CREATIS

Prostate Cancer Semantic Segmentation by Gleason Score Group in bi-parametric MRI with Self Attention Model on the Peripheral Zone

MIDL

6 - 9 July 2020

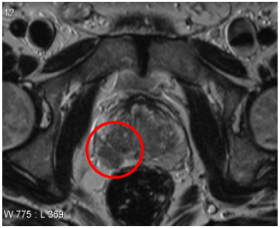
Audrey Duran [1] Pierre-Marc Jodoin [2] Carole Lartizien [1]

[1]Univ Lyon, INSA-Lyon, UCB Lyon 1,CNRS, Inserm, CREATIS UMR 5220, U1206, Lyon, France
[2]Computer Science Department, University of Sherbrooke, Sherbrooke, QC, Canada

This work was supported by the RHU PERFUSE (ANR-17-RHUS-0006) of Université Claude Bernard Lyon 1 (UCBL), within the program "Investissements d'Avenir" operated by the French National Research Agency (ANR).

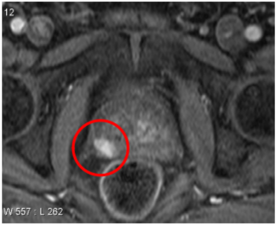
Context : Prostate Cancer Diagnosis with MRI

- Multiparametric MRI allows early detection of prostate cancer
- Need for computer aided diagnosis (CAD) system to assist radiologists facing difficult cases
- Need to detect cancer and predict their aggressiveness (clinical outcome, active surveillance, focal therapy etc.)



T2-w

ADC



DCE

CAD for prostate cancer segmentation: state-of-the-art

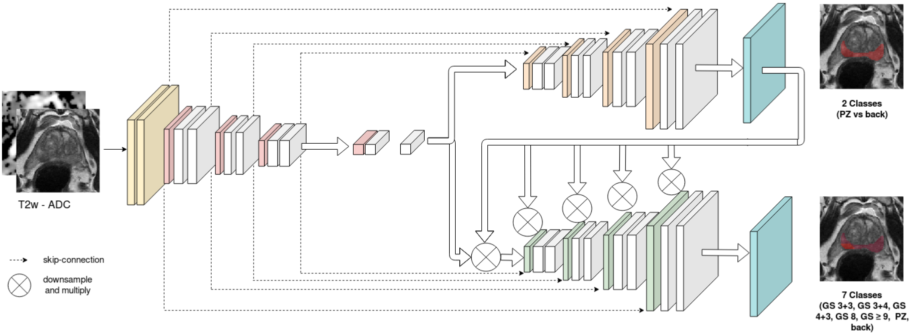
Deep Learning based prostate lesion segmentation:

- **Mainly binary segmentation** (cancer vs benign) [Yang *et al.*, MEDIA, . 2017; Wang *et al.*, IEEE TMI, . 2018]
- **Few studies performing multi-class segmentation** [Cao *et al.*, IEEE TMI, . 2019]
- **Some attempts to focus attention on the prostate zone** [Yang *et al.*, MEDIA, . 2017; Wang *et al.*, IEEE TMI, . 2018]

Our Contribution: ProstAttention-Net

A novel end-to-end architecture that :

- Jointly performs PZ segmentation and multi-class segmentation of PCa lesions by aggressiveness (Gleason Score)
- Focuses attention on the peripheral zone (PZ) of the prostate



Our Contribution: ProstAttention-Net

- Global loss = sum of the 2 branches' losses
- Combination of weighted dice loss and cross entropy

Loss : $L = \lambda_1 . L_{PZ} + \lambda_2 . L_{lesion}$ where

$$L_{PZ} = 1 - 2\frac{\sum_{c=1}^{2} w_c \sum_{i=1}^{N} y_{ci} p_{ci}}{\sum_{c=1}^{2} w_c \sum_{i=1}^{N} y_{ci} + p_{ci}} - \frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{2} \mathbb{1}_{y_i \in C_c} w_c \log p_{ci}$$

$$L_{lesion} = 1 - 2\frac{\sum_{c=1}^{7} w_c \sum_{i=1}^{N} y_{ci} p_{ci}}{\sum_{c=1}^{7} w_c \sum_{i=1}^{N} y_{ci} + p_{ci}} - \frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{7} \mathbb{1}_{y_i \in C_c} w_c \log p_{ci}$$

with w_c the class-specific weight, p_{ci} the probability predicted by the model for the observation i to belong to class c and y_{ci} the ground truth label for pixel i.

Dataset

- 98 patients dataset
  - 57 from a 1.5T scanner (Symphony; Siemens, Erlangen, Germany)
  - 41 from a 3T scanner (Discovery; General Electric, Milwaukee, USA)
- T2w and ADC modalities
- whole-mount histopathology slices of the prostatectomy specimens as ground truth

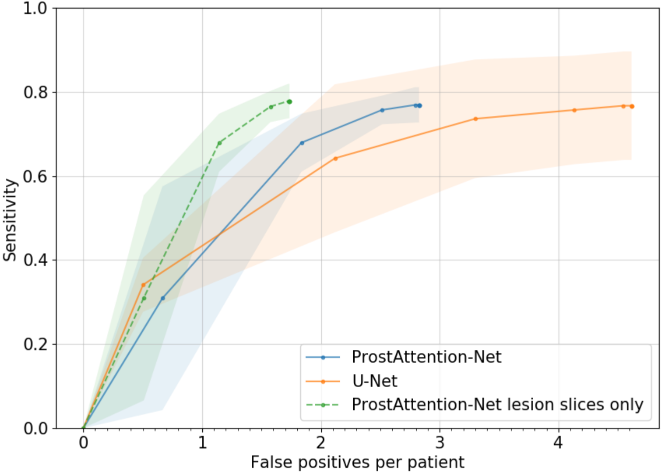
Table: Lesions distribution by Gleason Score

GS 3+3	GS 3+4	GS 4+3	GS 8	GS $\geq$ 9	Total
37	47	23	16	9	132

Experiments

- 2 segmentation tasks
  - discriminate **clinically significant** lesions (GS>6)
    - FROC on the whole volume or on slices with lesions only
  - discriminate lesions of each **Gleason score** (GS) group
    - FROC and quadratic-weighted kappa
- 5-fold cross-validation
- Ablation study to evaluate the influence of the **attention** model

Results: FROC analysis for CS lesion segmentation



Results: FROC analysis by Gleason Score Group

Table: Comparison between our ProstAttention-Net and U-Net detection sensitivity at given false positive (FP) per patient thresholds on each Gleason Score group - *preliminary results due to the few lesions per Gleason Score group*

	GS $\geq$ 9		GS 8		GS 4+3		GS 3+4		GS 3+3	
	1FP	1.5FP	1FP	1.5FP	1FP	1.5FP	1FP	1.5FP	1FP	1.5FP
U-Net	0.70	0.70	**0.43**	**0.45**	0.40	0.50	0.43	0.47	0.17	0.17
ProstAttention-Net	**0.80**	**0.80**	0.28	0.28	**0.48**	**0.54**	**0.46**	**0.54**	**0.19**	**0.25**

Table: Cohen's quadratic weighted kappa coefficient

U-Net	0.31 ± 0.08
ProstAttention-Net	$\mathbf{0.35 \pm 0.05}$

Visual Results

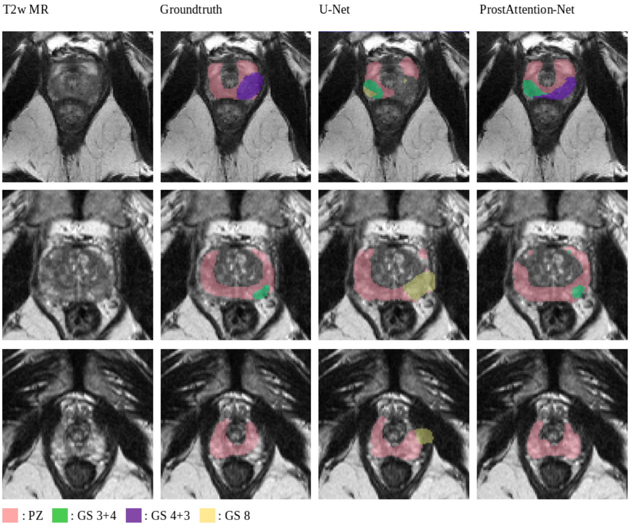


Figure: Prediction comparison for several images from the validation set.

Conclusion and perspectives

Conclusion :

Our ProstAttention-Net model allows:

- Joint segmentation of PZ and lesions by Gleason Score Group
- Outperforming U-Net
- Robust to a heterogeneous dataset

Perspectives :

- Include lesions of the prostate transition zone
- Add more patients, that might not be fully annotated
- Ranking based losses
- Evaluate the model on PROSTATEx-2 public dataset

Thank you for your attention !

References

Cao, R. *et al.* en. *IEEE Transactions on Medical Imaging* (2019).

Wang, Z. *et al. IEEE Transactions on Medical Imaging* **37,** 1127–1139 (2018).

Yang, X. *et al. Medical Image Analysis* **42,** 212–227 (2017).