
                                                                                                   [[[255, 255, 255], [126, 126, 126], [79, 79, 7...
   4
```

SQL DATABASE

List of tables

all_images
data_sources
emotions_ids
facs_emotions_units
facs_single_units
images_ddg
images_fer2013
images_kaggle
images_pixabay

Total nr of images 3357



Exosing data with API

Welcome to the facial emotion recognition database

The available data was collected for facial emotion recognition project and includes images that capture different facial expressions. There are 3357 images in total and they originate from diverse data sources. For those downloaded via API, faces were initially detected and extracted from images. Images from Kaggle and FER-2013 already possess the appropriate format.

The available options for exploration are below. Please enter the selected option in the explore window.

To adjust the number of results per page, modify the associated page and page_size parameters:

http://127.0.0.1:8080/images/?page=1&page_size=50

To see list of all collected images use this link:

List of all images

To access a single image, go to /images/{img_id} and replace {img_id} with the image number (1-3357).

Explore Images based on the source:

- 1 : data from PixaBay API
- 2 : data from DuckDuckGo API
- 3 : data from Kaggle
- 4: data from FER-2013

Source ID: Explore

Explore Images based on color:

- 0 : Grayscale
- 1 : RGB

Color: Exploret

```
// 20240213164729
  // http://127.0.0.1:8080/images/emotions?emotion=5
     "images": [
                   "aspect ratio": 1,0017921146953406.
                   "color space": "RGB",
                   "emotion": "Surprise",
                   "file size MB": 0.06939506530761719,
                   "height": 558,
                   "image format": "JPG",
                   "pixels": "[[[ 1 2 6]\n [ 1 2 6]\n [ 1 2 6]\n ...\n [ 4
      5 9]\n [ 4 5 9]\n [ 4 5 9]\n\n [[ 1 2 6]\n
                 2 6]\n ...\n [ 4 5 9]\n [ 4 5 9]\n [ 4 5 9]\n [ 7 5 9]\n [ 8 5 9]\n [ 9 5 9]\
 1 2 6]\n [ 1 2 6]\n [ 1 2 6]\n ...\n [ 4 5 9]\n [ 4 5
     9]\n [ 4 5 9]]\n\n ...\n\n [[ 20 118 172]\n [ 25 125 179]\n [ 33 133
  191]\n ...\n [ 7 13 20]\n [ 7 13 20]\n [ 5 13 20]\n\n [ 16 116
 170]\n [ 21 121 175]\n [ 26 126 184]\n ...\n [ 7 13 20]\n [ 8 14 21]\n
 [ 6 14 21]]\n\n [ 18 118 172]\n [ 23 123 177]\n [ 23 123 181]\n ...\n [
8 14 21]\n [ 8 14 21]\n [ 7 15 22]]]",
                   "source": "Pixabay API",
                 "url link": "https://pixabay.com/service/about/api/",
                   "width": 559
```



Year of data collection (February 2013 to April 2014)

id	Hours	Day	Pride	Love	Hope	Gratitude	Joy	Satisfaction	Awe	
1	1.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	14.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

- completed a total number of 65,721 emotion reports over an average of 35 days
- smartphone application monitored real-time emotions of an exceptionally large (N = 11,000+) and heterogeneous participants sample.

75% Female 25% Male

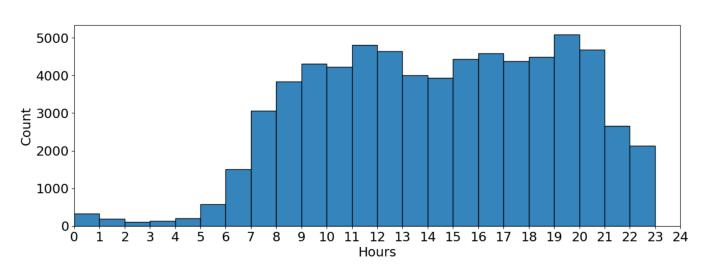
Age: 14-74 years

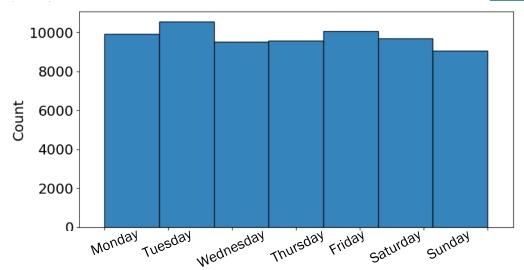
Nr of resonses: 1 - 263 per person

93% French, rest Swiss Belgian or other

- how often do people experience emotions in general?
- which emotions do people specifically experience?

Number of questioners completed during different days of the week and times of the day

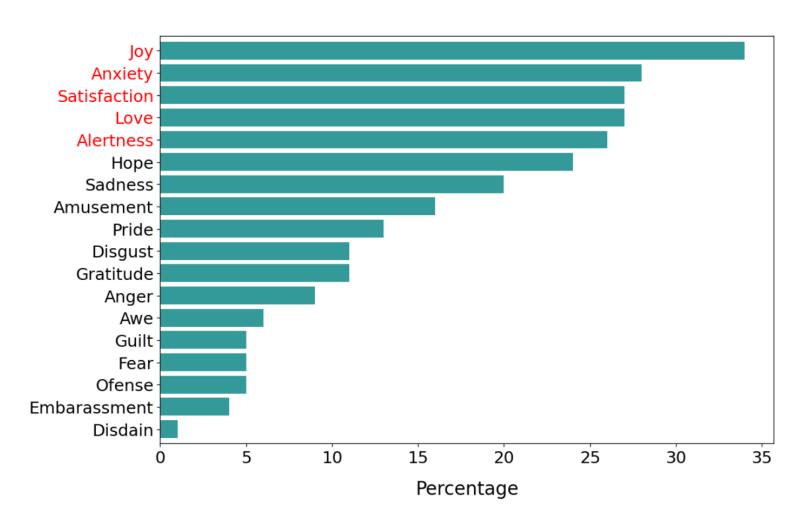




1614 only between 23-5

Excluded from further analysis

Evenly distributed across the week



Positive

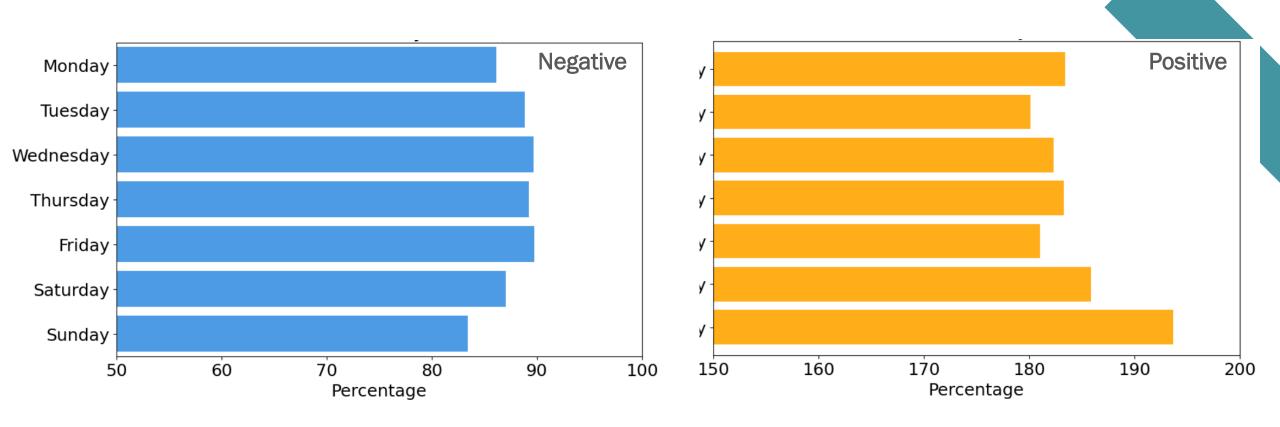
Joy
Satisfaction
Love
Alertness
Hope
Amusement
Pride
Gratitude
Awe

Negative

Anxiety
Sadness
Disgust
Anger
Guilt
Fear
Ofense
Embarrassment
Disdain

- Participants experienced at least one emotion 90% of the time.
- People experienced positive emotions
 2.5 times more often than negative emotions.

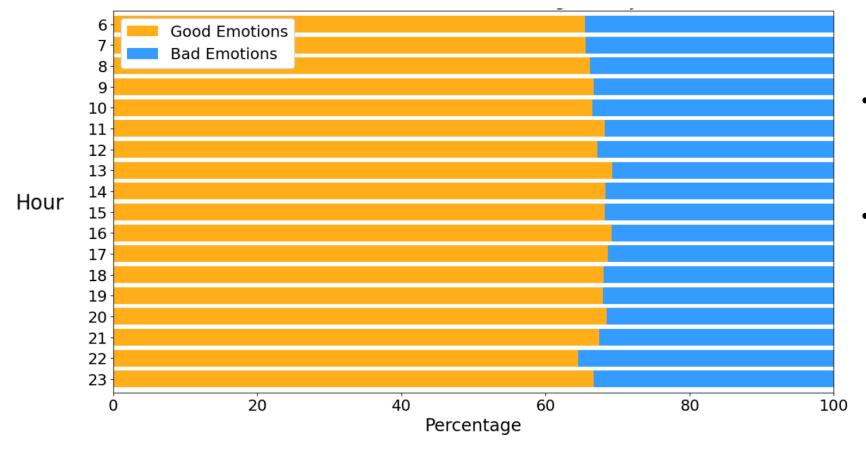
How do emotions change throughout **the week**?



We feel worse in the middle of the week

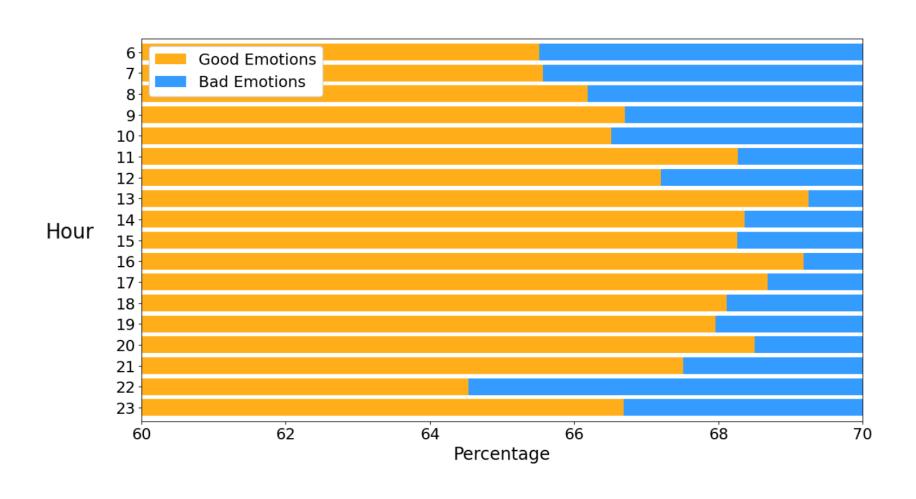
© We feel better during the weekend

How do emotions change throughout **the day**?



- Positive emotions dominate – over 60% of time
- It seems that proportion of positive and negative emotions is not changing much during the day ...

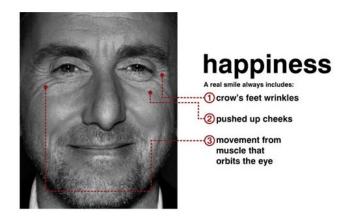
How do emotions change throughout **the day**?

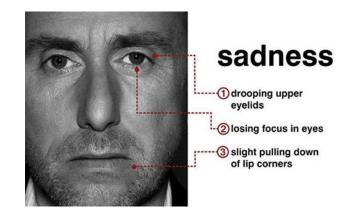


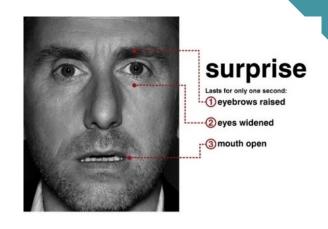
... but if we zoom in we can see fluctuations during the day

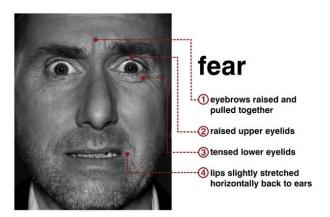
What emotions can be detected?

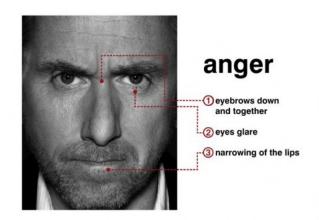
Universal facial expressions that we all use, even across cultural divides (research by Dr. Paul Ekman)

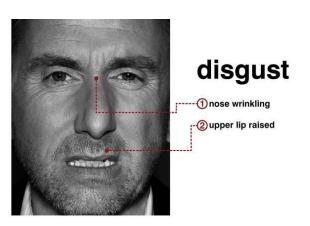








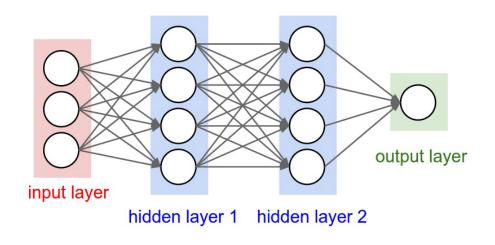




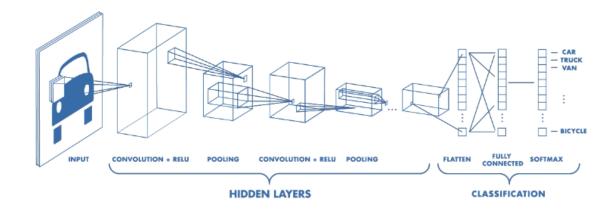
https://www.paulekman.com/

How?

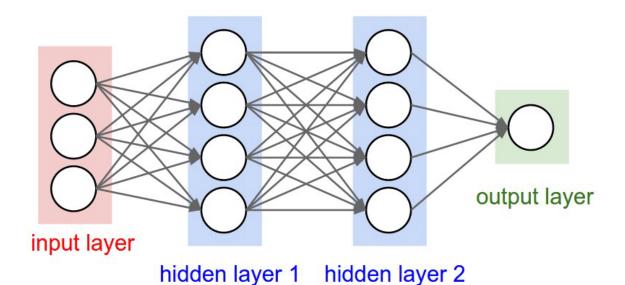
Deep Learning



Convolutional Neural Networks



Pre-trained CNN model



- Change all images to gray scale, put the same size
- Flatten the image before modeling
- Normalize values of pixels to be in range 0-1
- Split data into train and test set

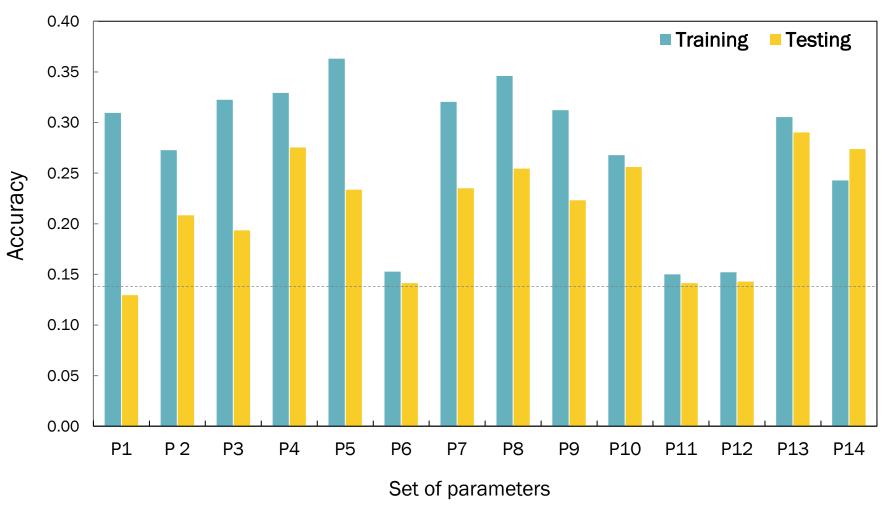
```
model = Sequential([
  Dense(2048, activation='relu', input_shape=(img_size*img_size,)),
  Dense(1024, activation='relu'),
  Dense(512, activation='relu'),
  Dense(256, activation='relu'),
  Dense(128, activation='relu'),
  Dense(7, activation='softmax'),
model.compile(
  optimizer=Adam(learning rate=0.001),
  loss='categorical crossentropy',
  metrics=['accuracy'],
history = model.fit(
 X train,
  to categorical(y train),
  epochs=20,
  batch size=60,
```

Testing of different parameters

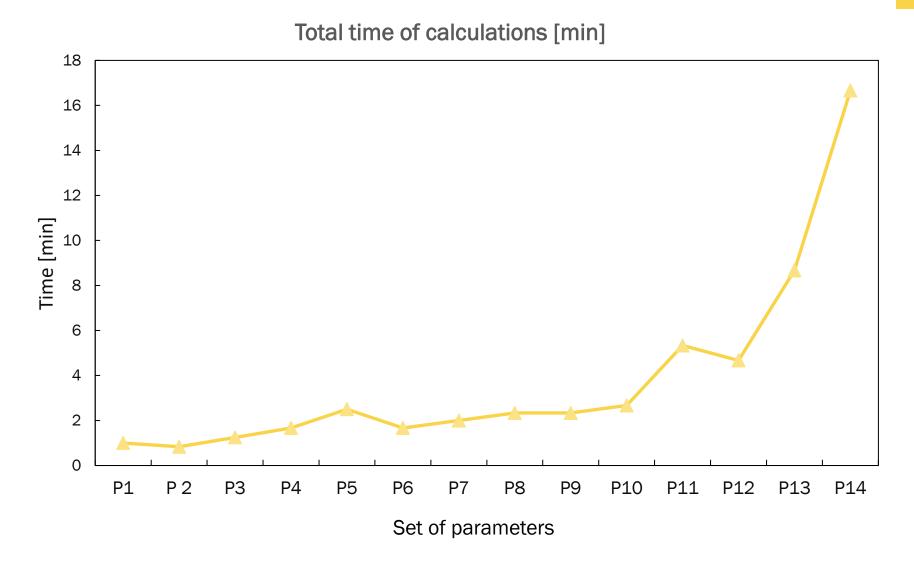
Params.	Nr. layers	Nuerons/layer	Activation	Learning rate	Epochs	Batch_size	Training loss	Training accuracy	Time/epoch [s]	Total time [min]	Test loss	Test accuracy
P1	3	128/64/32	relu	0.001	10	50	1.79	0.31	6	1	1.95	0.13
P2	3	128/64/32	relu	0.001	10	60	1.86	0.27	5	1	2.21	0.21
Р3	3	128/64/32	relu	0.001	15	60	1.76	0.32	5	1	2.09	0.19
P4	3	128/64/32	relu	0.001	20	60	1.74	0.33	5	2	1.89	0.28
P5	3	128/64/32	relu	0.001	30	60	1.68	0.36	5	3	1.95	0.23
P6	3	128/64/32	relu	0.01	20	60	1.95	0.15	5	2	1.95	0.14
P7	3	128/64/32	relu	0.0001	20	60	1.74	0.32	6	2	1.92	0.24
P8	3	256 / 64 / 32	relu	0.001	20	60	1.72	0.35	7	2	2.13	0.25
P9	4	256/128/64/32	relu	0.001	20	60	1.77	0.31	7	2	1.94	0.22
P10	5	256/128/64/32/16	relu	0.001	20	60	1.81	0.27	8	3	1.87	0.26
P11	6	512/128/64/32/16	relu	0.001	20	60	1.95	1.95	16	5	1.95	0.14
P12	6	512/128/64/32/16	sigmoid	0.001	20	60	1.95	0.15	14	5	1.95	0.14
P13	5	1024/512/256/128/64	relu	0.001	20	60	1.77	0.31	26	9	1.84	0.29
P14	5	2048/1024/512/256/128	relu	0.001	20	60	1.87	0.24	50	17	1.86	0.27

224x224 pixels





224x224 pixels



Decrease the image size to speed up calculations?

64x64 pixels

Nr. layers	Nuerons/layer	Activation	Learning rate	Epochs	Batch_size	Training loss	Training accuracy	Time/epoch [s]	Total time [min]	Test loss	Testing accuracy
5	2048/1024/512/256/128					1.80	0.26	6	6	1.86	0.25
6	2048/1024/512/256/128/64		0.001	20	60	1.77	0.28	6	6	1.88	0.24
6	4096/2048/1024/512/256/128	relu				1.95	0.15	15	15	1.95	0.14
7	4096/2048/1024/512/256/128/64					1.85	0.22	15	15	1.88	0.20
3+damping	512/d0.5/256/d0.5/128/d0.5					1.95	0.15	2	2	1.95	0.14

Decrease the image size to speed up calculations?

64x64 pixels

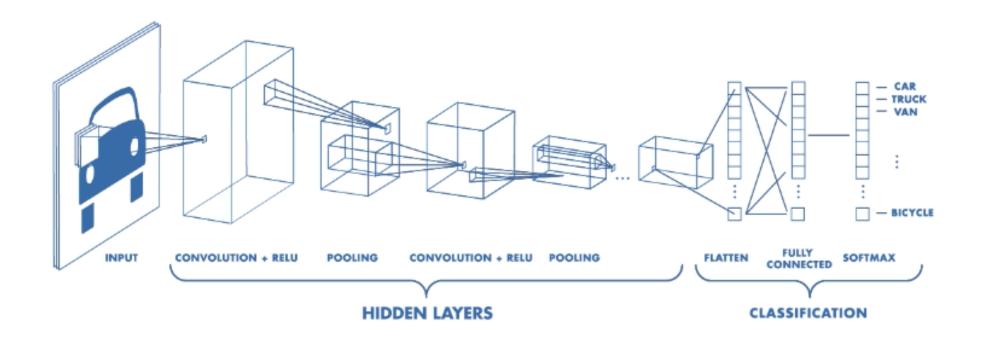
Nr. layers		Nuerons/layer	Activation	Learning rate	Epochs	Batch_size	Training loss	Training accuracy	Time/epoch [s]	Total time [min]	Test loss	Testing accuracy
5	2048	8/1024/512/256/128					1.80	0.26	6	6	1.86	0.25
6	2048/	1024/512/256/128/64				00	1.77	0.28	6	6	1.88	0.24
6	4096/2	048/1024/512/256/128	relu	0.001	20	60	1.95	0.15	15	15	1.95	0.14
7	4096/204	48/1024/512/256/128/64	ı				1.85	0.22	15	15	1.88	0.20
3+damping	g 512/d	0.5/256/d0.5/128/d0.5					1.95	0.15	2	2	1.95	0.14
	5 2	2048/1024/512/256/128	relu	0.001	20	60	1.87	0.24	50	17	1.86	0.27

224x224 pixels

With smaller image size the accuracy was similar, and the calculation were faster

However, making the model more complex leads to a decrease in accuracy ...

Specially designed to work with images



CNNs can retain spatial information as they take the images in the original format.

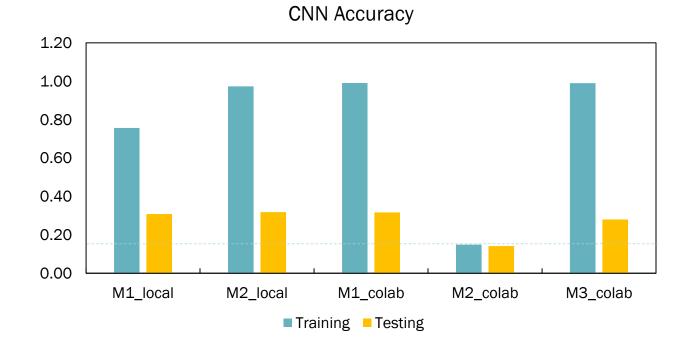
- No need of flattening the images
- Change all images to gray scale, resize
- Normalize values of pixels to be in range 0-1
- Split data into train and test set

Try different models

224x224 pixels

CNN	Descrition	Activation	Learning rate	Epochs	Batch_size	Training loss	Training accuracy	Time/epoch [s]	Total time [min]	Test loss	Testing accuracy
Model 1	Local computer	relu	0.001	5	60	0.75	0.76	60.00	5.00	2.15	0.31
Model 2	Local computer	relu	0.001	10	64	0.15	0.97	60.00	10.00	3.58	0.32
Model 1	colab	relu	0.001	30	64	0.04	0.99	18.00	9.00	4.64	0.32
Model 2	colab	relu	0.001	50	64	1.95	0.15	16.00	13.33	1.95	0.14
Model 3	colab	relu	0.001	50	32	0.03	0.99	33.00	27.50	3.79	0.28
Model 4	batch normalization	stopped 22 ou	stopped 22 out of 50 epoch		32	0.05	0.99	43.00	15.77	3.30	0.30
Model 5	with padding	memory	memory issues								
Model 6	data augmentation				men	nory issues, end	of free limit or	n colab			

Overfitting?



224x224 pixels

CNN	Descrition	Activation	Learning rate	Epochs	Batch_size	Training loss	Training accuracy	Time/epoch [s]	Total time [min]	Test loss	Testing accuracy
Model 1	Local computer	relu	0.001	5	60	0.75	0.76	60.00	5.00	2.15	0.31
Model 2	Local computer	relu	0.001	10	64	0.15	0.97	60.00	10.00	3.58	0.32
Model 1	colab	relu	0.001	30	64	0.04	0.99	18.00	9.00	4.64	0.32
Model 2	colab	relu	0.001	50	64	1.95	0.15	16.00	13.33	1.95	0.14
Model 3	colab	relu	0.001	50	32	0.03	0.99	33.00	27.50	3.79	0.28
Model 4	batch normalization	stopped 22 ou	ut of 50 epoch	50	32	0.05	0.99	43.00	15.77	3.30	0.30
Model 5	with padding	memor	memory issues								
Model 6	data augmentation		memory issues, end of free limit on colab								

Pre-trained CNN model

Load pre-trained CNN model

```
base_model = MobileNetV2(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
```

Take input layer, and one of tha lest output layers

```
base_input = base_model.layers[0].input
base_output = base_model.layers[-3].output
```

Modify last layers to train on new data

```
final_output = GlobalAveragePooling2D()(base_output)
final_output = layers.Dense(128, activation='relu')(final_output)
final_output = layers.Dense(64, activation='relu')(final_output)
final_output = layers.Dense(7, activation='softmax')(final_output)
new_model = keras.Model(inputs=base_input, outputs=final_output)
```

- Pre-trained on color images, expected format (img_size, img_size, 3)
- Issues with image format....
- Not so good results:

accuracy: 0.265

time: 50 min

Summary

Models

- CNN little bit better than Deep Learning
- Pre-trained models did not help much
- The best accuracy up to 0.3
- Not so easy to tune parameters
- Problems with overfitting in CNN

What can be impoved?

- Increase data set to avoid overfitting or
- Use in built methods for data augmentation
- For emotion recognition include facial features and not just compare full image
- Go beyond basic emotions.

Is Al good in recognizing human emotions?

http://localhost:8502/