MA Thesis: Deep Learning based model for detection and grading of prostate cancer using multiparametric MRI and Magnetic Resonance Fingerprinting

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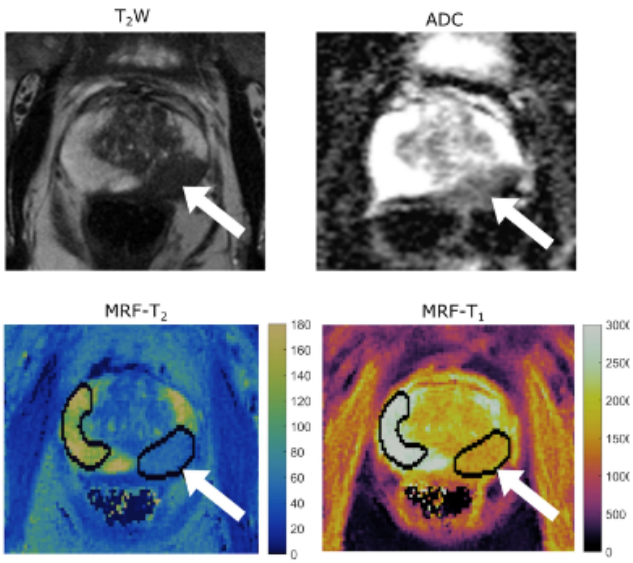
Abstract Prostate cancer (PCa) is the most common cancer in men and the second leading cause of cancer death in Germany [4,14]. Both digital rectal examination (DRE) along with the prostate-specific antigen (PSA) level in blood samples are typically used in PCa screening. Altogether, about 40% of males in Western industrialized countries have the risk of developing PCa during their lifetime, of whom only about 10% become symptomatic and 3% die [15,16]. To determine the clinical significance of PCa, prostate biopsies are assessed histologically. Prostate lesions with a pathology/histology of Gleason score ≥ 7, and/or volume ≥ 0.5 cc, and/or extraprostatic extension (EPE) are commonly considered clinically significant Prostate Cancer (csPCa). Readers are referred to [17,18] for further details about the acquisition and the interpretation.



The figure is taken from [6] and depicts a csPCa (Gleason 7) lesion in the left peripheral zone. Shown are a T2-weighted image and an ADC map taken from the standard multiparametric MRI examination and MRF T1- and T2-maps. Note the reduced T1-/T2-relaxation times in the lesion compared to the surrounding healthy tissue.

Treatment options of active surveillance, surgery, and/or radiotherapy are determined, accordingly. Multiparametric magnetic resonance imaging (mpMRI) has been increasingly utilized for the detection and staging of csPCa. The PI-RADS 2.1 scoring system [1][2] was introduced to standardize the image acquisition and the interpretation (scoring) of csPCa. Recently, Alice et al. [5], Lo et al. [6], and Panda et al. [13], among others, have shown that quantitative characterization of prostate lesions can be successfully performed using diffusion MRI and Magnetic Resonance Fingerprinting (MRF) [3]. MRF represents an MRI sequence with a novel data acquisition, post-processing, and visualization approach. A pseudorandomized acquisition pattern with the variation of flip angle, repetition time and echo time within a scan allows the measurement of specific signal patterns, so-called "fingerprints", which, via matching with a database ("dictionary"), enable the simultaneous generation of co-registered, multiparametric quantitative maps, based on T1-, T2- and T2*-relaxation times. In this project, we will investigate developing a data-driven deep learning based model to automatically detect and stage the csPCa cases using the MRF-based relaxometry, and potentially combined with the mpMRI examination, including high b-value imaging and apparent diffusion coefficient mapping (ADC).

Objectives:

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- Given a database of morphological high-resolution T2w images (in axial and sagittal orientation), diffusion MRI images including a high b-value image of 1500 and ADC mapping as well as MRF sequences and their corresponding pixel-wise delineation of the Prostate lesions, the PI-RADS v2.1 scoring (1-5), and histopathological grading - if available - we aim to **develop** a **deep learning (DL) model** to:
    - **segment the prostate lesions**
    - **automatically detect and stage** the prostate lesions in csPCa, and
    - **eventually, predict the histopathological grading** (Gleason score) – *if time allows*

- Run a **comparative analysis** between the DL-models trained on T2w, high b-value DWI and ADC, and the one trained on MRF sequences - potentially combined with the high b-value DWI and ADC image.
- Report relevant **evaluation metrics** such as the Dice Coefficient, and Area Under the Precision-Recall Curve (AUPRC).

Dataset:

- **Cohort:** Up to date, 171 patients with elevated PSA levels have been included in this ongoing study.
- **MRI:** Patients received an MRI examination on a 3T MRI scanner (Philips Ingenia) including the following sequences:
    - High-resolution T2-weighted sequences in axial and sagittal orientation
    - DWI, including b-values of 100, 400, and 800 with the calculation of an ADC map, and a high b-value of 1500
    - Magnetic Resonance Fingerprinting (MRF)
    - Perfusion imaging
    - Pre- and post-contrast T1-weighted axial images of the pelvis
- **Data annotation:** Axial high-resolution T2-weighted images are labeled by a radiology resident with 4 years of experience to include the following labels: i) Peripheral Zone, ii) Transitional Zone, iii) Lesion
- **Histopathological evaluation:** Patients that were graded with a PI-RADS score of 3 or higher will receive a systematic/targeted biopsy that allows histopathological correlation with lesions.

Roadmap:

- Familiarize yourself with the current literature on
    - Radiomics model for prostate [10] and its repeatability with MRF [12]
    - Deep Learning with MRF in Parameter Estimation [7-9], Correlation with Histopathology [11], and lesions catheterization [13]
- Develop the baseline and proposed method
- Run extensive experiments and analysis
- Write up your thesis

Requirements:

- Solid background in Machine/Deep Learning
- Familiar with discriminative deep learning models and SOTA architectures
- Sufficient knowledge of Python programming language and libraries (Scikit-learn)
- Experience with a mainstream deep learning framework such as PyTorch.
- Machine/Deep learning hands-on experience

If you are interested in this project, please write an email to shadi.albarqouni@ukbonn.de

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