ML4HC Project 3:
Medical imaging segmentation

09/04/2020

Background

Types of medical imaging

Computer Tomography (CT)

often used to evaluate:

- Presence, size and location of tumors
- Organs in the pelvis, chest and abdomen
- Colon health (CT colongraphy)
- Vascular condition/blood flow
- Pulmonary embolism (CT angiography)
- Abdominal aortic aneurysms (CT angiog
- Bone injuries
- Cardiac tissue
- Traumatic injuries
- Cardiovascular disease

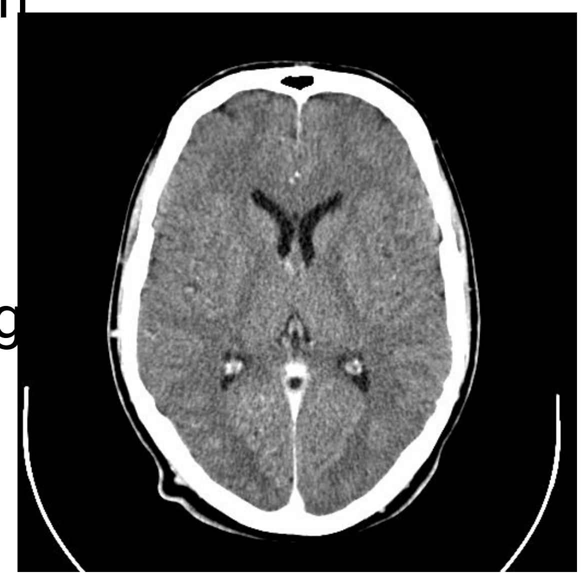


Image source: wikipedia

Types of medical imaging

Magnetic Resonance Imaging (MRI)

often used to evaluate:

- Blood vessels
- Abnormal tissue
- Breasts
- Bones and joints
- Organs in the pelvis, chest a
  spleen)
- Spinal injuries
- Tendon and ligament tears

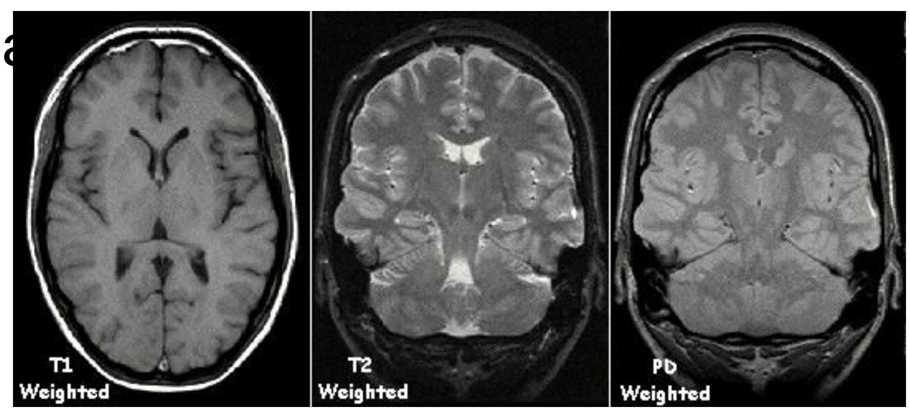


Image source: wikipedia

Types of medical imaging

Positron Emission Tomography (PET)

often used to evaluate:

- Neurological diseases such as Alzheimer’s and Multiple Sclerosis
- Cancer
- Effectiveness of treatments
- Heart conditions

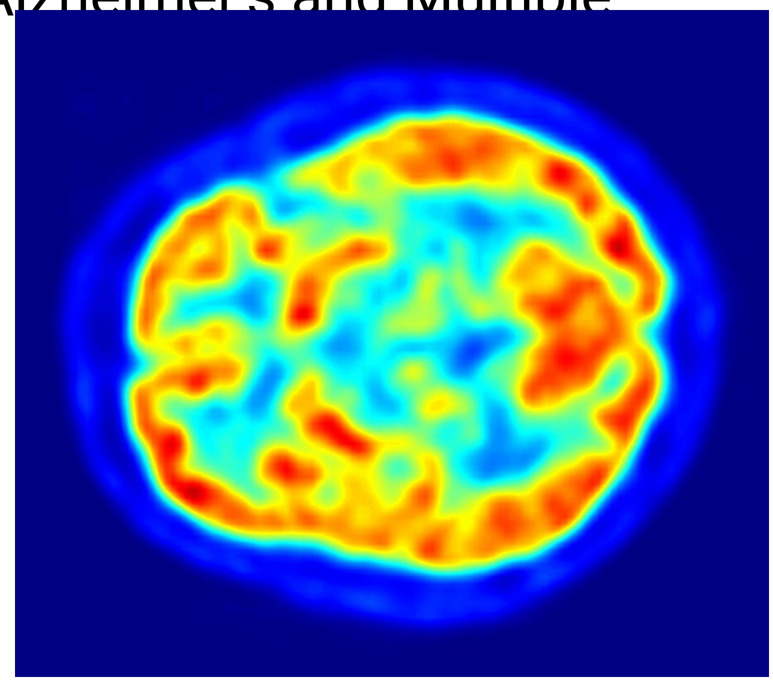


Image source: wikipedia

Types of medical imaging

Ultrasound

often used to evaluate:

- Pregnancy
- Abnormalities in the heart and blood vessels
- Organs in the pelvis and abdomen
- Symptoms of pain, swelling and infection

Image source: wikipedia

Types of medical imaging

X-Ray

typically used to evaluate:

- Broken bones
- Cavities
- Swallowed objects
- Lungs
- Blood vessels
- Breast (mammography)

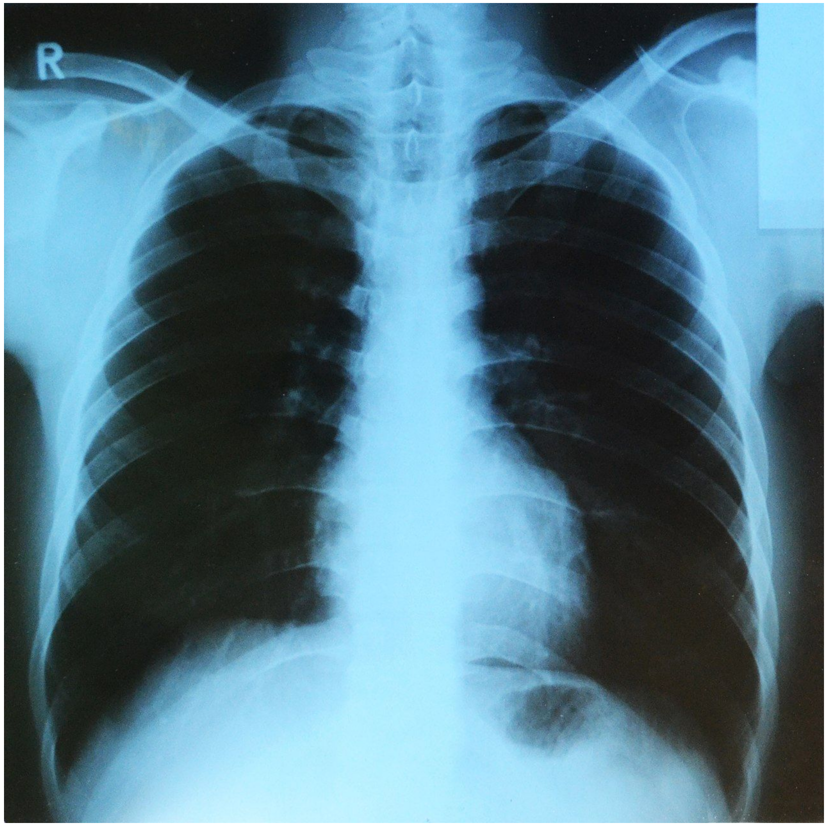
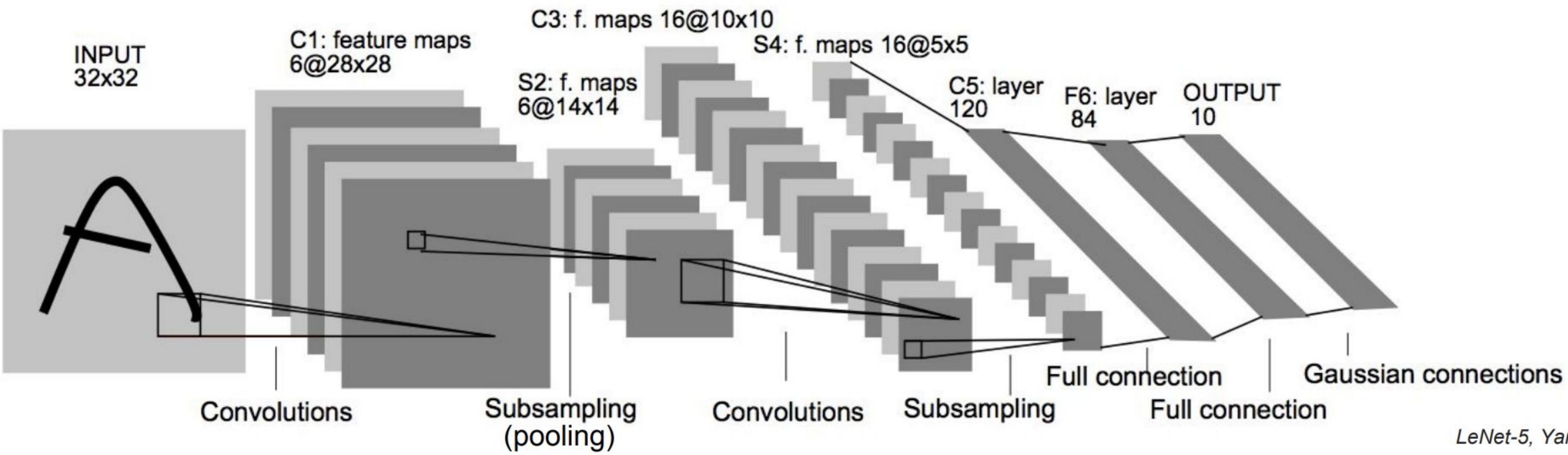


Image source: wikipedia

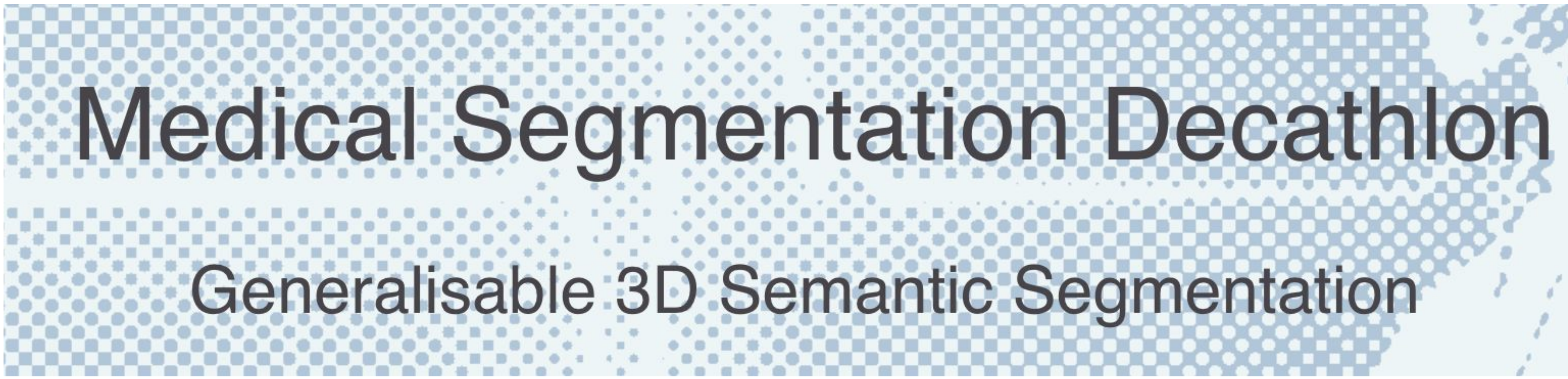
Convolutional neural network architecture



LeNet-5, Yann LeCun et al

Medical imaging dataset

http://medicaldecathlon.com/



Covid-19 CT scan dataset (for your own interest):

https://github.com/ieee8023/covid-chestxray-dataset

Project 3
Prostate structure segmentation

Prostate cancer

- Second most common cause of cancer death in male (⅙)
- Prostate anatomy from diagnostic biopsies is difficult to determine, leading to cancer detection failure.
- Some attributes the failure to the hesitation to sample one of the two major parts of the glands
  - Peripheral zone (PZ, more easily reached)
  - Central gland (CG, less accessible)
- **Task: outline these two non-overlapping adjacent regions of the gland**

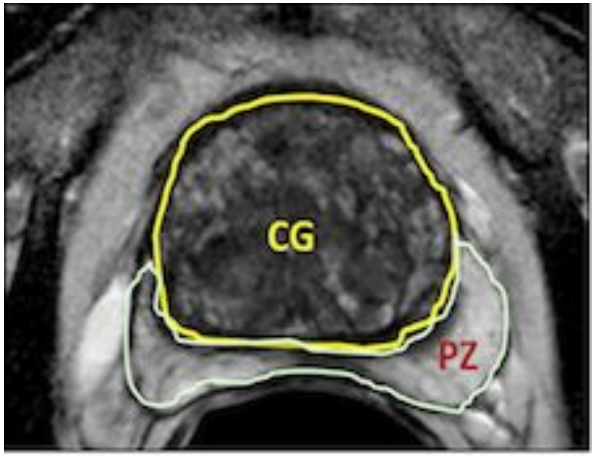
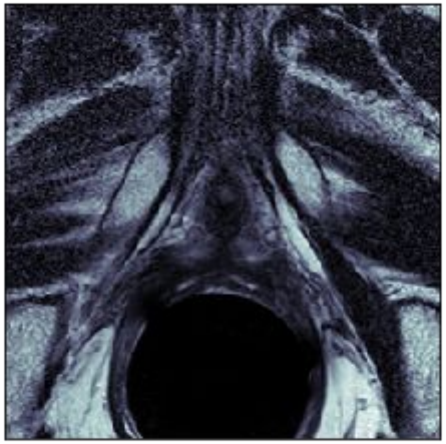


Image source: https://wiki.cancerimagingarchive.net/display/Public/NCI-ISBI+2013+Challenge+-+Automated+Segmentation+of+Prostate+Structures

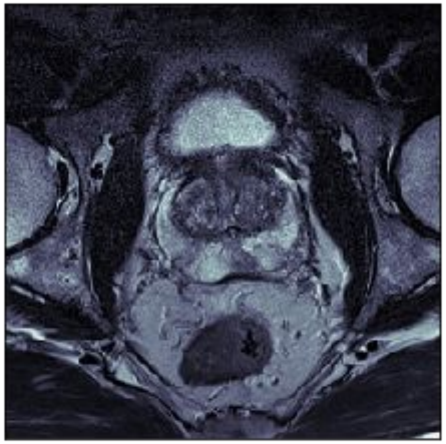
Data

- **3D prostate magnetic resonance images (MRIs) from**
  - Boston University
  - Radboud University, Nijmegen Medical Centre, the Netherlands.
- **Image types: a mix of**
  - 1.5T (standard)
  - 3T (higher clarity and better detail, more likely to have artifacts present)

1.5T



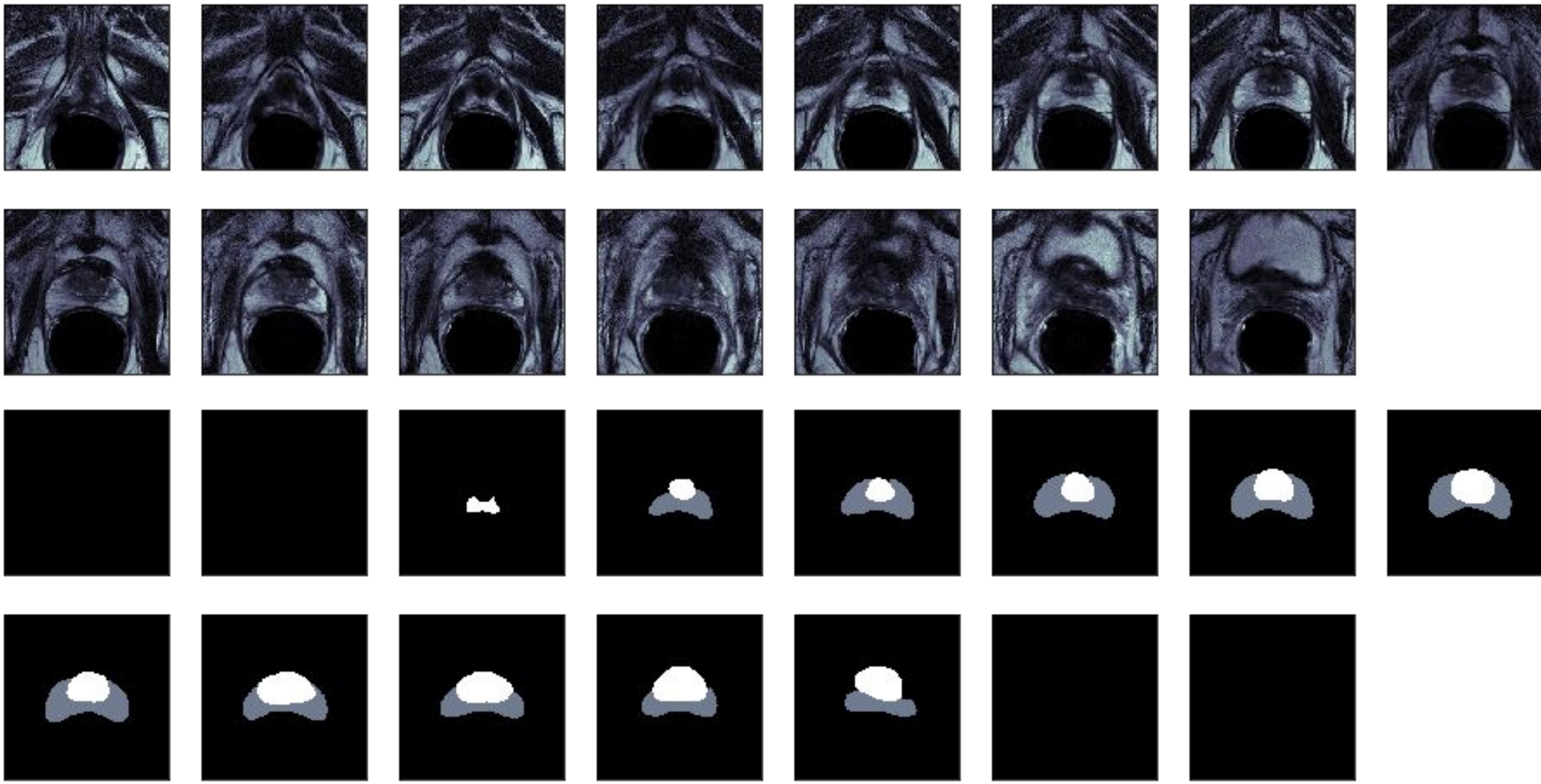
3T



Data

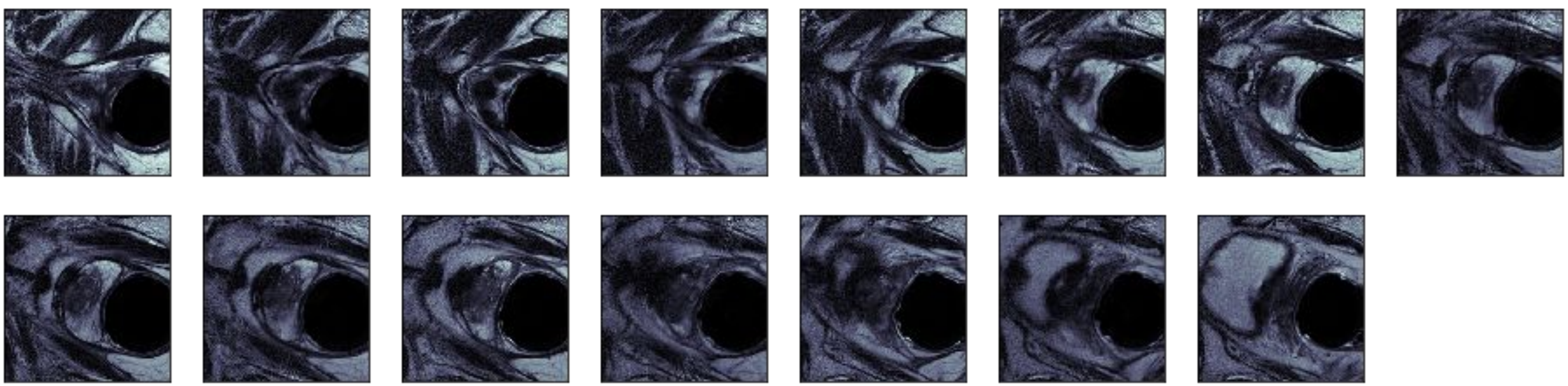
- **Image size**
  - depth x 256 x 256 (original size: 1.5T 320x320; 3T 400x400)
- **Labels**
  - 0: background
  - 1: Peripheral zone (PZ)
  - 2: Central Gland (CG)

Example



Data

- **60 subjects**
  - Training: 50 subjects
  - Testing: 10 subjects
  - 2 test sets: one with random rotation , the other without
- Example (degree=73º, counter-clockwise)

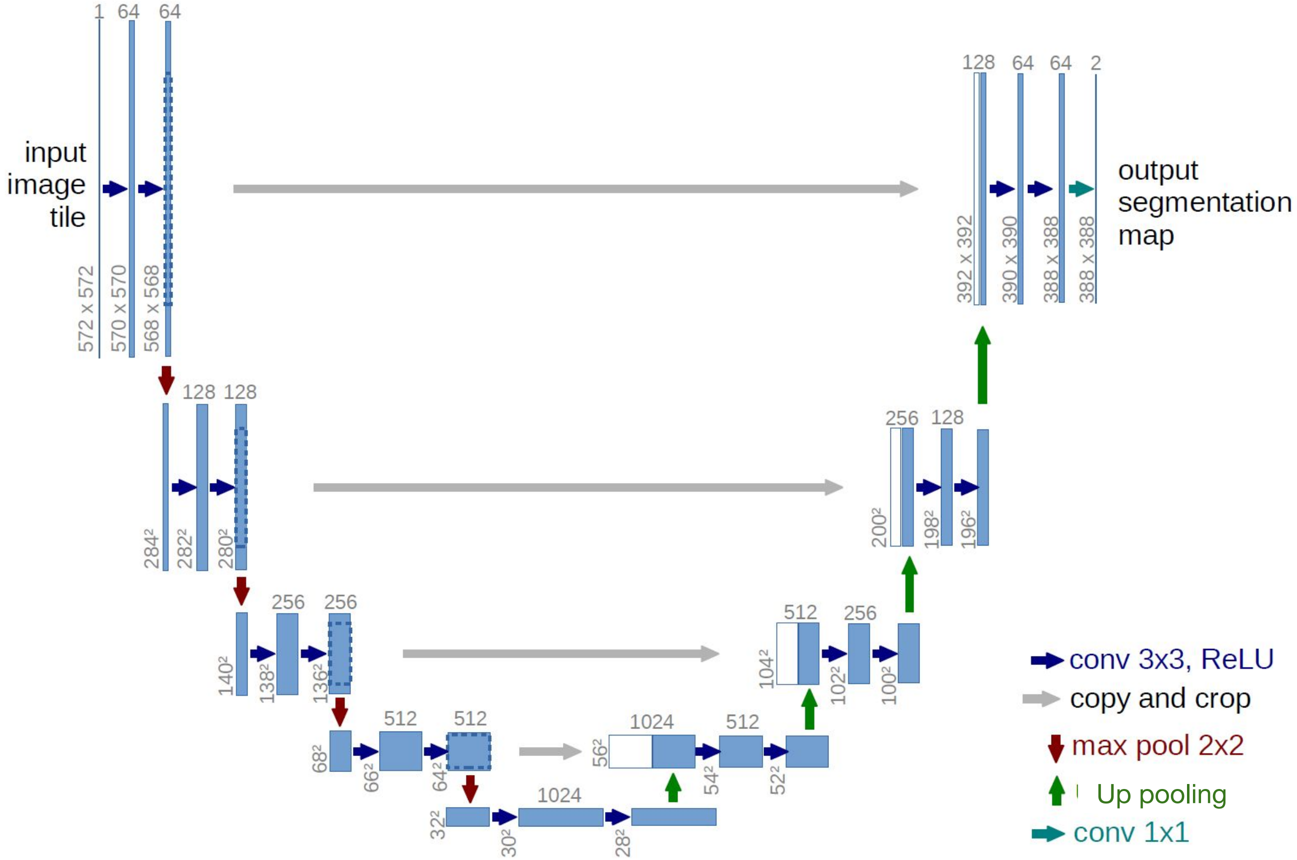


Segmentation methods

- Simple Linear Iterative Clustering (SLIC)
- Markov random field (MRF)
- Convolutional neural networks (U-Net and etc.)

U-net: Convolutional networks for biomedical image segmentation.

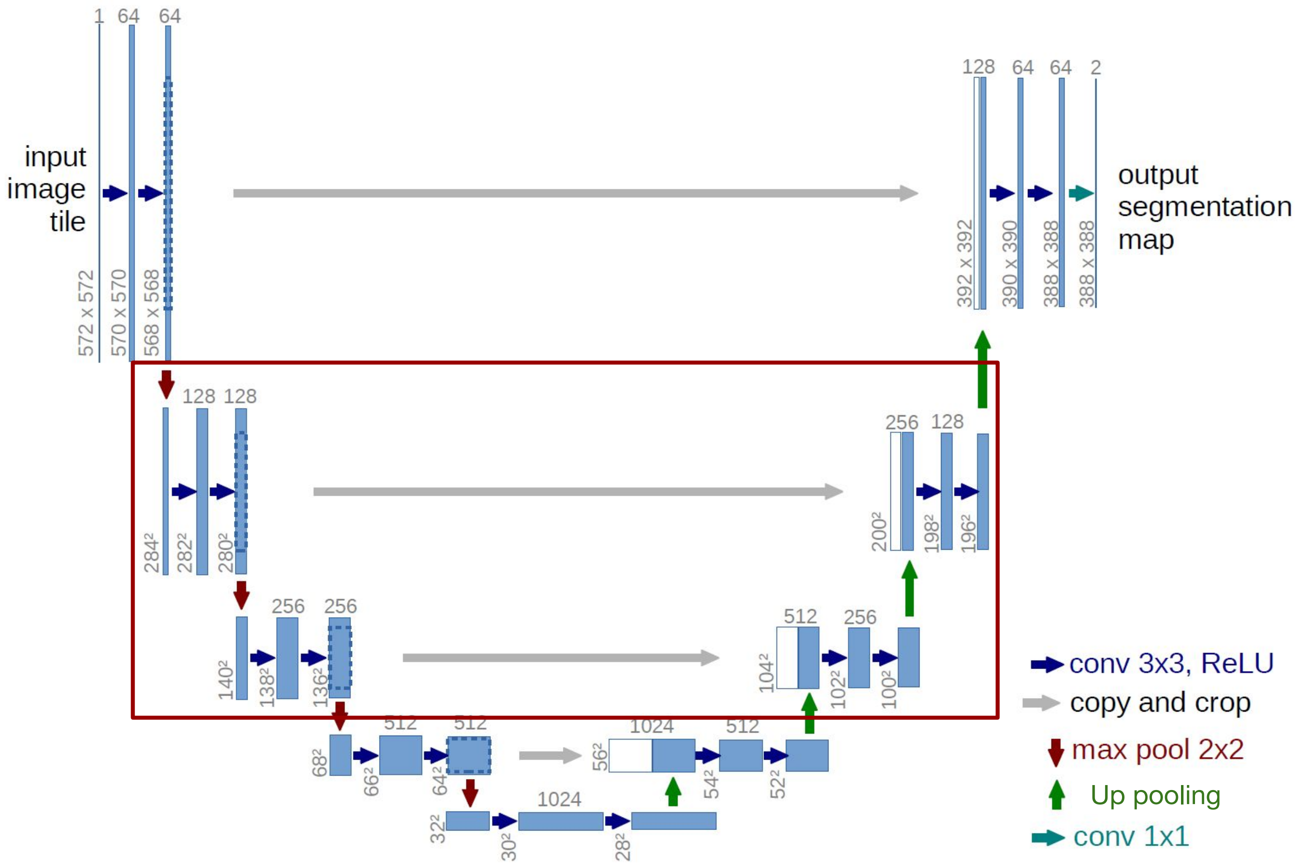
Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.



https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

U-net

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.



https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

U-net

128 128
284²
282²
280²
256 256
140²
138²
136²
copy
256 128
200²
198²
196²
up-pooling
512 256
104²
102²
100²

Segmentation evaluation metrics

Precision

- Overall:
  - measures the prevalence of correctly labelled pixels
  - limitation: it has bias in the presence of very imbalanced classes
- Per-class:
  - measures the proportion of correctly labelled pixels for each class and then averages over the classes.
  - limitation: not suitable for data with strong background class

Segmentation evaluation metrics

Intersection over Union (IoU, also called Jaccard index)

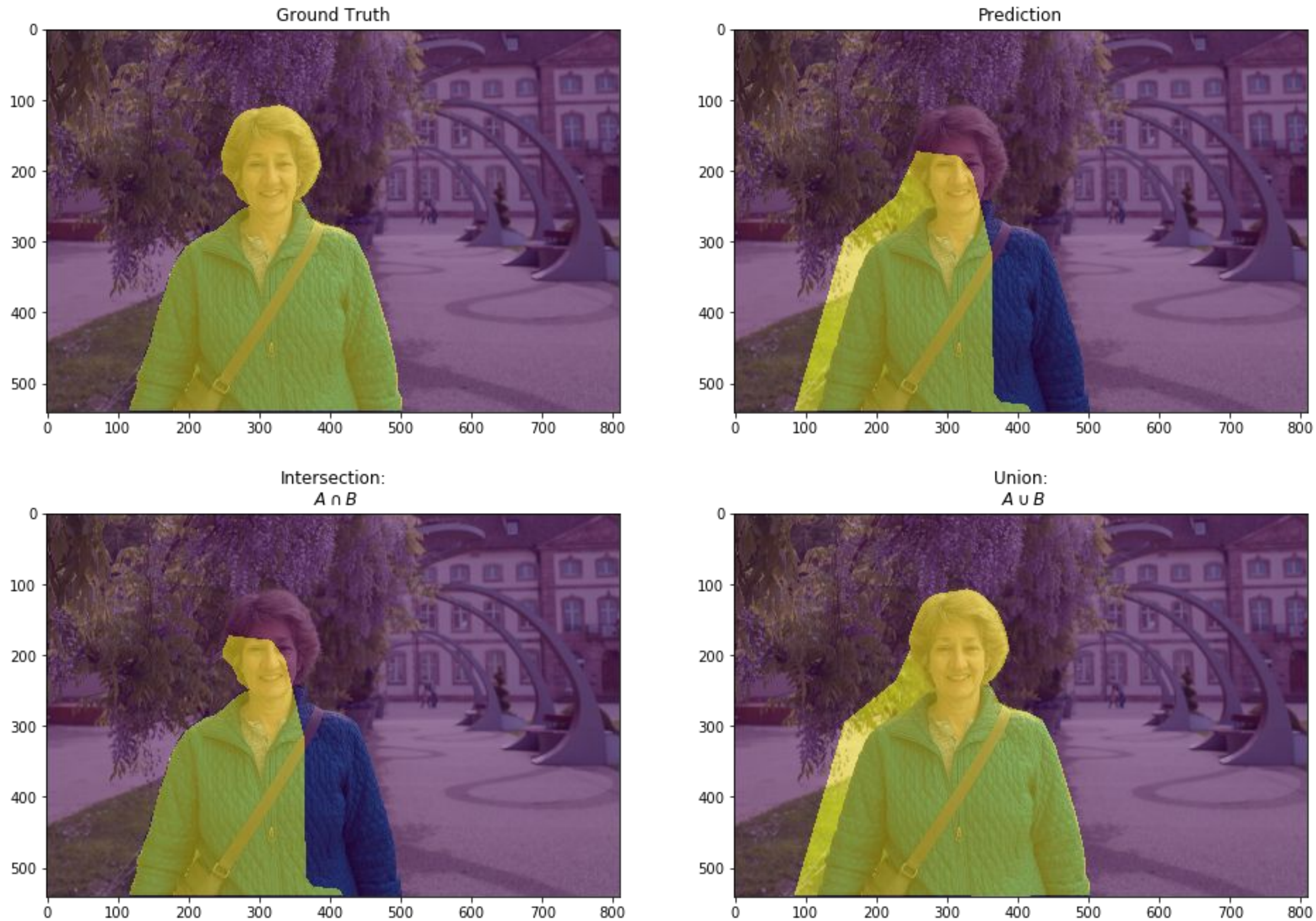
- measures the intersection over the union of the labelled segments **for each class** and **reports the average**

$$\mathrm{IoU} = \frac{\text{groundtruth} \cap \text{prediction}}{\text{groundtruth} \cup \text{prediction}}$$

- limitation: it evaluates the amount of pixels correctly labelled, but not necessarily how accurate the segmentation boundaries are.

Intersection over Union (IoU)

Example



Segmentation evaluation metrics formulation

Confusion matrix *C*

$$C_{ij} = \sum_{I \in \mathcal{D}} |\{x \mid L^I_{gt}(x) = i \text{ and } L^I_{pd}(x) = j, x \in I\}|$$

Overall precision

$$OP = \frac{\sum_i^L C_{ii}}{\sum_i^L \sum_j^L C_{ij}}$$

Per-class precision

$$PC = \frac{1}{L} \sum_i^L \frac{C_{ii}}{\sum_j^L C_{ij}}$$

IoU

$$IoU = \frac{1}{L} \sum_i^L \frac{C_{ii}}{\sum_j^L C_{ij} + \sum_k^L C_{ki} - C_{ii}}$$

Tasks

- Segment images in the test sets into background, PZ and CG regions.
- The method/model need to be invariant to rotation

Deliverable

- Environment
- Segmentation results of two test sets.
  - Report OP, PC and IoU
- You can use more than one jupyter notebooks
- Document in details the usage of each jupyter notebook in a README.txt file (in a sequential order)
- A short report including methods, results (in tables or figures) and individual contribution.
- Please do not hardcode results
- Deadline: 29/04/2020 (send the zip file to xlyu@inf.ethz.ch)