Artificial intelligence in medical imaging– industry collaboration enabling advanced analysis of disease burden in patients with metastatic prostate cancer to improve individualized treatment

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Introduction

The clinical benefits of artificial intelligence (AI) and deep-learning techniques in medical imaging are proving to be highly beneficial. Collaborators at the Australian Centre for Quantitative Imaging, UWA and AIQ Solutions, aim to utilize deep-learning models to:

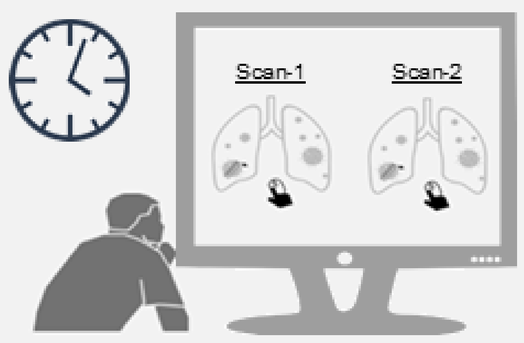
(i) quantify metastatic disease burden, and

(ii) investigate prognostically important image features ("radiomics") from positron emission tomography (PET) and computed tomography (CT) scans.

More accurate and efficient assessment has the potential to aid clinicians in quantifying burden of disease, assess heterogeneity and enable effective treatment planning.

Current Practice

Manual and Subjective



- Manually identify a subset of lesions for assessment
- Manually establish longitudinal or cross-modality lesion concordance
- Nuclear Medicine Physician interprets findings and provides clinical report

AIQ Solutions Technology

Automated and Objective

- AI-powered segmentation of lesions and toxicity-susceptible organs
- Deformable image registration for automatic and robust lesion concordance
- Quantify temporal change in each lesion across time points
- Automated visual summary report provided to assist in interpretation of findings

Figure 1. Comparison of *AIQ Solutions* Technology to current practice.

Objectives

The state-of-the-art research conducted in Western Australia aims to train predictive lesion models, and extract key predictive features for patients with metastatic prostate cancer. The results of the model are validated against the work of an expert Nuclear Medicine clinician to improve accuracy.

Methods

Between 2015 and 2016, a total of 256 men (mean age of 70) with prostate cancer had [^{68}Ga]Ga-PSMA-11 PET/CT scans acquired for biochemical recurrence. A 3D U-Net model architecture was trained on 323 [^{68}Ga]Ga-PSMA-11 PET/CT scans (225 patients) and tested on an external validation cohort of 37 scans (28 patients). Lesions on all images were manually contoured by an expert and reviewed by a Nuclear Medicine clinician. The performance was quantified by researchers and AI engineers to test the model sensitivity and false positives per patient. Results were aggregated for all lesions and for lesions with SUV_{max}> 5 and SUV_{max}> 10 (SUV being a measure of tracer uptake (image intensity)).

Results

In the validation dataset, a total of 414 lesions across all regions were contoured. Early model performance data demonstrated median detection sensitivity was 96% [IQR: 0.59-1], with median 0 false positive [IQR: 0-1] for all lesions. For 59% of lesions with SUV_{max}> 5 (243 lesions), median sensitivity was 100% [IQR: 0.83-1] with 0 false positives per patient [IQR: 0-0]. Median sensitivity for SUV_{max} > 10 (141 lesions) was 100%. Overall, the model identified > 83% of lesions with fewer than a mean of 0.87 False Positives/patient achieved across both SUV_{max} values.

Anatomical region-based performance for all patients is shown in Table 1. Most lesions (260) presented in the pelvis area and are consistent with a low disease burden prostate cohort. The best performance was found in the pelvis, abdomen and legs, then chest and head/neck respectively for all lesions. Leg lesions with SUV_{max}> 10 did not perform as well.

Table 1. Lesion detection performance across full body regions. For all performance metrics, the median and interquartile range of detection sensitivity is shown.

Lesion Uptake	Region	H/N	Chest	Abdomen	Pelvis	Legs
All Lesions	Lesion Number	18	91	39	260	6
	Sensitivity	0.33 [0.0, 1.0]	0.67 [0.33, 1.0]	1.0 [1.0, 1.0]	1.0 [0.67, 1.0]	1.0 [0.25, 1.0]
SUV_{max}> 5	Lesion Number	10	58	25	145	5
	Sensitivity	1.0 [0.25, 1.0]	1.0 [0.66, 1.0]	1.0 [1.0, 1.0]	1.0 [1.0, 1.0]	1.0 [0.0, 1.0]
SUV_{max}> 10	Lesion Number	7	36	15	80	3
	Sensitivity	1.0 [1.0, 1.0]	1.0 [0.78, 1.0]	1.0 [1.0, 1.0]	1.0 [1.0, 1.0]	0.0 [0.0, 0.5]

Conclusion

These preliminary results suggest the model has a high sensitivity for lesion detection with few false positives and gives a positive indication towards using the AI model as an assistive tool in clinical applications.

Further work is being undertaken by the group to:

(i) improve model accuracy,

(ii) expand into treatment response to provide directions for advancing clinical practice, and

(iii) investigate model performance for other PET radiotracer combinations.

This industry-academic innovation project highlights research and development opportunities in Western Australia.

Consumer and community involvement

The Australian Centre for Quantitative Imaging group partners with several consumers who actively participate in the development of research aims and understanding of findings. The ongoing engagement of consumer representatives has assisted in understanding research priorities.

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