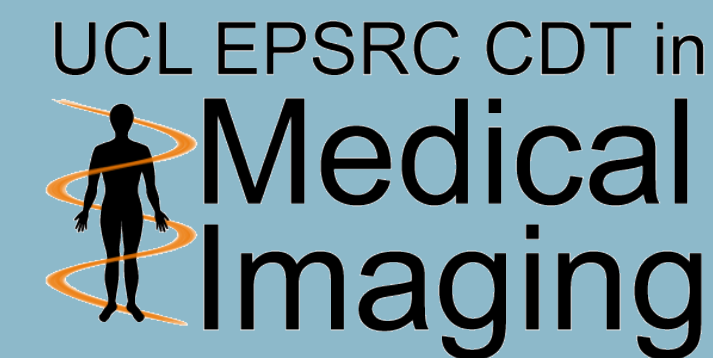


AUTOMATIC PROSTATE SEGMENTATION FROM TRANSRECTAL ULTRASOUND IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract- Identification of clinically important targets, is challenging on TRUS images, yet, much better defined on MRI. An important step for many MRI-TRUS registration involves automatic segmentation of the prostate on both modalities. In this work, a CNN is proposed for segmenting the prostate in 2D TRUS slices. achieving mean 2D DSC and absolute boundary distance error of 0.89 ± 0.12 and 1.80 ± 2.05 mm respectively, suggesting a promising approach to aiding TRUS-guided prostate cancer procedures.

Background

- Prostate cancer is the most commonly diagnosed cancer in men in the UK, with more than 11,000 deaths per year.
- PSA testing leads to over-diagnosis and over-treatment of patients with low-risk prostate cancer [1].
- TRUS guided biopsies allow for more accurate patient stratification- however, clinically important tumours are frequently missed.

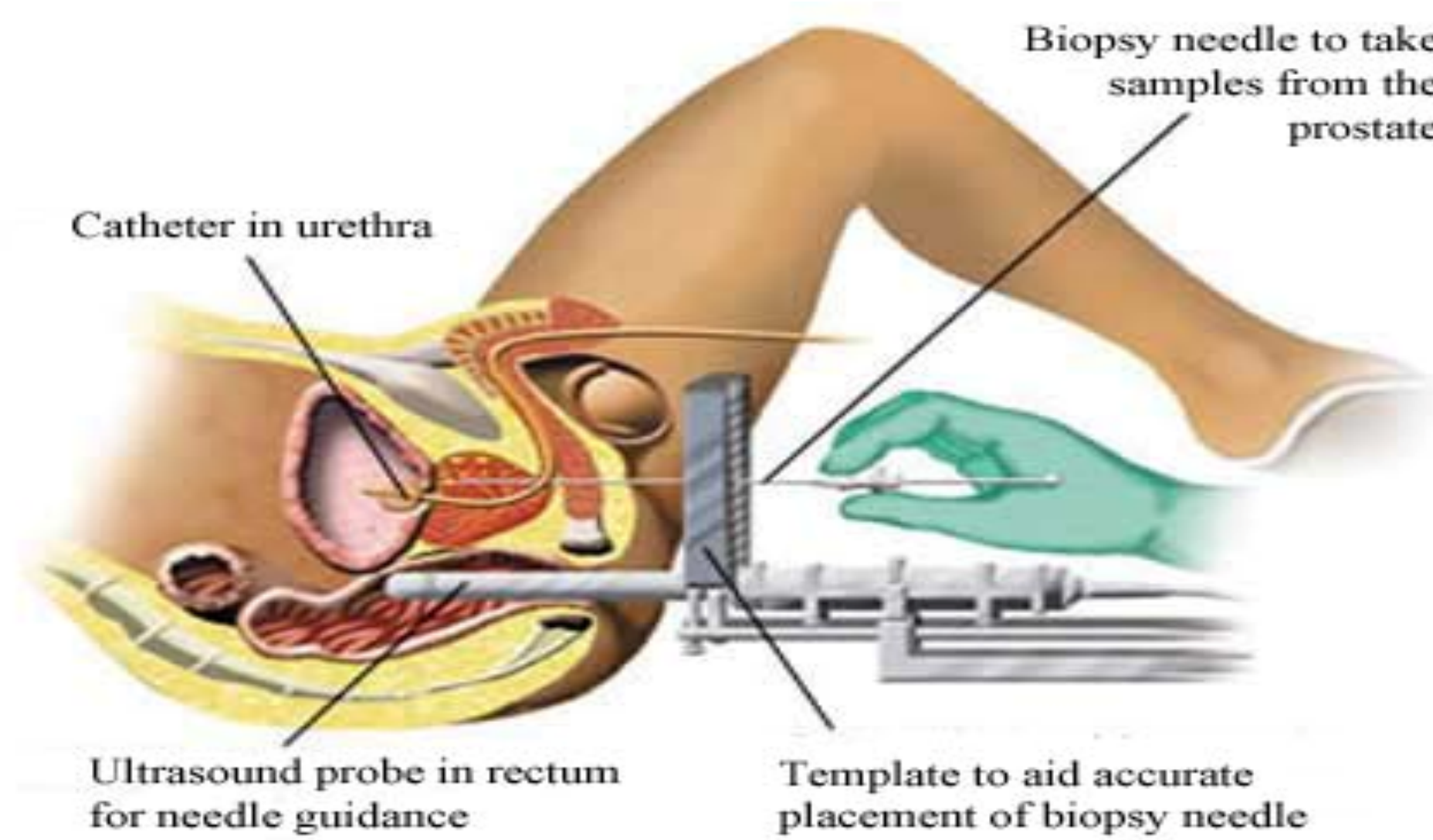


Fig.1 – Diagram of TRUS guided biopsy.

- MRI allows better visualisation, and fusion of the two modalities allows a cheaper, better localisation method [2].
- Automatic segmentation allows more accurate results with reduced time and variability compared to manual segmentations.

Aims

- Evaluate the accuracy of a convolutional neural network (CNN) method for automatic prostate segmentation
- Incorporation of an additive up-sampling.
- Investigate effect of integration of adjacent slices into the network

Methods

- Data was acquired from the SmartTarget Biopsy Trial [3], a total of 4034 slices were used.
- Automatic segmentations was carried out using CNN based on an adapted UNet architecture (Fig.2).
- 10-fold patient level cross validation was carried out, within each fold segmentation metrics such as the Dice similarity coefficient (DSC) and symmetric boundary distance were computed.

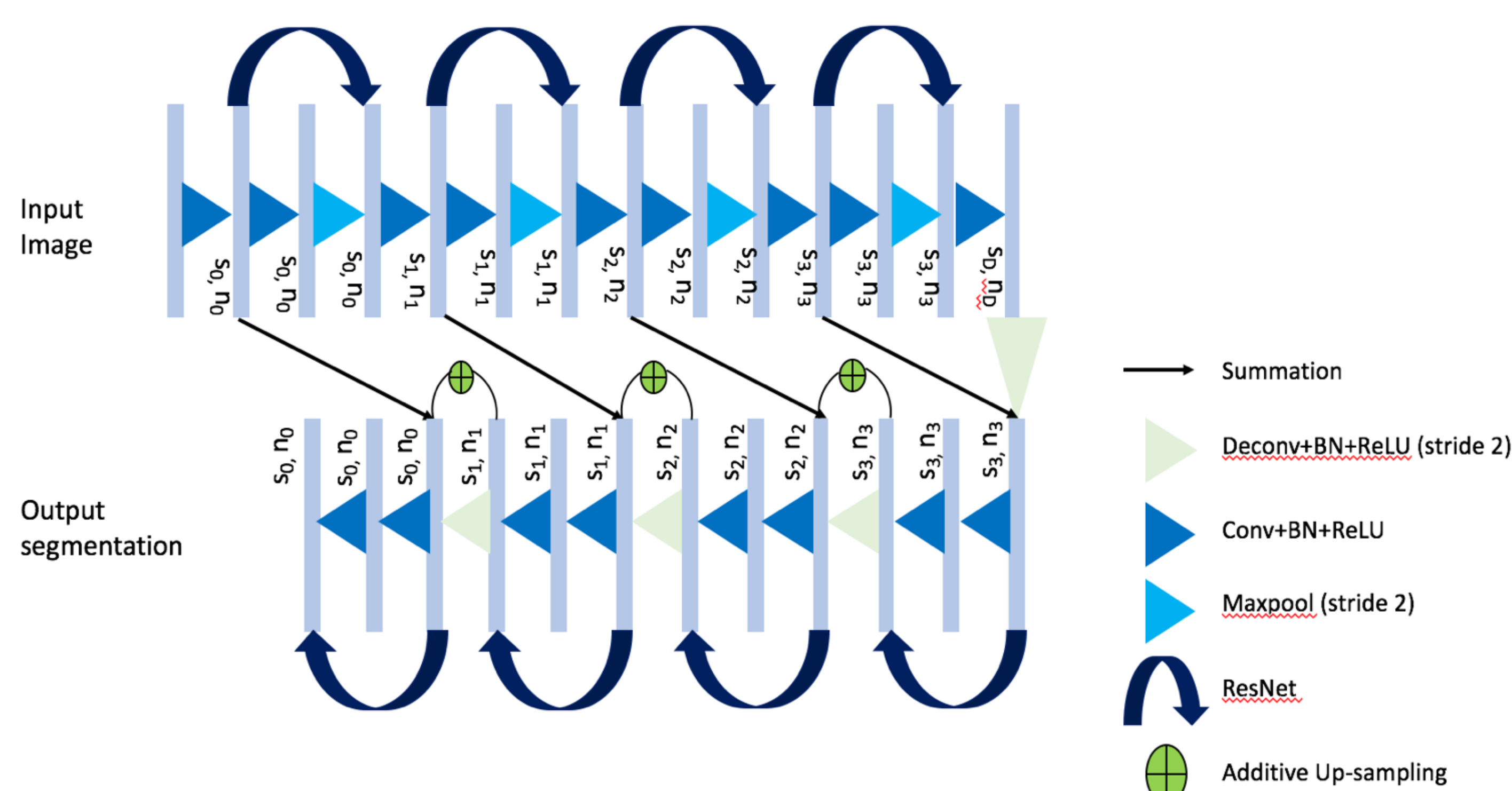


Fig.2 – Proposed network architecture.

Results

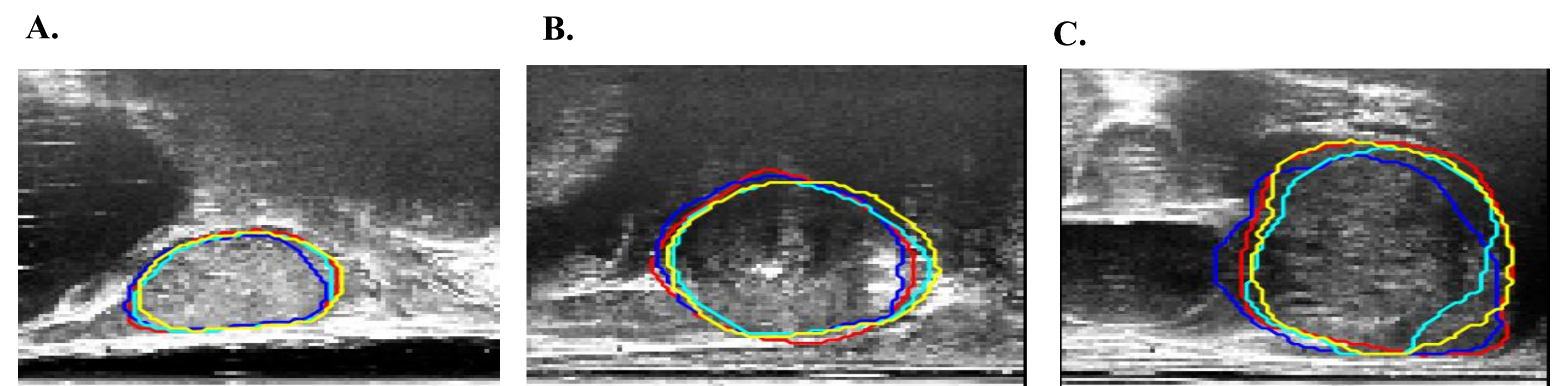


Fig.3 – Differences in the automatically segmented prostate when incorporating different number of adjacent slices for 3 arbitrarily chosen slices (A-C).

Number of Adjacent Slices on Each Side	2D DSC	3D DSC	Boundary Distance
None	0.88 ± 0.13	0.88 ± 0.06	1.80 ± 1.68
1	0.89 ± 0.12	0.89 ± 0.05	1.80 ± 2.05
2	0.89 ± 0.12	0.88 ± 0.04	1.77 ± 1.46
3	0.89 ± 0.12	0.88 ± 0.05	1.75 ± 1.77

Table.1 – Segmentation metrics obtained from the automatic segmentation results when using different number of adjacent slices.

- Inter-observer Comparison

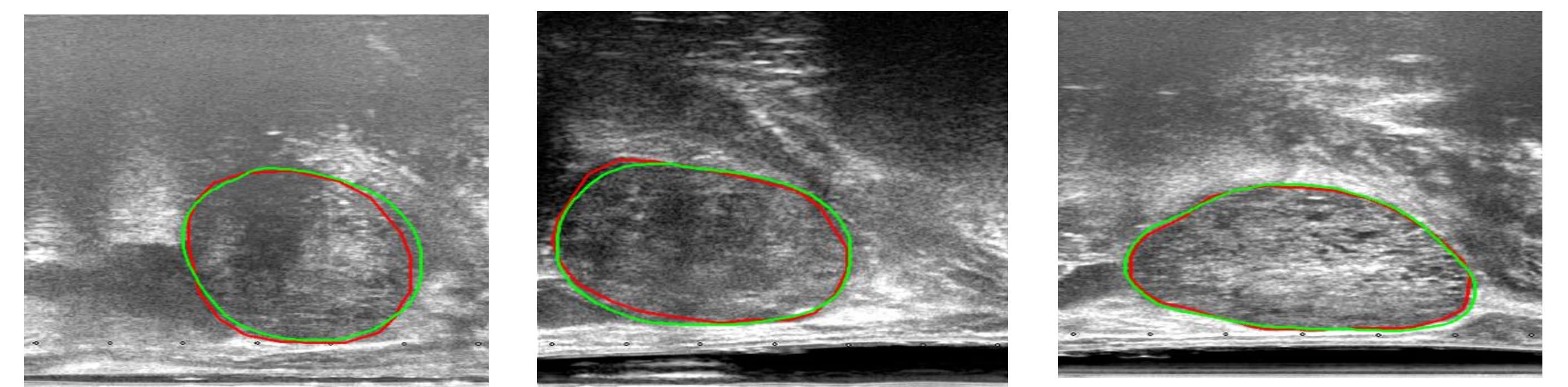


Fig.4 – Inter-observer segmentation comparisons for three arbitrarily shown slices.

Conclusion and Future Work

- Good agreement is shown between automatic and manual segmentations.
- DSC achieved close to inter-observer computed DSC (0.92 ± 0.06)
- Obtain data from different centres.
- Use the segmentations within a MR-TRUS registration workflow- MR segmentations have already been carried out (Fig.5).

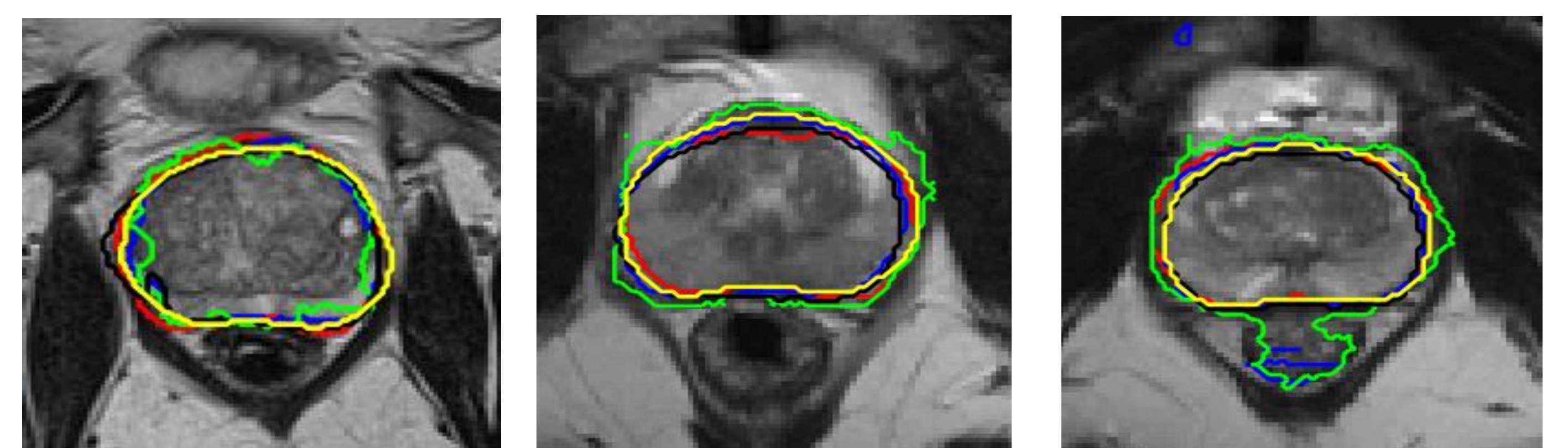


Fig.5 – Overlay images of the automatic segmentations from different CNNs on top of the original prostate image for three arbitrarily chosen slices.

References

- [1]- Klotz, L., & Emberton, M. (2014). Management of low risk prostate cancer-active surveillance and focal therapy. *Nature Reviews Clinical Oncology*, pp. 324-334.
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