Auto-segmentation of structures in cervical cancer treatment planning using a deep learning framework

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Purpose

We seek to evaluate whether the lean deep learning PocketNet model yields results comparable to the larger nnU-Net model in the automated segmentation of clinical target volumes and pelvic organs in CT imaging of cervical cancer patients.

Introduction

- Cervical cancer is the fourth most prevalent cancer in women worldwide, primarily due to infection with human papillomavirus (HPV).
- Radiotherapy workflow requires manual contouring of tumor volumes and pelvic organs, but this process is time-consuming and resource-intensive.
- Automatic segmentation of medical images has been proposed to address these shortcomings. Convolutional neural networks (CNNs) are the first-line choice of deep learning model architecture for this task. The U-Net form, with its symmetric contracting and expansive paths, is best suited for the pixel-by-pixel classification and image localization.[1]
- U-Net optimization led to the creation of PocketNet, a lightweight model with reduced parameters designed to operate in low-resource environments.[2]
- Another variant, nnU-Net, was designed with the intention of automatically configuring itself to address cumbersome manual tuning of parameters.[3]

Methods

Autocontouring

- The dataset consisted of 82 abdominal CT scans of patients who received radiotherapy.
- Four structures were specifically delineated by a radiologist according to consensus guidelines, the remaining 12 were clinically approved structures used from treatment planning.
- A custom preprocessing pipeline was applied to remove overlap between structures using manually-defined set of rules. These masks were then compiled into a single file to train the model **(Figure 1)**.
- Models with nnU-Net and PocketNet architectures were trained on 92 cases, accompanied by 5-fold cross validation.

Quantitative evaluation

- The model performances were evaluated through calculation of the Dice-Sorensen coefficient (DSC) and 95th percentile Hausdorff distance (HD95) per predicted contour.
- The Dice metric was compared between models using a one-sided Wilcoxon signed-rank test ($p < 0.05$).

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Results

- The nnU-Net model achieved mean Dice scores > 0.70 for all structures except the vagina, and a mean Dice score > .90 for the sacrum, femurs, and pelvis **(Figure 3)**.
- The PocketNet model achieved mean Dice scores > 0.70 for all structures except the vagina and parametrium, and a mean Dice score > .90 for the sacrum, femurs, and pelvis **(Figure 3)**.
- Results from the Wilcoxon signed-rank test revealed that nnU-Net performed better than PocketNet for auto-segmentation of the sacrum, bladder, L4, L5, kidneys, pelvis, CTVn, PAN, parametrium, and utero-cervix **(Figure 4).**

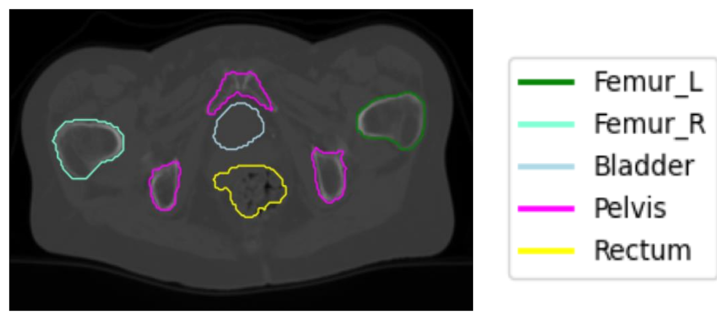

Fig 1. Visualization of combined mask file after removal of overlap between masks.

Contour	p-value
Sacrum	3.15E-13
Femur_L	3.44E-03
Femur_R	3.44E-03
Bladder	7.78E-07
L4	1.74E-01
L5	6.55E-02
Kidney_R	7.10E-06
Kidney_L	3.97E-06
Pelvis	1.28E-13
Rectum	5.08E-03
Spinal Cord	6.43E-03
CTVn	1.66E-11
PAN	1.04E-04
Parametrium	7.97E-06
Utero-Cervix	4.52E-07
Vagina	8.66E-04

Figure 4. Wilcoxon-signed rank test. Differences in Dice values from the median are captured with p-values, which confirms a difference in model performance by contour.

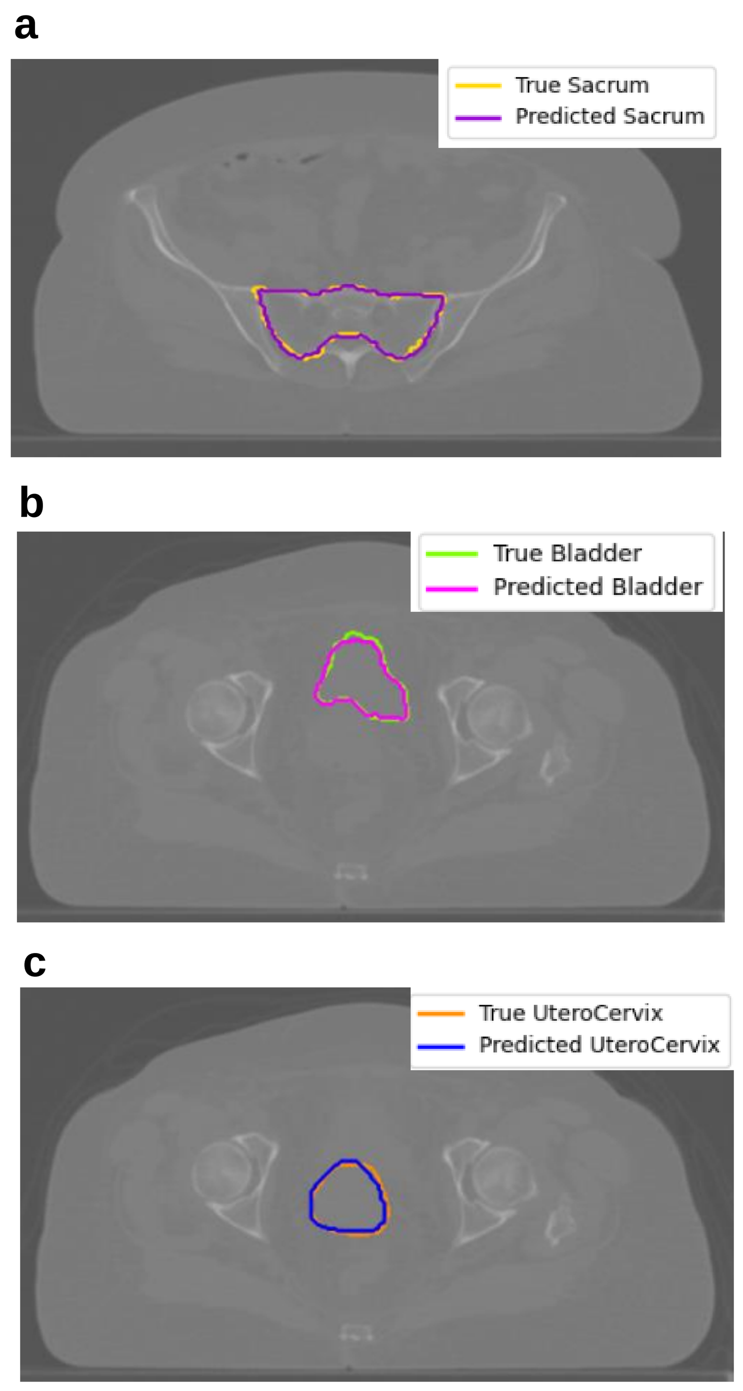

Figure 2. Visualization of sample predicted contours against their ground truth equivalent. Sample contours from the **(a)** bony, **(b)** soft tissue organs, **(c)** target subgroups are plotted.

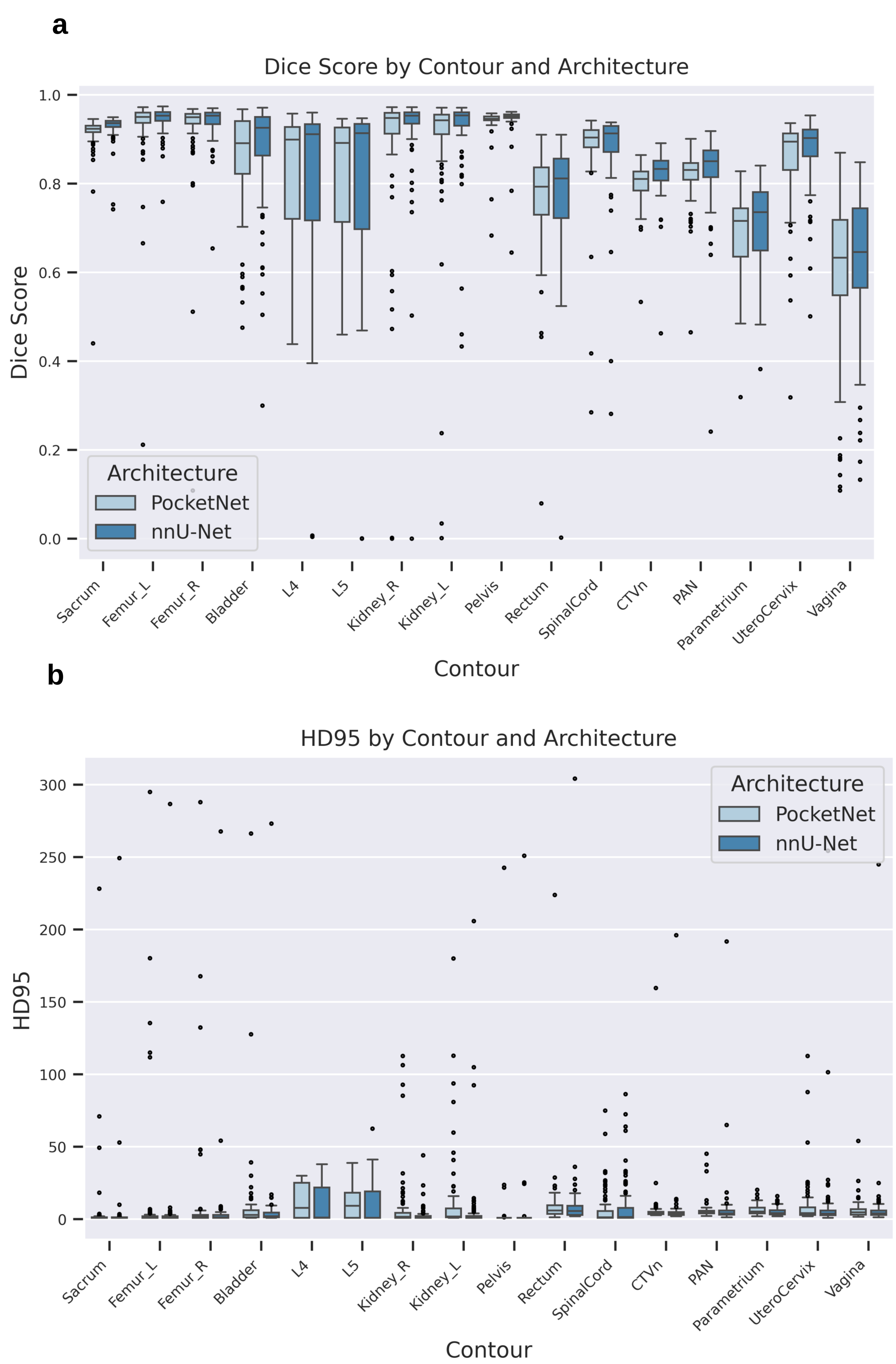

Figure 3. Quantitative performance compared between both models. (a) Mean DSC and **(b)** HD95 were calculated for each predicted contour against its ground truth delineation.

Discussion

- Both PocketNet and nnU-Net have a stronger performance on bony structures and a weaker performance on soft tissue organs and target structures.
    - There is lower contrast for anatomical boundaries on CT images between soft tissue organs, so it is harder to differentiate compared to MRI images.
    - Higher contrast in bony structures allows for easier differentiation on CT.
    - Both models achieved better accuracy at the center of structures, as opposed to the boundaries.
- nnU-Net performed significantly better than PocketNet at segmentation for most structures,
- More work must be done in model optimization to differentiate between soft tissue densities on CT imaging, namely in the vagina and parametrium structures.
- A more detailed qualitative analysis of the outliers will be conducted to evaluate model weaknesses.
- Future work will involve physician review of model results to corroborate these findings in a clinical context. Testing clinical acceptability of contours will determine whether the discrepancy in performance is patent in a clinical context, and whether PocketNet outputs can be sufficient in low-resource settings.

Conclusions

- Both PocketNet and nnU-Net architectures can successfully and reliably auto-contour pelvic structures and tumor volumes.
- nnU-Net predicted certain structures significantly better ($p < 0.05$) than PocketNet at the cost of greater computational power.

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