Dynamic Segmentation of Pre-Clinical Imaging Using Deep Learning

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ABSTRACT

Automatic multi-organ segmentation in preclinical micro-CT is essential for quantitative animal imaging. This study evaluates the impact of learning pipeline optimization and model architecture on segmentation performance using a public mouse micro-CT dataset.

A 3D U-Net pipeline was evaluated using different data augmentation strategies, learning rate optimization methods, and architectures (ResUNet, U-Net++, and TransUNet). Performance was assessed using Dice and HD95 metrics.

Pipeline optimization had a greater impact on segmentation performance than network complexity. The optimized 3D U-Net achieved performance comparable to more complex architectures while requiring fewer training epochs and less training time.

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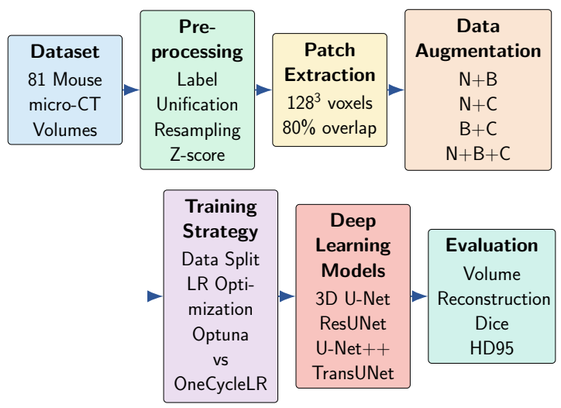
Introduction

Multi-organ 3D segmentation is essential for quantitative analysis and preclinical using micro-CT imaging [1, 2]. However, manual delineation remains challenging due to low contrast, noise, and anatomical variability [3]. Deep learning approaches, including 3D U-Net, nnU-Net, and Transformer-based models, have significantly improved segmentation performance [4, 5, 6]. However, the respective roles of model complexity and learning pipeline optimization remain insufficiently explored. This study investigates whether an optimized 3D U-Net pipeline can achieve performance comparable to more complex architectures.

Experimental Pipeline



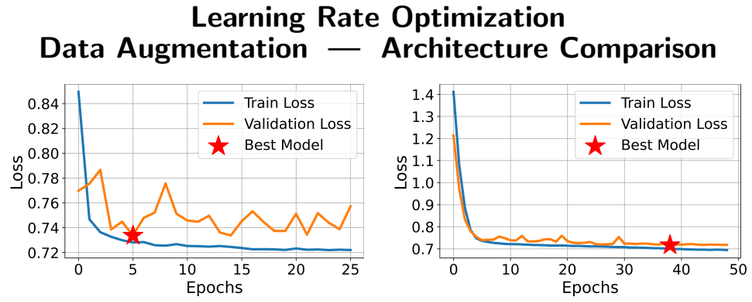
N = Noise, B = Brightness, C = Contrast.
Dataset: 81 contrast-enhanced mouse micro-CT volumes (8 mice).
Training: 128^3 patches, Optuna optimization, BCE + Dice loss.
Evaluation: Dice and HD95.

Computational Cost

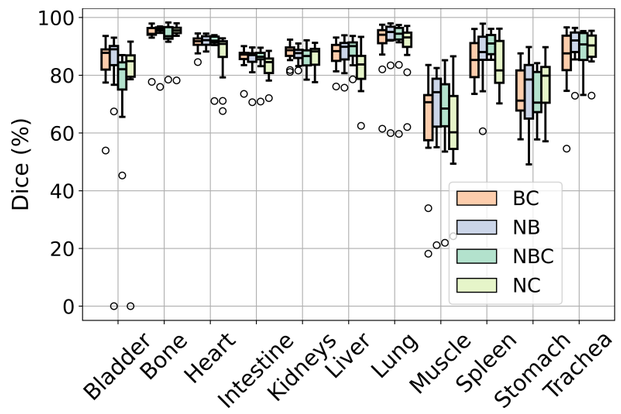
Model	Ep.	Time (h)	En. (kWh)	CO_2 (g)
3D U-Net	23	56.3	24.71	12.35
ResUNet	52	118.8	30.05	15.02
U-Net++	38	69.4	22.18	11.09
TransUNet	49	77.1	23.90	11.95

Training on an NVIDIA A100-SXM4 40GB GPU; energy measured by the Narval scheduler.

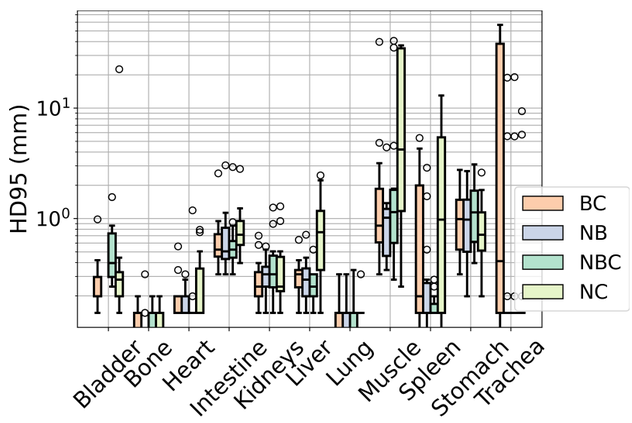
Results



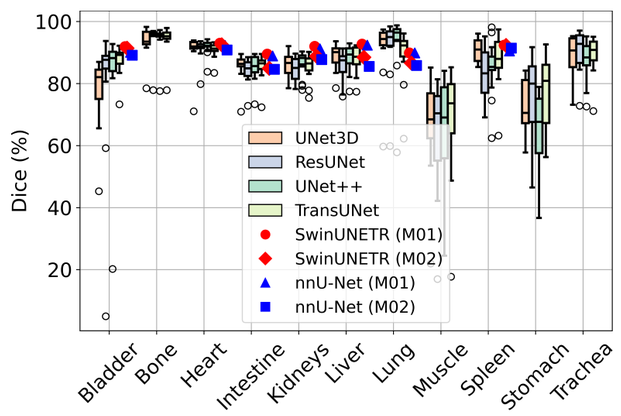
Comparable performance; Optuna converged in 6 epochs (vs. 39) and was retained.



Augmentation effects were organ-dependent. NBC often produced the most stable Dice scores for challenging organs, although no single strategy consistently outperformed the others across all structures.



NBC generally achieved lower HD95 values for several challenging organs, indicating improved boundary accuracy.



Comparable Dice performance was observed across all evaluated architectures, with no consistent superiority of more complex models over the optimized baseline 3D U-Net.

Discussion

- Data augmentation effects were organ-dependent. NBC generally improved segmentation stability for challenging structures, whereas NC produced greater variability.
- Despite architectural differences, 3D U-Net, ResUNet, U-Net++, and TransUNet achieved comparable segmentation performance for most organs.
- Our results indicate that optimizing the training pipeline was sufficient to achieve performance comparable to more complex architectures.
- The study was conducted on a single public preclinical dataset; validation on additional datasets would further assess the generalizability of the proposed pipeline.

Conclusions

- An optimized 3D U-Net pipeline achieved segmentation performance comparable to more complex architectures, including ResUNet, U-Net++, TransUNet, Swin UNETR, and nnU-Net.
- Pipeline optimization (pre-processing, augmentation, patch extraction, and learning rate optimization) contributed more to segmentation performance than increasing model complexity.
- The proposed framework provides a reproducible, computationally efficient, and robust solution for multi-organ segmentation in preclinical micro-CT imaging.

References

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