Training Neural Networks to Predict Cancer-Prone Regions within the Prostate

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INTRODUCTION

Multiparametric magnetic resonance imaging (mpMRI) is increasingly used in the detection of prostate cancer. However, a large number of prostate cancers often go undetected on MRI due to their similarity to the normal gland and benign conditions. With better prostate cancer detecting algorithms in place, we can benefit from a more confident targeted approach. As we navigate through deep learning algorithms to better predict the location of prostate cancer on mpMRI, we take a closer look at 40 different patients exhibiting clinically significant symptoms

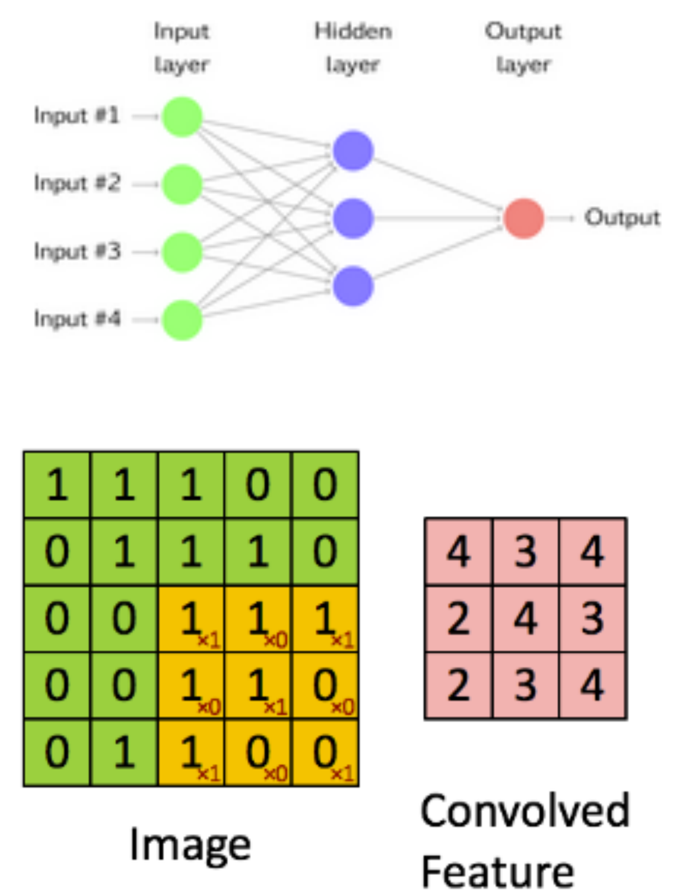


FIGURE 1 General outline of our Input Neurons, Hidden Layer, and our output node.

METHODS

The **RCC consultants** are implementing a deep learning tool for automatic classification **of clinical significance of prostate cancer findings using 3D convolutional neural networks (CNNs)**, the main element of deep learning mechanism. The parameters used as input of the convolutional network are: **the T2-weighted images, apparent diffusion coefficient (ADC), diffusion weighted images (DWI) at high *b*-value, and K^{trans} (measure of capillary permeability obtained using dynamic contrast-enhanced – DCE MR)**. Since the prostate cancer appear mostly in some regions of the prostate gland, the following sectors were taken into account: PZ (Peripheral Zones), TZ (Transition Zone), and AS (Anterior fibromuscular stroma). **10,000 training sets** and **2,000 validation sets** were prepared. Patches of size 64 X 64 X 12 pixels were extracted around the finding. MRI dataset of about 250 patients was prepared and the CNNs was designed using *Keras* neural-network API based on Python and capable of running on top of either *TensorFlow* or *Theano* software libraries for implementing machine learning. GPU capabilities of Midway are used in this experiment. Different experiments are performed for testing which input parameters are most significant in this study. As future work, we will design 3D CNN for automatic prediction of Gleason score and automatic segmentation of the prostate sectors.

RESULTS

Convolution Neural Networks

Perceptrons take several inputs into account and produce a single binary output. For each neuron output, a weighted sum of every input is used to produce such binary output. The neuron's output is either a 0 or 1 depending on whether this weighted sum is greater than a given threshold value. For any given input there may be more weight given to a particular variable if there is more confidence for such condition. Suppose we make some change to the weight, or bias, in the network - for example, a change in position of the cancerous region of the prostate – we will need to account for this small change in the output. However, we wouldn't want this change to dramatically shift our output, as we would like for our algorithm to learn the slight changes that can occur with regards to the **npm patch** in our given prostate cancer model. For this reason, the trend will lean more towards sigmoid neurons and not perceptrons; however, perceptrons are a basic neuron model used to learn the basics of convolution neural networks. For sigmoid neurons we will use a deeper complexity of $\sigma(w \cdot x + b)$ where $\sigma(z) \equiv \frac{1}{1+e^{-z}}$ to determine the weight for a given input neuron.

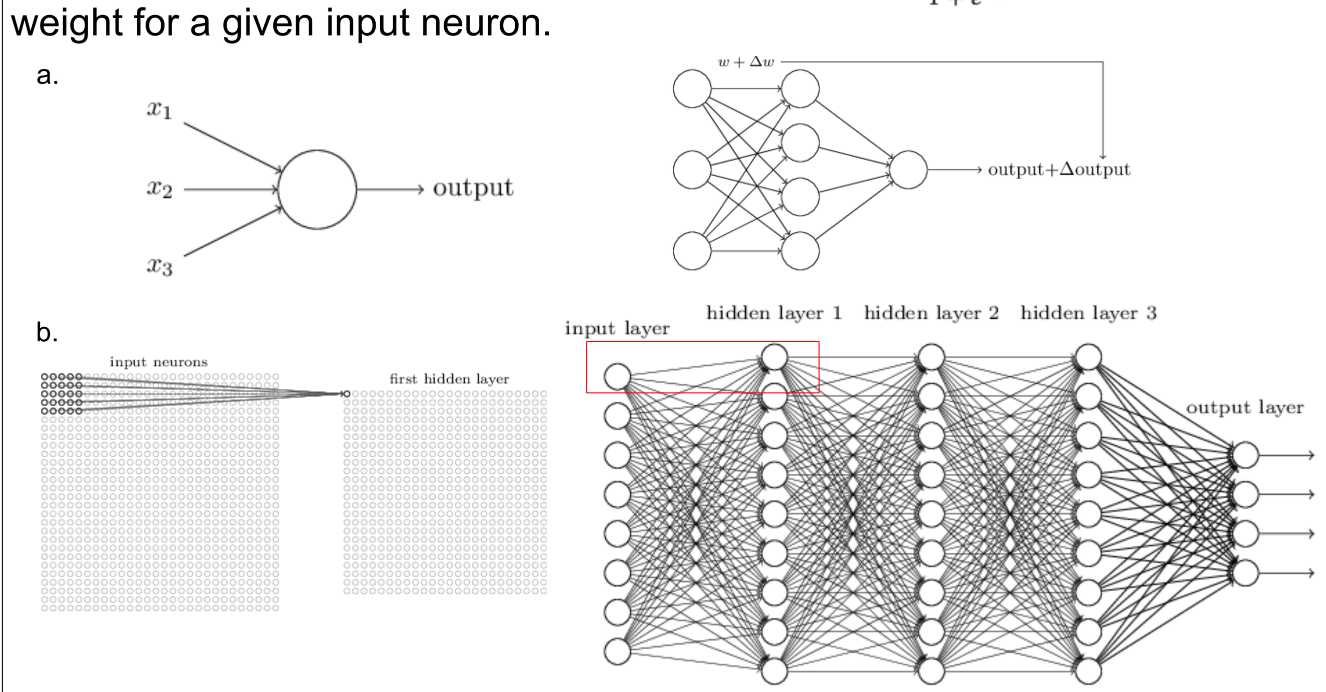


FIGURE 2. Convolutional networks provide a way to specialize neural networks to work with data displaying a grid-like structure topology. For medical imaging we will proceed with a 3-dimensional convoluted neural network. Convoluted networks provides a more confident approach with regards to training multilayers. Figure 2(**a**) depicts the inner neurons $\{x_1\ x_2\ x_3\}$ respectfully contributing to one output node with perceptrons. We can also visualize a need for the change in output requiring the use of sigmoid neurons. Figure 2(**b**) displays a breakdown of how the inner neurons visually make up the hidden layers.

Using 3-Dimensional Kernels for Training

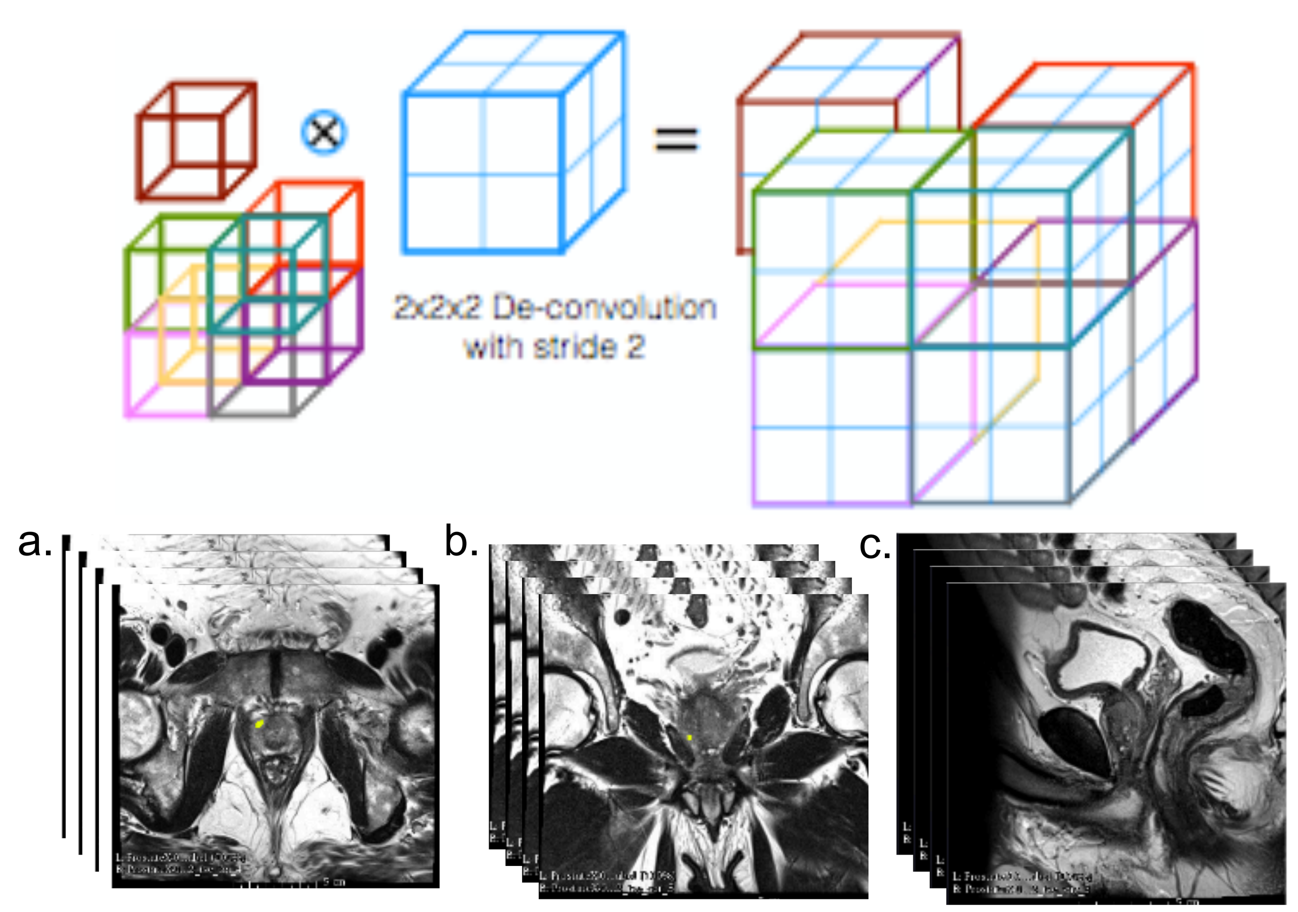
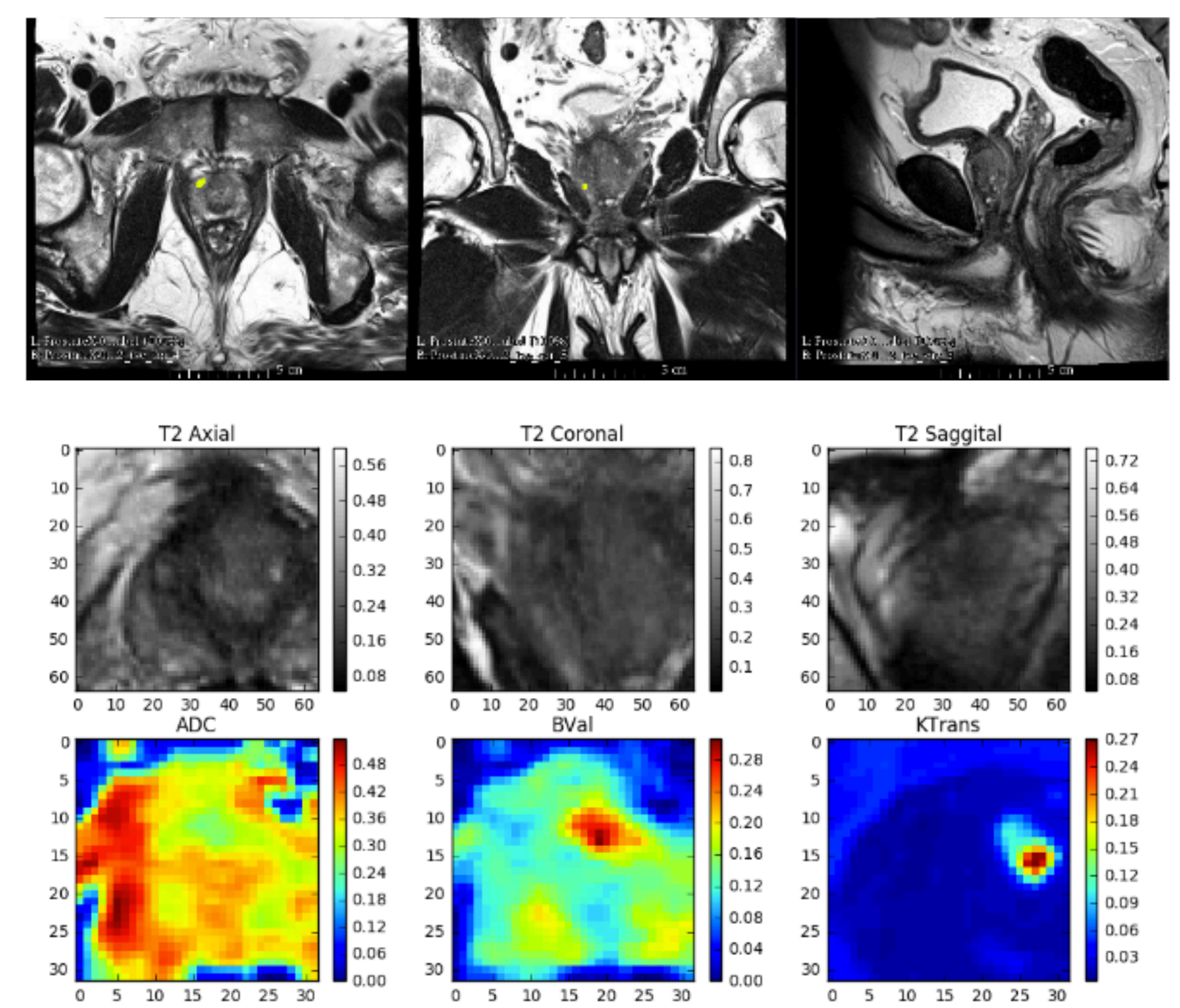
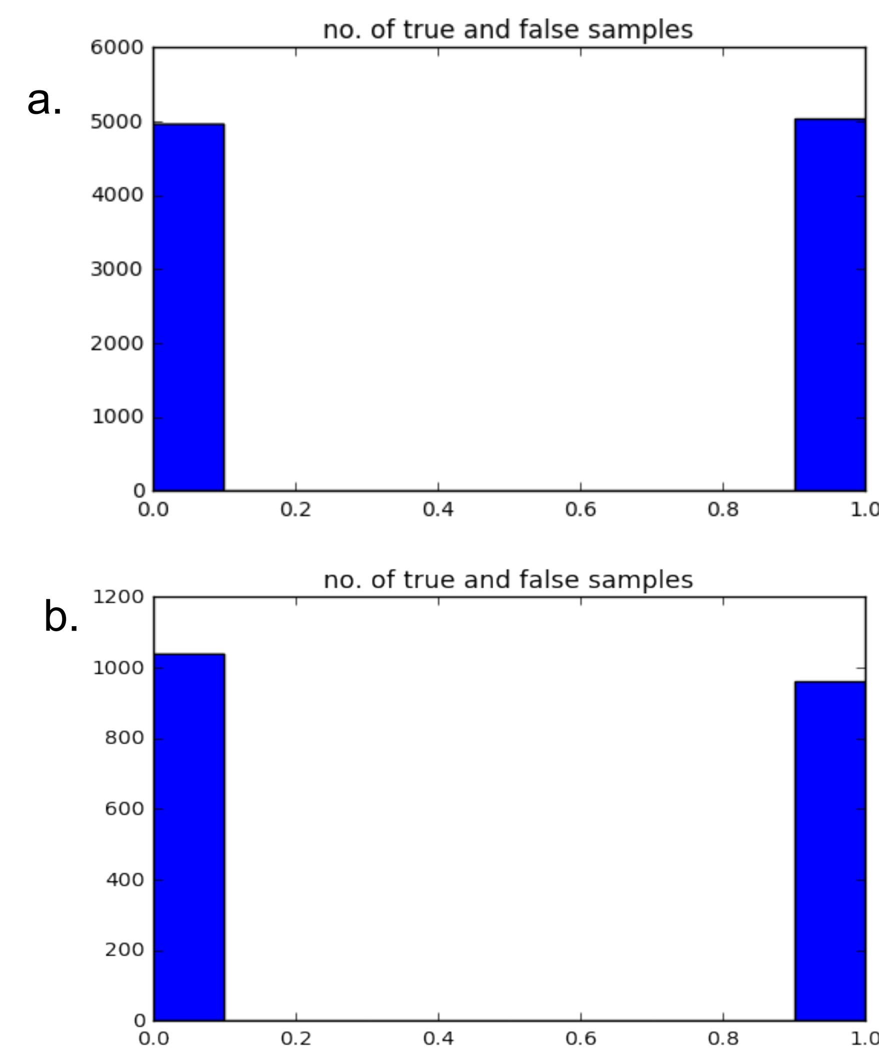


FIGURE 5. In order to train our model using the 3-dimensional magnetic resonance images we must use a volumetric convolution, taking into account every layer – 5(a) Axial, 5(b) Coronal and 5(c) Sagittal - and dimension.

Axial, Coronal and Sagittal Views of Prostate Cancer Regions of the Prostate Gland

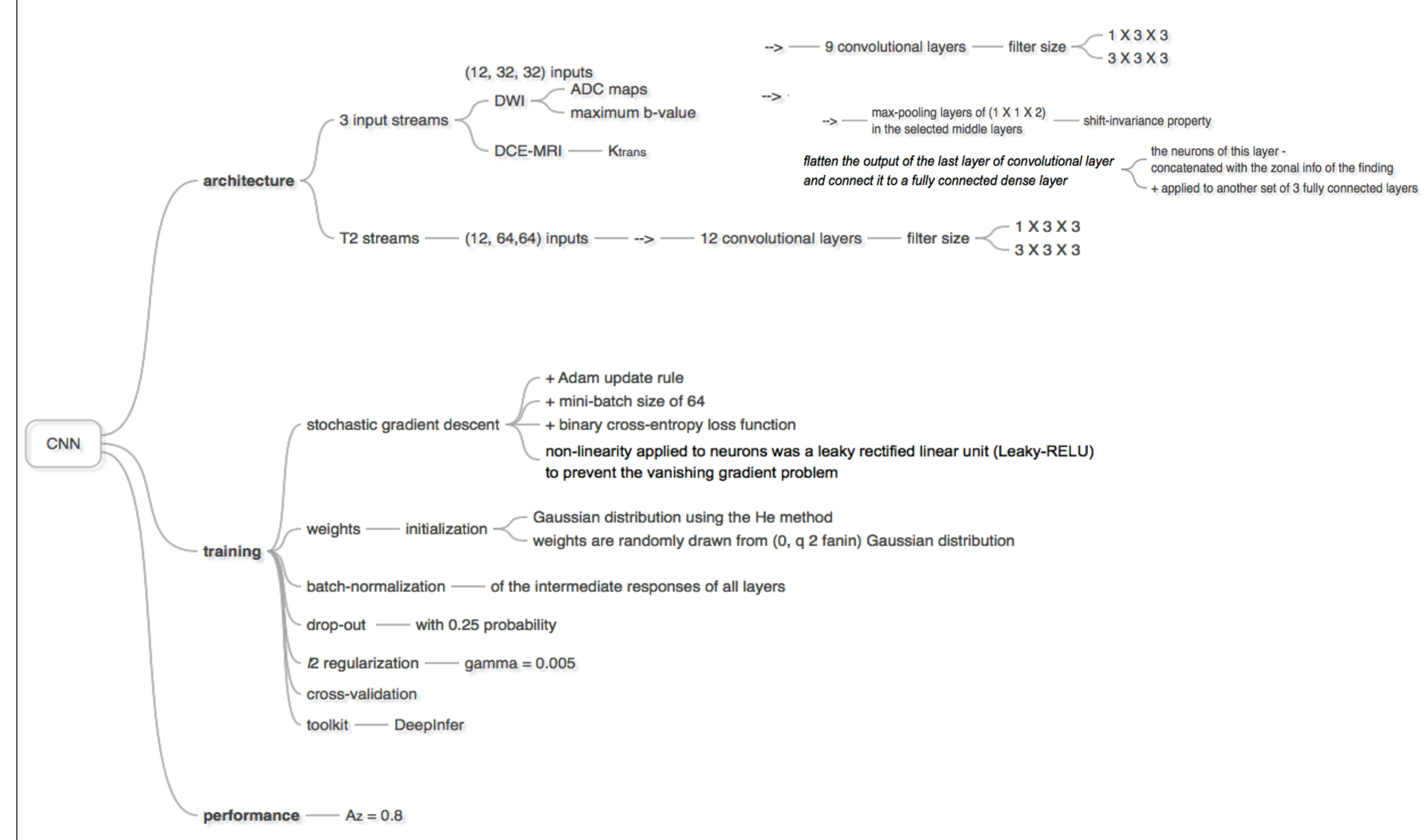




Patients with prostate cancer with a Gleason score of **7** or higher were considered clinically significant cancers. Gleason score 6 cancers were considered non-significant. They are called well differentiated or low-grade and are likely to be less aggressive; that is, they tend to grow and spread slowly.

FIGURE 4. Example of a training dataset – Patient – 0115. There is a significant finding in TZ, at location [-46.3136 16.0335 -18.7278] (world coordinates). T2-wighted (axial, coronal, sagittal), ADC, B-values, and Ktrans images are displayed together with the finding (highlighted with yellow). Data from 40 patients were used for training. 4(**a**). The distribution of clinical significance (1.0 or 0.0) for training data and 4**(b)**. the distribution of clinical significance (1.0/0.0) for validation data.

3D Convolution Neural Networks Design



CONCLUSIONS

In this project, consultant and development experience from RCC implement deep learning based tools for automatic classification of the cancerous findings in multi-parametric MRI of prostate for the Radiology department of The University of Chicago. Other tools will be designed for automatic segmentation and prediction of the prostate cancer. This will have a great impact in the research studies of the department and can be further on implemented for other datasets, imaging other types of cancer.

FUTURE OUTLOOK

- **Improving prediction of Prostate Cancer using Risk Map (include new parameters, e.g., DCE signal kinetics parameters: signal enhancement rate)**
- **Automatic segmentation of different sectors of the gland.**

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REFERENCES

[1] *Neural Networks and Deep Learning*, Michael Nielsen, 2017 Jan

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