Comparative Evaluation of Deep Neural Networks for Intracranial Aneurysm Segmentation

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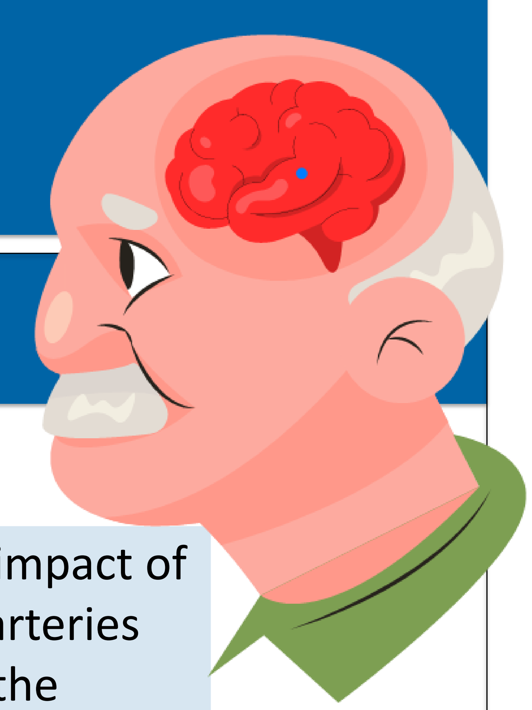


Introduction

Intracranial Aneurysms

Intracranial Aneurysms (IAs) are sac-like pathological dilatations of cerebral arteries with a global prevalence of 3-5%. Often asymptomatic, they pose risks like Subarachnoid Hemorrhage (SAH) and are commonly found in the Circle of Willis (CoW). Detection in routine angiographic imaging is challenging due to the overwhelming amount of information radiologists must process.

Problem Statement

This master's thesis investigates the automatic detection and segmentation of intracranial aneurysms in 3D medical imaging using Deep Learning (DL) methods.

Relevance

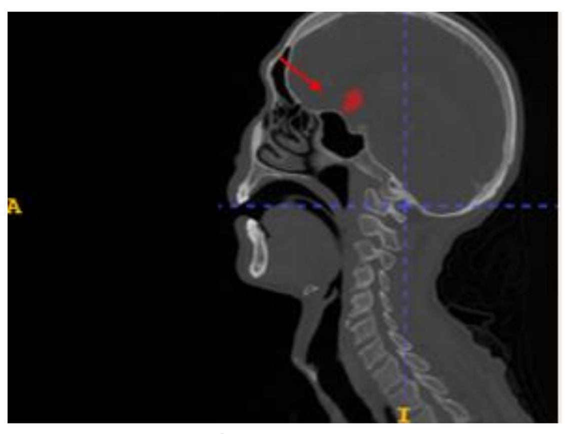
This master's thesis will contribute to a study investigating the impact of morphologic and topologic characteristics of primary cerebral arteries on aneurysm rupture. The tool developed herein will facilitate the automatic localization of aneurysms within extensive bio-banks—a prerequisite for large-scale studies utilizing 3D medical imaging. In practice, this research may culminate in the creation of a CAD tool, expediting the early detection of aneurysms during routine angiographic imaging by radiologists.

Methodology

Datasets

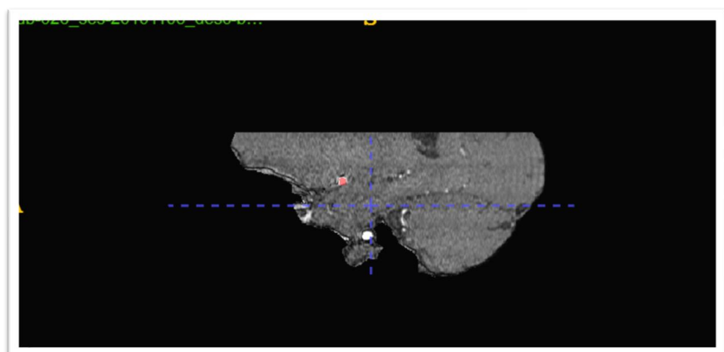
Two types of data modalities and datasets were utilized in this study: a CTA dataset and an MRA dataset, both of which included intracranial aneurysm Nifti images and their corresponding segmentations.

Dataset	#Pats	#IAs	Rup-tured	Non-rupt.
Internal training	1,186	1,363	474	712
Internal test	152	126	42	60



CT dataset

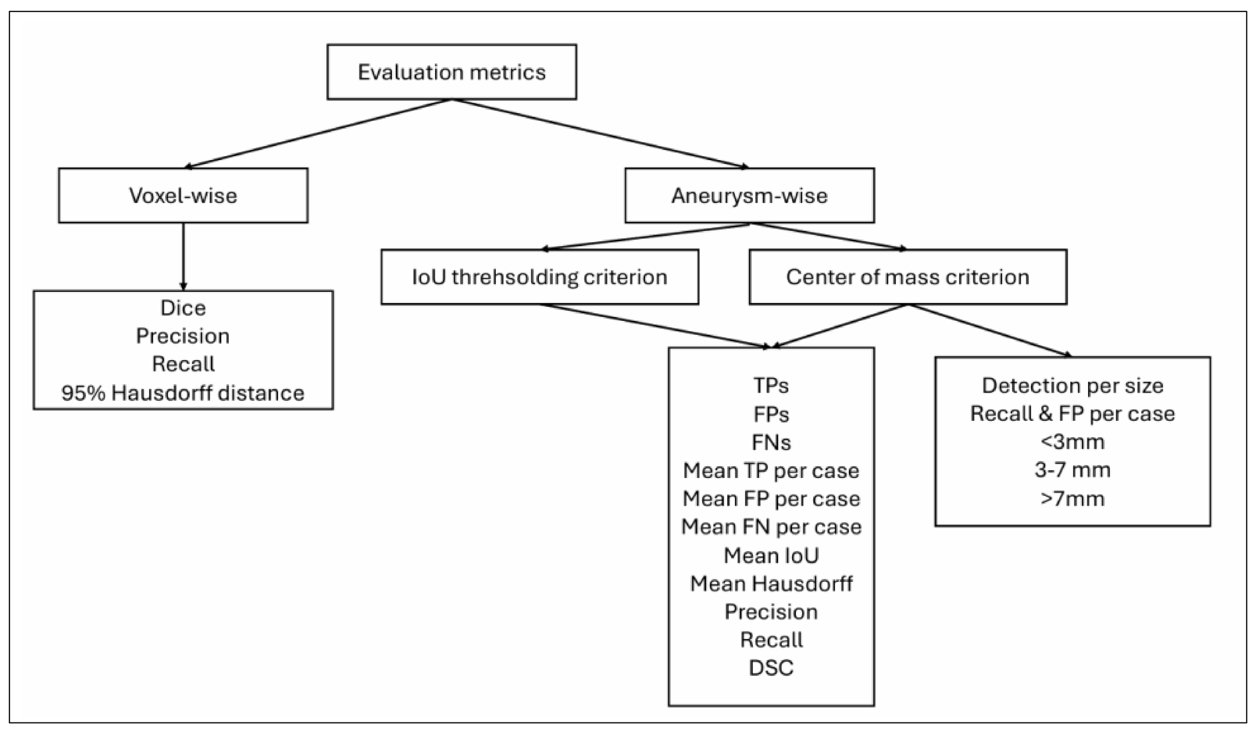
	Patients	Controls	Whole Sample
N	157	127	284
Age (y)	56 ± 14	46 ± 17	51 ± 16
Sex	53 M, 104 F	61 M, 66 F	114 M, 170 F
# UIA	198	0	198

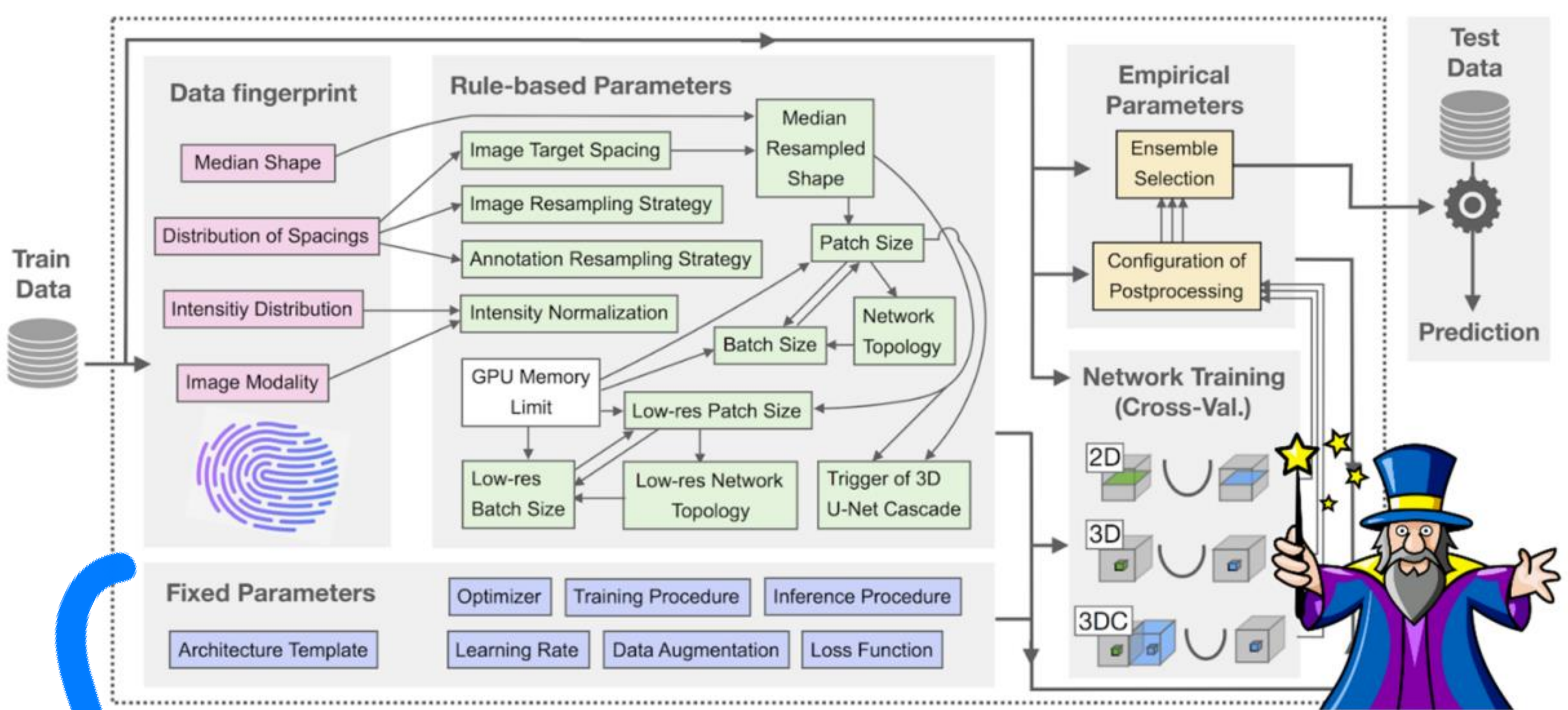


MR dataset

Segmentation model

The nnU-Net model, based on the U-Net architecture, is used for aneurysm segmentation. It features a symmetric U-shaped structure with an encoder that reduces spatial dimensions and a decoder that upsamples features for precise segmentation. nnU-Net adapts to the dataset by analyzing training cases and automatically configuring the segmentation pipeline. The model includes convolutional layers, instance normalization, leaky ReLU activation, and convolutional transpose layers, with skip connections to retain spatial information. With around 30 million parameters, nnU-Net generates 2D and 3D U-Net configurations tailored to the dataset's characteristics, ensuring optimal segmentation accuracy.

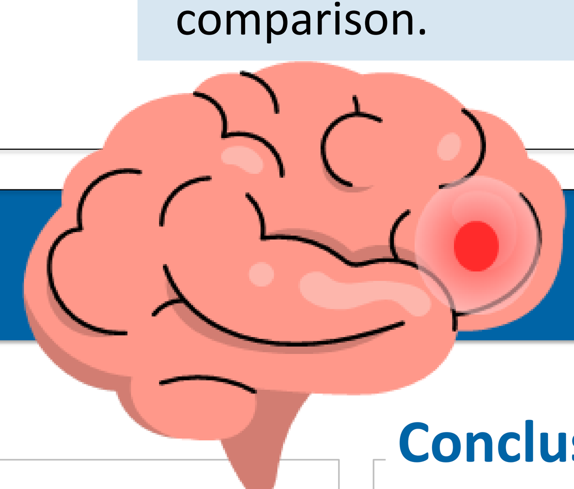




NN-Unet workflow

Evaluation

Following the preprocessing, training and post-processing phases, the model's performance was assessed utilizing standard metrics, including the Dice Similarity Coefficient (DSC), Intersection over Union (IoU), recall, precision, Hausdorff Distance (HD) and other pertinent measures of segmentation accuracy. The selected metrics were deliberately chosen to align with those used in previous studies, facilitating a direct comparison.



Results

Dataset	Model	Precision (%) ↑ (95% CI)	Recall(%) ↑ (95% CI)	DSC ↑ (95% CI)
Internal test (n= 151)	U-Net	14.0 (11.9–16.2)	71.3 (63.9–78.7)	23.2 (20.5–25.9)
	HeadXNet	16.2 (13.1–19.2)	55.6 (33.0–78.2)	23.2 (20.6–25.9)
	GLIA-Net	48.8 (44.5–53.0)	72.9 (66.9–78.9)	57.9 (56.4–59.5)
	nnU-Net	71.0 (69.0–73.0)	70.0 (68.0–72.0)	70.0 (69.0–72.0)

TABLE 3.1: Voxel-wise segmentation performance on the CT dataset

The study demonstrates the superior performance of the nnU-Net model in segmenting and detecting IAs in large CT datasets, outperforming GLIA-Net in voxel-wise precision and DSC. However, the model's performance on MR datasets is significantly lower, highlighting the importance of dataset size and label quality for robust model training.

Model	Recall	Avg. FP rate
3D-UNet [7]	68%	2.50
nn-UNet	68%	0.24

Target-wise detection performance on the MR comparison

Size Category	Metric	Value
<5mm (n=12)	Recall(%) ↑	43.34 (38.71–47.96)
	FPs per case ↓	0.65 (0.43–0.88)
5-10mm (n=70)	Recall(%) ↑	85.23 (81.97–88.48)
	FPs per case ↓	0.17 (0.12–0.21)
>10mm (n=43)	Recall(%) ↑	94.29 (92.74–95.84)
	FPs per case ↓	0.03 (0.01–0.04)

Performance on CT per size category

Discussion

Study limitations include inconsistent metrics across literature, different aneurysm size definitions, and difficulties in comparing CT and MR segmentation performance due to discrepancies in dataset sizes and label quality. Future work should focus on increasing dataset sizes and extending training epochs to improve model performance. Customizing the nnU-Net architecture, particularly the foreground sampling strategy for small instances, and exploring alternative models with attention mechanisms for vascular structures can enhance segmentation accuracy. Additionally, adopting standardized guidelines and benchmarks for models and datasets will enable coherent comparisons and consistent evaluation metrics, including definitions of aneurysm size, metrics, and criteria for true positives, using large benchmark datasets.

Conclusion

The nnU-Net model showed superior performance in the segmentation and detection of IAs in larger CT datasets with voxel-wise labels compared to other segmentation models. The creation of benchmark datasets would facilitate easier comparison of models. It is crucial to adopt standardized guidelines to ensure consistent evaluation metrics, including definitions of aneurysm size, choices of metrics, and criteria for true positives.

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References

1. T. Di Noto, G. Marie, S. Tourbier, et al. "Towards Automated Brain Aneurysm Detection in TOF-MRA: Open Data, Weak Labels, and Anatomical Knowledge". In: Neuroinformatics 21 (2023), pp. 21–34. DOI: 10 . 1007 /s12021 -022-09597-0
2. Z.-H. Bo et al. "Toward human intervention-free clinical diagnosis of intracranial aneurysm via deep neural network". In: Patterns 2.2 (2021), p. 100197. DOI: https://doi.org/10.1016/j.patter.2020.100197
3. Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 18(2), 203-211.

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