Kidney Tumor Segmentation

Machine Learning Course
Project Progress
April 2019

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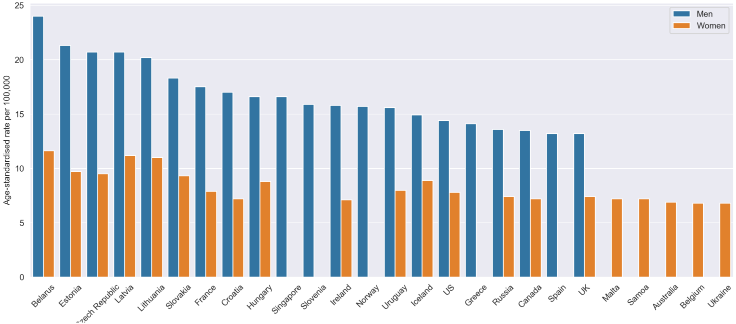
Motivation

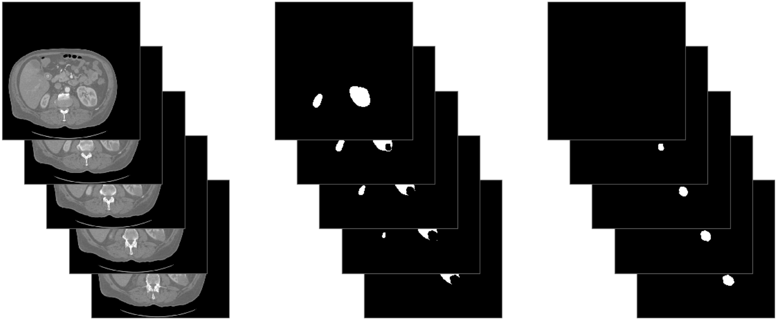


- Kidney cancer is the ninth most commonly occurring cancer in men and the 14th most commonly occurring cancer in women[1]
- Automatic semantic segmentation is a promising tool for developing advanced surgical planning techniques

[1] Kidney Cancer Statistics 2018, www.wcrf.org/dietandcancer/cancer-trends/kidney-cancer-statistics

Data: Abdominal Computing Tomography scans (volumetric images)

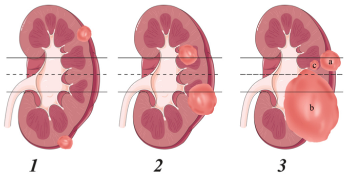
Goal: Kidney and kidney tumor semantic segmentation



3D image segmentation problem: an input is a volumetric data; outputs are collections of binary masks corresponding to object classes.

- Multivariate Analysis[3], Scoring System[4]

	1pt	2pts	3 pts
(R)adius (maximal diameter in cm)	≤4	>4 but < 7	≥ 7
(E)xophytic/endophytic properties	≥ 50%	<50%	Entirely endophytic
(N)earness of the tumor to the collecting system or sinus (mm)	≥7	>4 but <7	≤4
(A)nterior/Posterior	No points given. Mass assigned a descriptor of a, p, or x		
(L)ocation relative to the polar lines* * suffix "h" assigned if the tumor touches the main renal artery or vein	Entirely above the upper or below the lower polar line	Lesion crosses polar line	>50% of mass is across polar line (a) or mass crosses the axial renal midline (b) or mass is entirely between the polar lines (c)



Anatomical features*	Score
Longitudinal (polar) location	
Superior/inferior	1
Middle	2
Exophytic rate	
≥50%	1
<50%	2
Endophytic	3
Renal rim	
Lateral	1
Medial	2
Renal sinus	
Not involved	1
Involved	2
Urinary collecting system	
Not involved	1
Dislocated/infiltrated	2
Tumour size (cm)	
≤4	1
4.1–7	2
>7	3

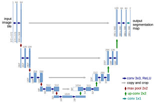
* Anterior or posterior face can be indicated with a letter ("a" or "p") following the score.

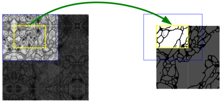
[3] Kutikov, Alexander, and Robert G. Uzzo. "The RENAL nephrometry score: a comprehensive standardized system for quantitating renal tumor size, location and depth." (2009)

[4] Ficarra, Vincenzo, et al. "Preoperative aspects and dimensions used for an anatomical (PADUA) classification of renal tumours in patients who are candidates for nephron-sparing surgery." (2009)

- CNNs[5], 3D CNNs[6−8]

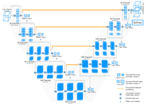
U-Net

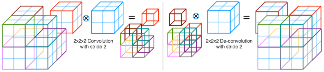




Overlap-tile strategy

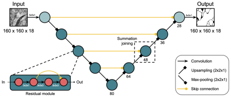
V-Net

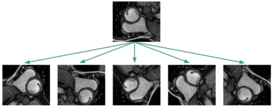




Convolution in 3D space

Residual Symm. U-Net





Augmentation

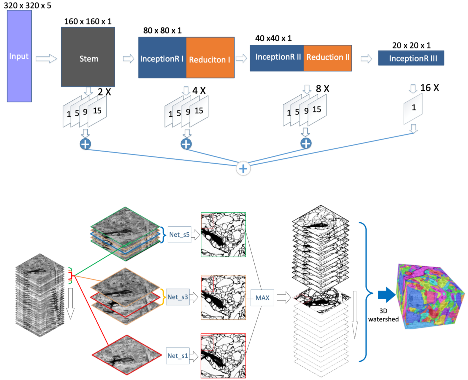
[5] Ronneberger, Olaf, et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation." (2015)

[6] Çiçek, Özgün et al. "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation." (2016)

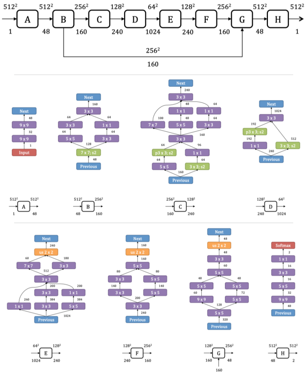
[7] Milletari, Fausto, et al. "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation." (2016)

[8] Lee, Kisuk et al. "Superhuman Accuracy on the SNEMI3D Connectomics Challenge." (2017)

DeepEM3DNet[9]

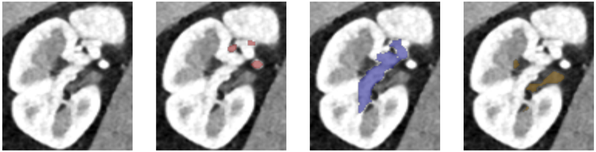


ICv1[10]



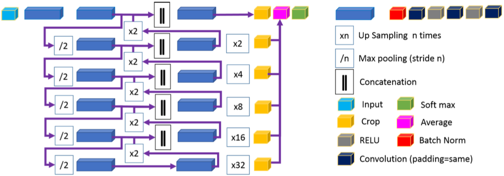
[9] Zeng, Tao et al. "DeepEM3D: Approaching human-level performance on 3D anisotropic EM image segmentation." (2017)
[10] Beier, Thorsten et al. "Multicut brings automated neurite segmentation closer to human performance." (2017)

- Kid-Net[7]

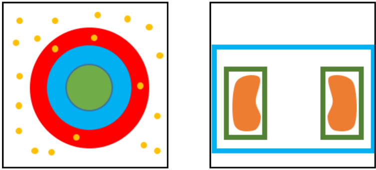


(a) CT Slice (b) Artery (c) Vein (d) Ureter

Architecture



Sampling Approach



[8] Taha, Ahmed, et al. "Kid-Net: Convolution Networks for Kidney Vessels Segmentation from CT-Volumes." (2018)

Exploratory Data Analysis

In total: data of 300 unique kidney cancer patients:

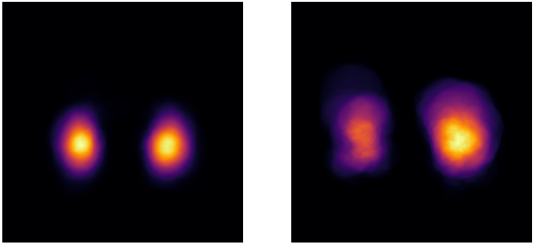
- 210 for training
  - further spilt into 168 (train) + 42 (validation)
- 90 for final evaluation

Training data case example.

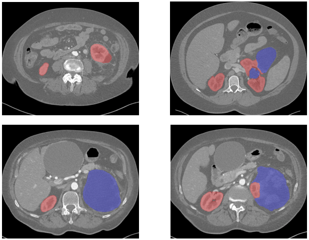
A CT scan slice through an axial (left), sagittal (middle) and coronal (right) plane.
Masked segments: kidney (red) and tumor (blue).

Exploratory Data Analysis

- Raw / Interpolated Data
- Location
- Data Balance
- Kidney-Tumor Boundary

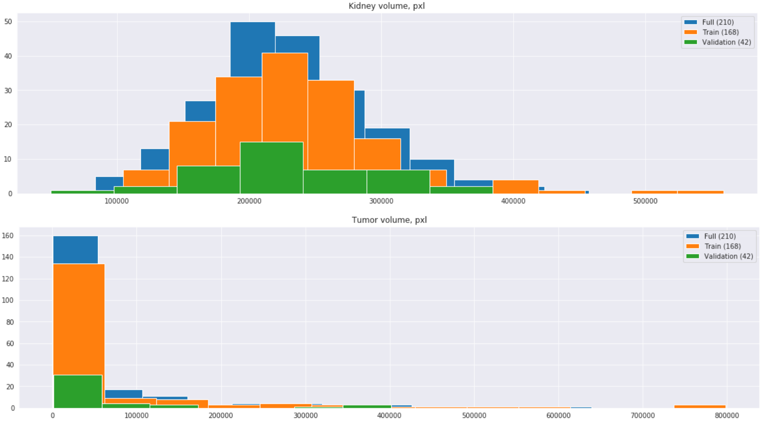


Mean average kidney (left) and tumor (right) location in the axial plane.



Edge cases: location, sizes, intersecting, boundaries.

Distribution of kidney size (top) and tumor size (bottom) in the full 210 data samples and separated 168 train and 42 validation cases.



- Generate all crop positions for window size 64 with stride 32 along all axes
- Calculate statistics (kidney volume, tumor volume) for each crop
- Drop crops for which kidney volume is 0
- Convert original data voxels from NIFTI to greyscale images
- Min-max scaling to avoid gradient explosion during the training

Augmentation

- random rotation in range $[-10^\circ, 10^\circ]$
- random scale change in range $[0.8, 1.2]$;
- random brightness change in range $[-0.4, 0.4]$;
- random contrast change in range $[-0.4, 0.4]$
- contrast limited adaptive histogram equalization (CLAHE).

3DUnet architecture

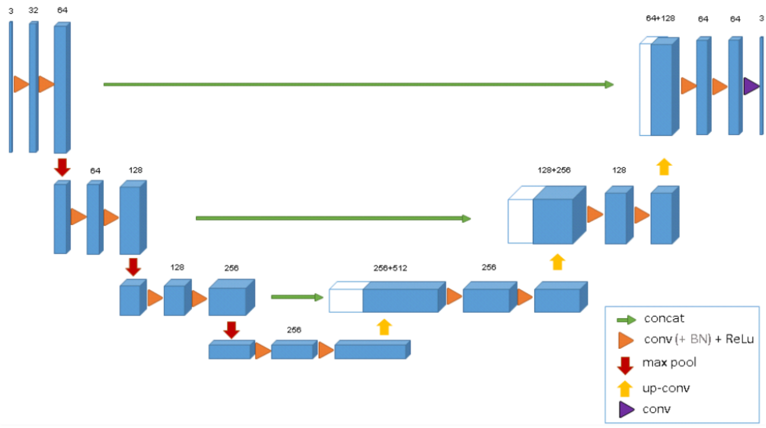


Figure 1: 3DUnet Architecture

Training pipeline

- Load data from the hd5f file and prepare crop
- Predict segmentations masks on the crops
- Compute the loss on predictions
- Back propagate and update weights

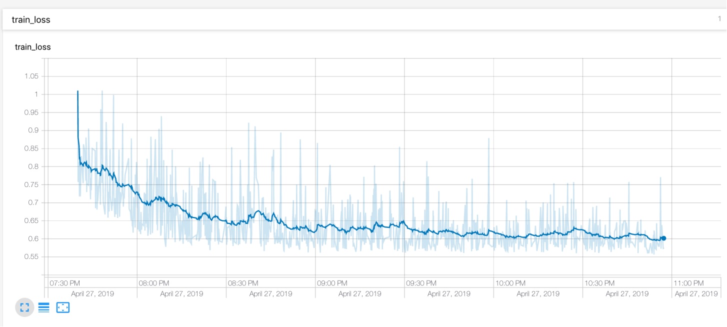


Figure 2: Train Loss

Evaluation pipeline

Scoring function

$$S = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\left(\frac{2\ n_{t,tp}^{(i)}}{2\ n_{t,tp}^{(i)} + n_{t,fp}^{(i)} + n_{t,fn}^{(i)}} + \frac{2\ n_{k,tp}^{(i)}}{2\ n_{k,tp}^{(i)} + n_{k,fp}^{(i)} + n_{k,fn}^{(i)}}\right)$$

- Prepare the evaluation sample crops
- Initialize an empty reference mask of the image size (for storing crop prediction result)
- Iterate over crops, predict and add to the corresponding place in the reference mask
- Calculate entries (number of predictions per pixel)
- Get a mean (by the entries) of the predictions mask

Training results

Mean training score: 0.7

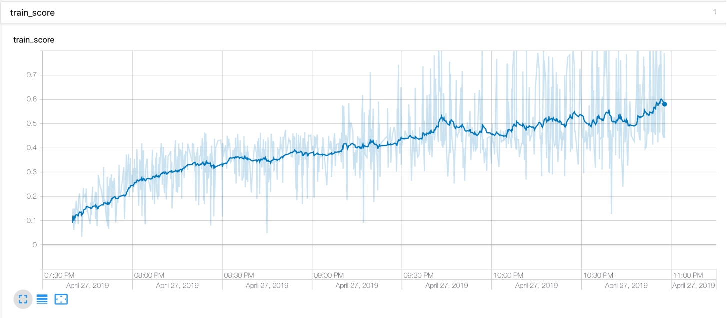


Figure 3: Train Score

Validation results

Mean validation score: 0.61

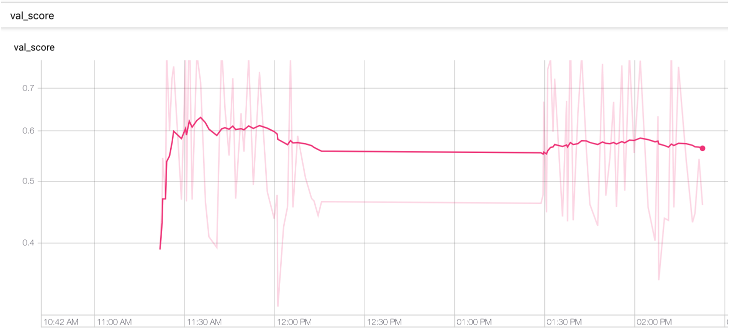


Figure 4: Validation Score