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Signed Distance Field Regression-based Intracranial Vessel Segmentation in MR Vessel Wall Imaging

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Abstract

Problem: Accurate intracranial vessel segmentation from non-contrast vessel wall imaging (VWI) is challenged by low wall-to-lumen contrast, thin tortuous anatomy, and severe class imbalance, which often cause voxel-wise classification to produce gaps and disconnected branches even when overlap metrics appear adequate.

Main Idea: Signed distance field (SDF) regression offers a geometric alternative: rather than classifying voxels, a network predicts continuous distance-to-boundary values, providing a shape descriptor that encodes spatial relations beyond binary inclusion and encourages continuous, boundary-consistent output.

Method: A U-Net was trained to regress SDF maps from VWI, with segmentation recovered as the zero level set. This was compared against standard nnUNet and an nnUNet variant trained with an added skeleton recall loss, a term that directly penalizes missed centerline voxels during training to help preserve thin, low-contrast connections that overlap-based losses tend to overlook.

Experiment Setup: 61 ICAD patients with paired VWI/TOF-MRA. Performance was assessed using Dice, centerline Dice (clDice) — which measures overlap between predicted and reference centerlines and is more sensitive than Dice to small breaks in thin structures — and surface/centerline distance metrics.

Results: SDF regression achieved clDice of 0.66 ± 0.05 and Dice of 0.68 ± 0.05, comparable to nnUNet (clDice 0.66 ± 0.04, Dice 0.68 ± 0.05), while the skeleton-recall variant achieved higher centerline fidelity (clDice 0.70 ± 0.05).

Main Observations: SDF regression provides a principled geometric descriptor that encodes shape relations beyond binary inclusion and encourages spatial continuity as a consequence. Incorporating explicit centerline-aware objectives such as skeleton recall loss can further improve centerline performance.

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Introduction

Intracranial atherosclerotic disease (ICAD) is a major cause of ischemic stroke, and accurate vessel delineation from non-contrast vessel wall imaging (VWI) is essential for assessing plaque burden and wall remodeling. VWI segmentation is challenging: low wall-to-lumen contrast, thin tortuous vessels, and severe class imbalance often cause voxel-wise classification models to produce topological errors, such as gaps and disconnected branches, even when overlap metrics look reasonable.

This motivates looking beyond per-voxel classification toward representations that encode vessel geometry more directly. Signed distance fields have long been used in shape modeling to represent continuous, differentiable surfaces,[1] well suited to thin structures where small discretization errors can break connectivity. Motivated by this, we reframe segmentation as regression, training a U-Net to predict continuous distance-to-boundary values from which the vessel mask is recovered as the zero level set. This formulation is inherently smooth and boundary-aware, though whether it yields a practical topological advantage over recent centerline-aware loss functions has yet to be explored.

Purpose: To investigate the feasibility of SDF regression for improving geometric and topological fidelity of intracranial vessel segmentation from non-contrast VWI, compared to standard nnUNet and an nnUNet variant trained with an added skeleton recall loss that directly supervises centerline connectivity.

Results

- The proposed SDF regression model had comparable Dice scores to baseline nnUNet, with mildly better ASSD and ACD agreement.
- On centerline/topology metrics, the skeleton-recall nnUNet variant outperformed both the proposed method and standard nnUNet, achieving higher clDice and lower ACD (Tab 1).
- Visual inspection revealed that both the proposed method and nnUNet exhibited occasional discontinuities in peripheral vessel branches; these were partially mitigated in the skeleton-recall variant, likely reflecting its increased sensitivity to thin structures (Fig 2).

Methods

Data: Retrospective cohort of 61 ICAD patients with paired MR VWI and TOF MRA. Since manual voxel-level annotation is impractical at this scale, reference vessel labels were generated by applying a pretrained MRA segmentation network to the registered, high-contrast TOF-MRA images. A Euclidean distance transform was applied to these labels to produce reference SDF maps for training and evaluation. An 80/20 train-test data split was used.

SDF model: A U-Net maps 3D VWI intensity volumes to a continuous signed distance field, where the sign indicates interior/exterior of the vessel and the magnitude gives distance to the nearest vessel boundary (Fig 1). The training objective combines: (1) Distance-weighted MAE loss that penalizes regression error more heavily near vessel boundaries where segmentation accuracy matters most, and (2) eikonal regularization to enforces the property that a valid SDF has unit-magnitude gradient, encouraging geometrically consistent output. At inference, the predicted vessel mask is obtained by thresholding the SDF at its zero-level set.

Comparison models: (1) standard nnUNet segmentation, and (2) nnUNet with an added skeleton recall loss,[2] which explicitly supervises centerline overlap rather than relying on implicit geometric smoothness.

Evaluation: Dice (volumetric overlap) and ASSD (surface distance) served as general accuracy metrics, while centerline Dice (clDice) and average centerline distance (ACD) served as the primary measures of topological/centerline connectivity, the property most directly tied to the discontinuities motivating this study.

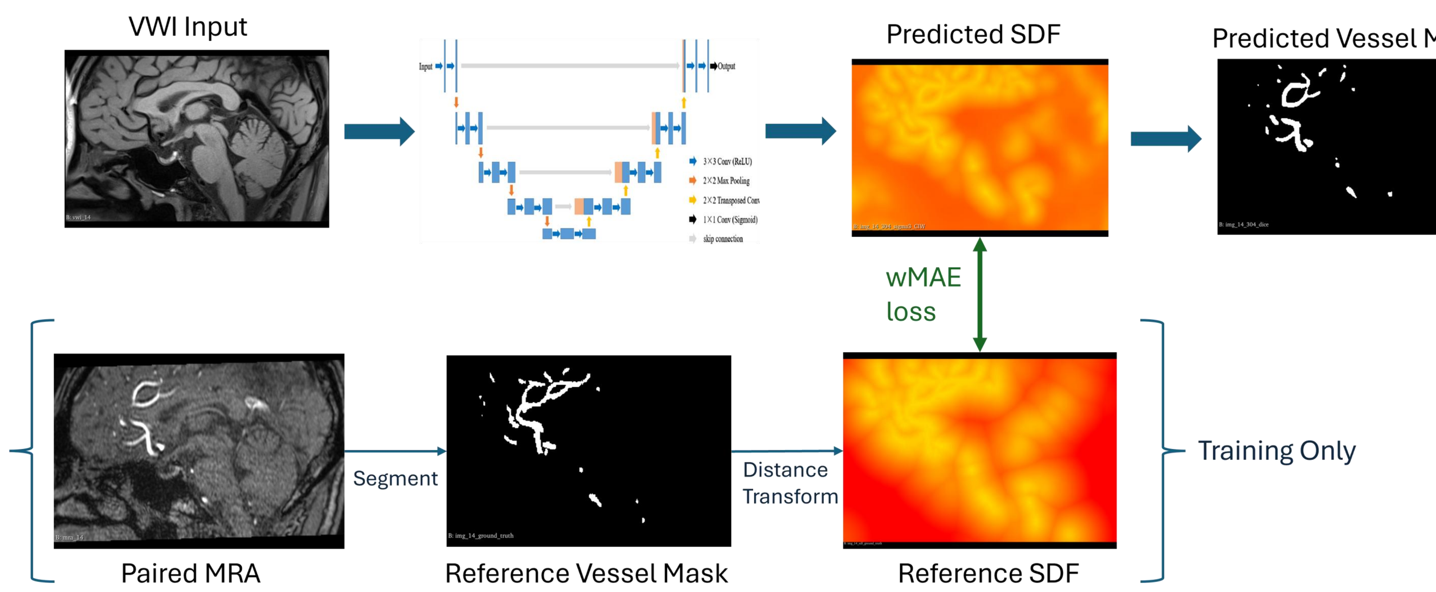

Figure 1. Schematic of proposed method. SDF are predicted directly from VWI and thresholded to obtain predicted vessel label

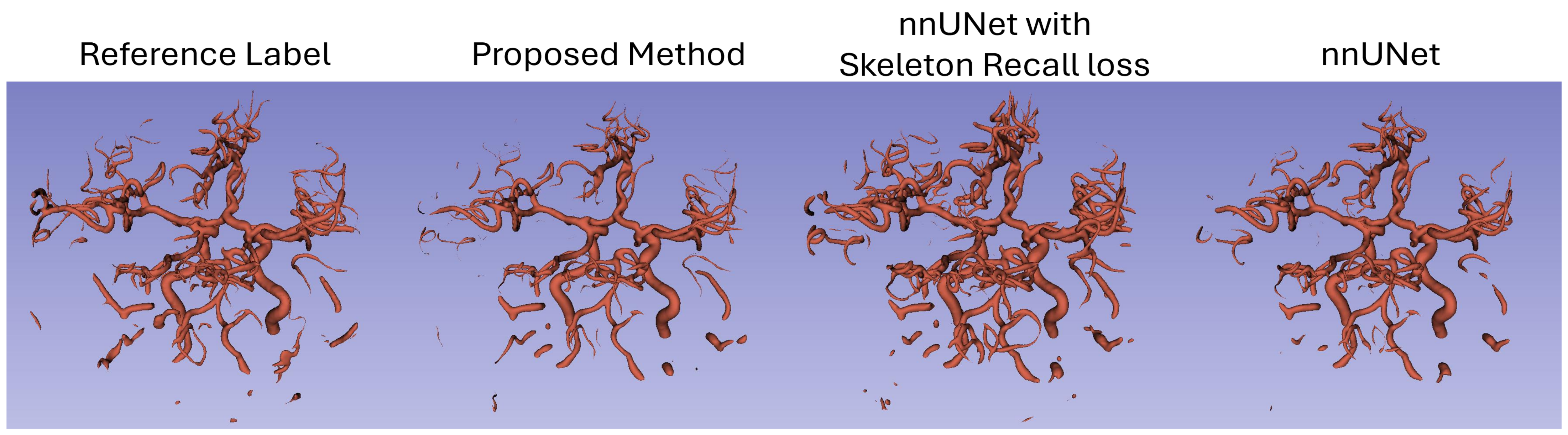

Figure 2. Comparison of predicted vessel segmentations for one example test patient.

	Dice	clDice	ASSD (mm)	ACD (mm)
Proposed SDF Model	0.68 (0.05)	0.66 (0.06)	1.40 (0.47)	2.48 (0.63)
nnUNet w/ Skeleton Recall Loss	0.68 (0.04)	0.70 (0.05)	1.14 (0.55)	2.18 (0.66)
nnUNet	0.68 (0.05)	0.66 (0.04)	1.48 (0.44)	2.59 (0.52)

Table 1. Model evaluation on the N=12 held-out test set, reported as mean (std).

Discussion

SDF regression matches nnUNet on overlap and surface distance, confirming it as a viable geometric alternative to voxel-wise classification. On the topology-sensitive clDice metric, however, the skeleton-recall nnUNet model outperforms both SDF regression and standard nnUNet. Because skeleton recall loss is directly derived from clDice, part of this advantage may be attributable to objective-metric alignment rather than a superior geometric prior alone.

Regardless, the results suggest the two approaches target different failure modes rather than compete directly: SDF regression and eikonal regularization encourage smooth, valid boundary geometry, but neither explicitly rewards preserving thin, low-contrast branch connections, which is what skeleton recall does directly.

Limitations: Reference labels derive from a pretrained MRA segmentation network (not manual annotation), so discontinuities there may propagate into training/evaluation for all methods.

SDF regression's geometric prior and skeleton recall's centerline supervision appear complementary. Combining them is a natural next step.

Conclusion

This work demonstrates that reframing vessel segmentation as boundary regression is a practical, competitive strategy for non-contrast VWI, matching established baselines on overlap and surface accuracy. Closing the remaining gap in centerline fidelity likely requires pairing this geometric prior with explicit connectivity supervision, motivating future work that combines the two directly.

References

[1] Park et al. CVPR. 2019. doi:10.1109/CVPR.2019.00025
[2] Kirchhoff et al. arXiv. 2024. doi:10.48550/arXiv.2404.03010