

From Hyperintensity to Edema: An Edema-Specific Segmentation Algorithm on T2-FLAIR

Hyungyou Park¹, Sunghwan Park¹, Minho Lee¹, Regina EY Kim¹, Chong Hyun Suh², Donghyeon Kim¹

¹ Research Institute, Neurophet Inc., Seoul, Republic of Korea ² Department of Radiology and Research Institute of Radiology, Asan Medical Center, University of Ulsan College of Medicine, Seoul, Republic of Korea

01 Background & Objective

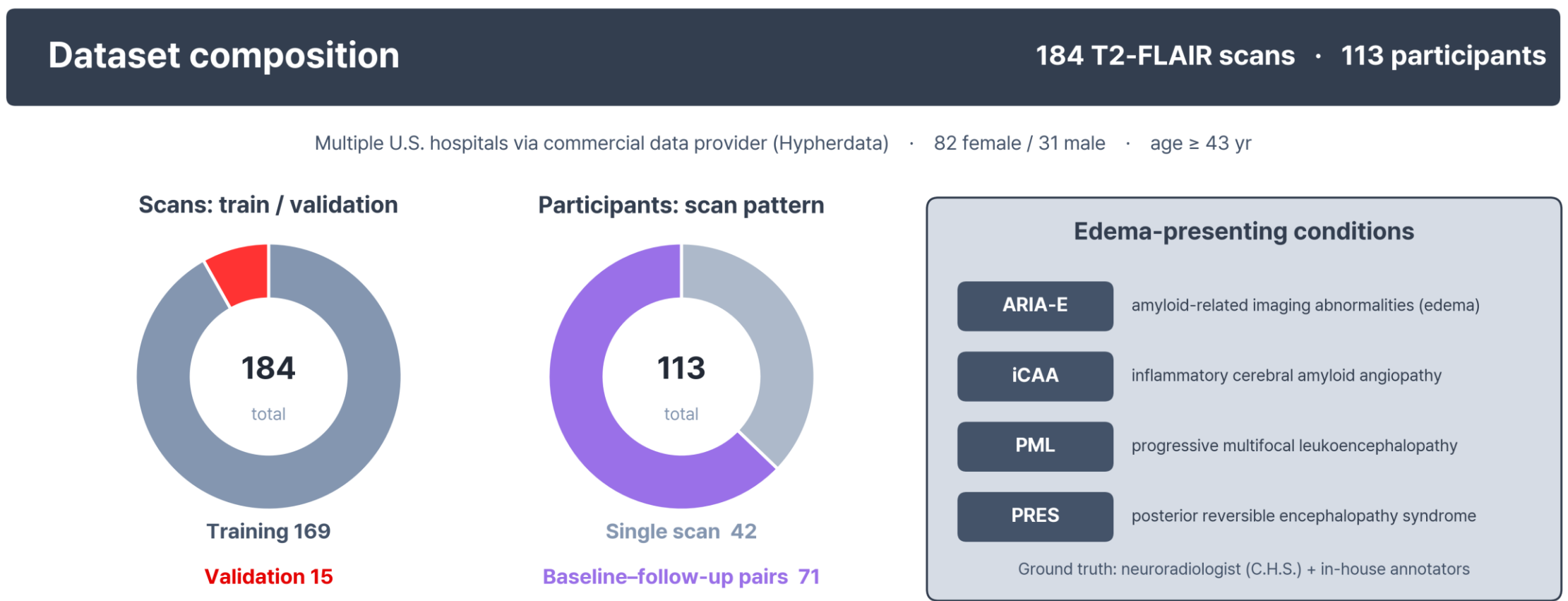
- The clinical need.** With anti-amyloid therapies now in routine use, MRI-based **safety monitoring for amyloid-related imaging abnormalities with edema/effusion (ARIA-E)** has become essential — informing dosing, pausing, and treatment decisions.
- The imaging problem.** On T2-FLAIR, **edema is hard to interpret and delineate: its hyperintensity overlaps with non-specific white-matter hyperintensities (WMH)**. Manual delineation is time-consuming and shows high inter-rater variability, and generic hyperintensity models cannot tell edema apart from other bright lesions.

OBJECTIVES

Develop and validate an **edema-specific T2-FLAIR segmentation algorithm** that distinguishes edema from other hyperintense lesions for accurate, single-scan quantification.

02 Methods

Dataset



Model & training

- 3D nnU-Net with Multi-Scale Feature Fusion (MSFF)**
- Transfer learning:** the model is initialized from an in-house T2-FLAIR hyperintensity model, then fine-tuned to discriminate edema from other hyperintense regions.
- How edema is isolated:** the network predicts three classes — background, edema, and WMH — and only the edema class is retained. Learning WMH as its own label explicitly separates edema from non-specific hyperintensities.

Evaluation

- Dice similarity coefficient (DSC) ↑, average symmetric surface distance (ASSD) ↓, volume similarity (VS) ↑.
- Ablation: proposed model (with hyperintensity guidance) vs. a model trained solely for edema (without guidance).

03 Results

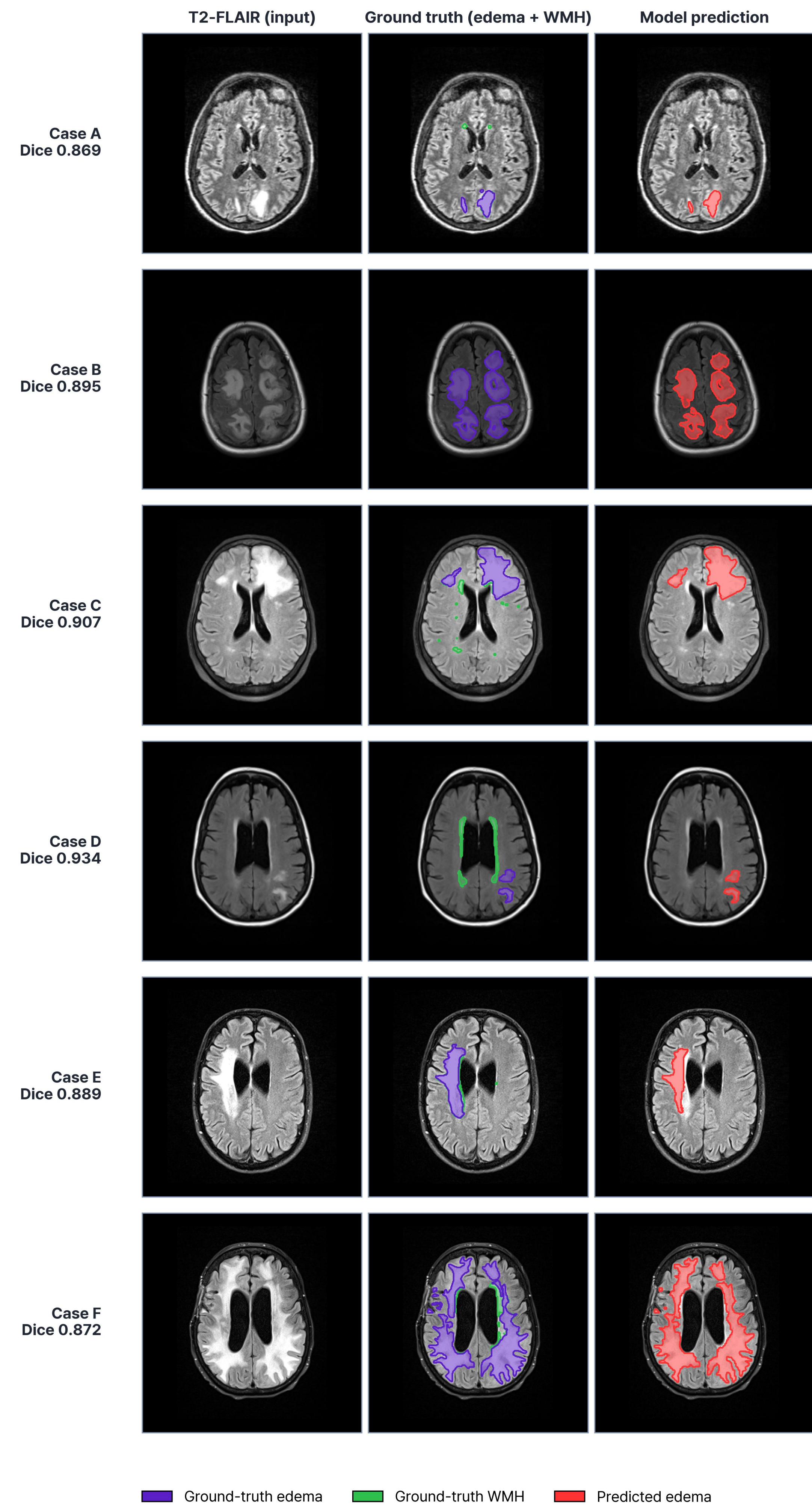
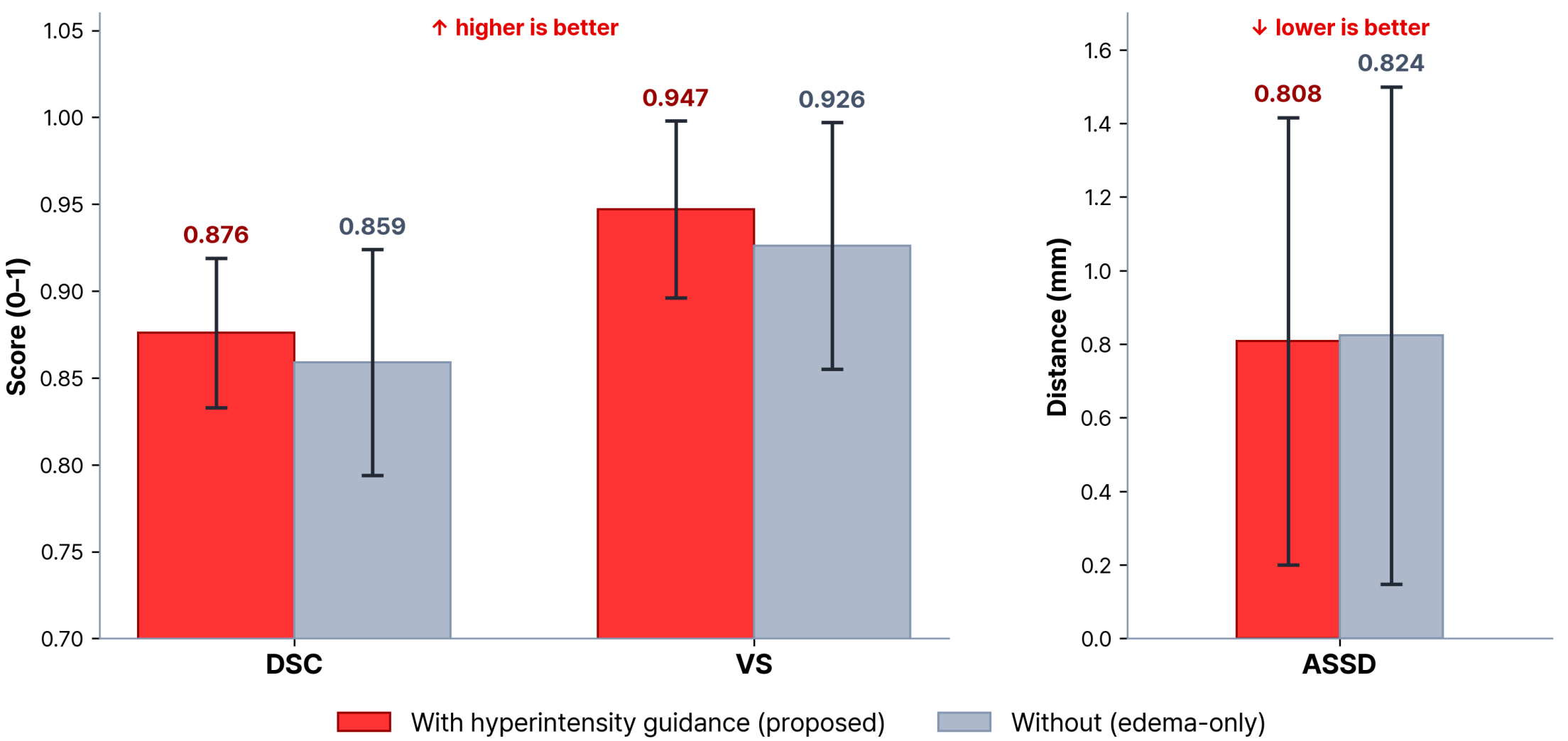


Figure 1. Representative cases: ground truth shows edema (purple) and non-specific white-matter hyperintensities (green); the model's predicted edema (red) matches GT edema while excluding WMH (Dice 0.869–0.934). Axial slices in radiological orientation (anterior at top; patient right on image left)."

Table 1. Segmentation accuracy: with vs. without hyperintensity guidance

Metric	With hyperintensity guidance (proposed)	Without (edema-only)
DSC ↑	0.876 ± 0.043	0.859 ± 0.065
ASSD ↓ (mm)	0.808 ± 0.608	0.824 ± 0.676
VS ↑	0.947 ± 0.051	0.926 ± 0.071

Values mean ± SD. DSC, Dice similarity coefficient (higher = better); ASSD, average symmetric surface distance (lower = better); VS, volume similarity (higher = better).



Values mean ± SD (validation, n=15). Improvement is consistent across all three metrics; the abstract reports no significance test and SD ranges overlap.

Absolute differences are modest, but relative to a near-ceiling baseline they are meaningful: hyperintensity guidance reduces the Dice error by ~12% (0.141 → 0.124) and the volume-similarity error by ~28% (0.074 → 0.053) and lowers surface distance by ~2%. (Note: the abstract reports no significance test, and the SD ranges overlap — describe as a consistent directional improvement across all three metrics, not a significance claim.)

04 Conclusion

- Edema can be segmented accurately via a dedicated fine-tuning strategy that isolates edema within T2-FLAIR hyperintense regions — hyperintensity guidance beats edema-only training on DSC, ASSD, and VS.
- No longitudinal imaging required — works on a single time-point scan, easing integration into routine clinical workflows.
- Supports objective, quantitative monitoring of edema-presenting conditions, including ARIA-E (edema burden and radiographic severity) in the anti-amyloid therapy era.

References

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*hyungyou.park@neurophet.com