DEDICATED RADIOMICS FEATURES FOR GRADING PROSTATE CANCER

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Abstract

- Prostate cancer (PCa) is the most common cancer in elderly males in Europe. On PCa Initial biopsy detection rates are approximately 40–45%. Multiparametric MRI (mMRI) visualizes and quantifies cell density and tissue perfusion/permeability in a non-invasive manner. The main goal of this project is to develop a high risk PCa classifier based on mMRI Radiomics features. Our proposed method use a deep network to extract such features on the images and classify them according to Gleason score.

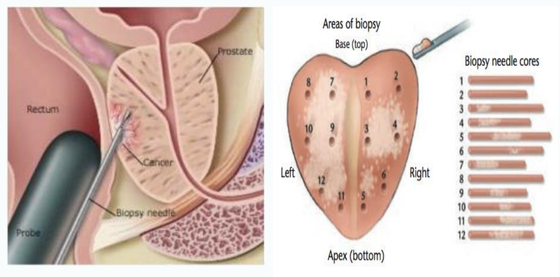

Figure 1 Transrectal ultrasound guided biopsy scheme.

Goal of the project:

- The main goal of this project is to develop a high risk PCa classifier based on mMRI Radiomics features.
- Obtaining spatially matched MR images of whole prostate specimen.
- Dataset :
  - 150 Patients from 3 healthcare centers in The Netherlands.
  - MR sequences : T2-Weighted., diffusion weighted imaging(DWI) apparent diffusion coefficient (ADC) .
  - Pathology: pathology reports , microscopy images and pathology slides of the whole prostate specimen.

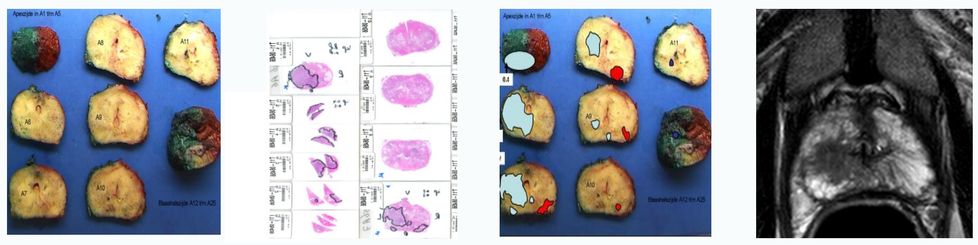

Figure 2 *From left to right*. Pathology macroscopic picture, histology slides, drawing on macroscopic picture and T2 weighted image.

Method 1

- Generate labeled data through registration.
- We take the pathology and MRI slices and stack all the images to make a 3D volume.
- Both volumes are manually registered.

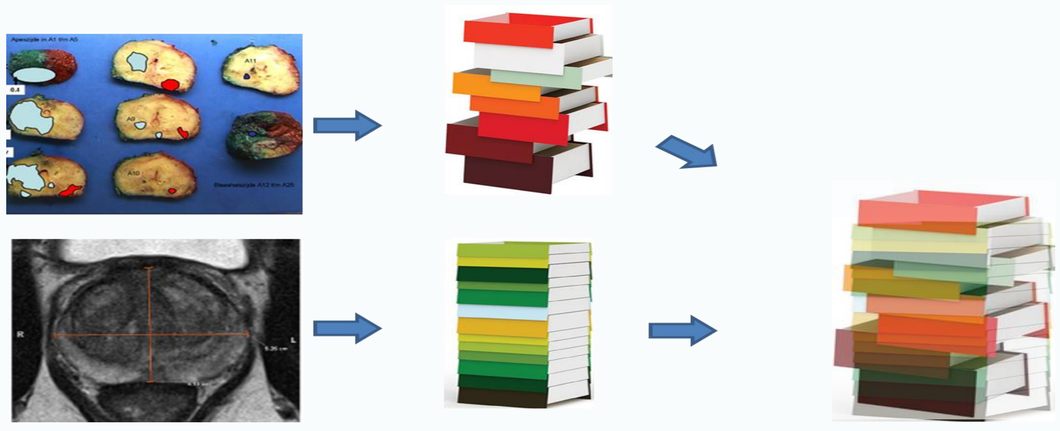

Figure 3 *Registration Scheme*. The red stack represents the pathology images(moving images) and the green one the MR slides(fixed images).

Method 2 : Deep learning model to extract radiomics features.

- The previous step sallow us to have the tumors location on the MR.
- From the data we train a convolutional neural network to classify the prostate MR slices according to the lesion present on the slice and its correspondent Gleason score.
- Gleason score higher than 6 are considered clinical relevant PCa.
- The networks architecture is inspired in VGG net.

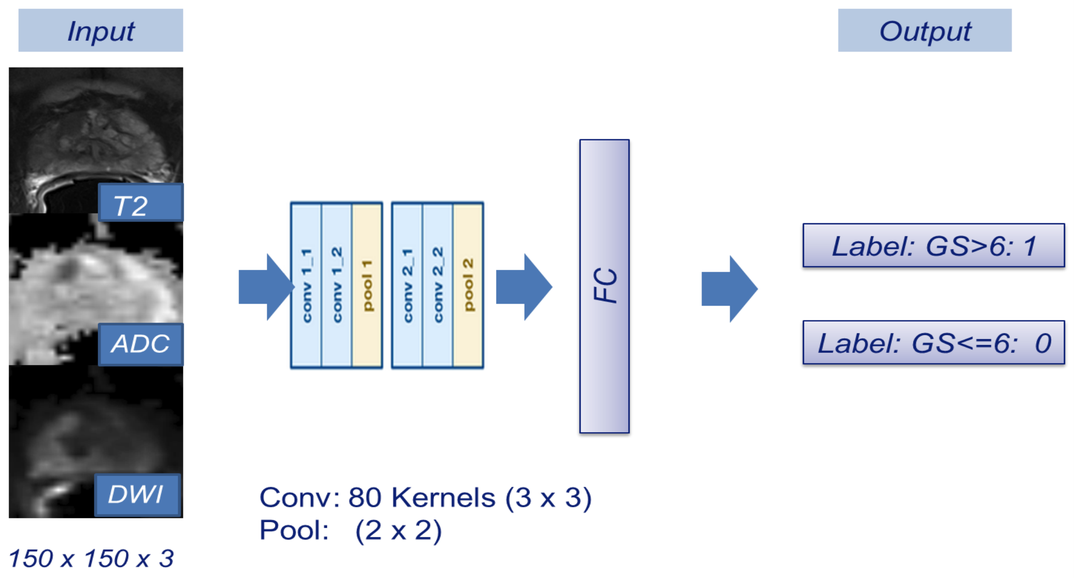

Figure 4 *Training model scheme:* The model input size is a 150 x 150 x3 array corresponding to the T2 –weighted, ADC and DWI. The output is a label corresponding to Gleason score of the slide. **FC**: Fully connected layer **Conv**: Convolutional layer **Pool:** Pooling layer **GS:** Gleason score.

Results

- Preliminary results computed with 1/3 of the whole data set.
- Our metrics were computed after 20 cross validations:
- Data splitting:
  - Training: 170 slices
  - Validation: 30 slices
  - Test : 30 slices

C.I 95%	A.U.C	Sen	Spe	Acc
Min	*51.88%*	*36.06%*	*51.46%*	*49.04%*
Max	*61.96%*	*63.64%*	*76.51%*	*60.48%*

Table 1 *Metrics of the model performance.* **CI:** confidence interval . **A.U.C**: area under the curve . **Sen**: Sensitivity. **Spe:** specificity. **Acc:** Accuracy.

Conclusions and further steps

- Multiparametric MR features have the potential to describe clinical relevant cancer lesions.
- We had develop a full pipe line to process our raw data and give it the required structure to develop a computer aided decision support system.
- We establish a first line of experiments to automatically extract radiomics feature using a convolutional neural network.
- In further steps we plan to develop a model with 100% of the data set and validate it with an external data set.
- Compare deep learning methods with handcrafted features and conventional machine learning methods.