

Deep Learning-Based Super-Resolution Enhances Perivascular Space Quantification in Heterogeneous MRI Data



Hyunwoo Lim, BS¹, Yeong-Hun Song, BS^{1,3}, Woosik Kim, BS^{2,3}, Seung Hong Choi, PhD^{4,5}, Roh-Eul Yoo, PhD^{4,5}, Joon-Kyung Seong, PhD^{1,2,3}, for the Alzheimer’s Disease Neuroimaging Initiative*

¹School of Artificial Intelligence, Korea University, Seoul, Republic of Korea
²School of Biomedical Engineering, Korea University, Seoul, Republic of Korea
³NeuroXT Inc., AI Imaging Research Center, Seoul, Republic of Korea
⁴Department of Radiology, Seoul National University College of Medicine, Seoul, Republic of Korea
⁵Department of Radiology, Seoul National University Hospital, Seoul, Republic of Korea

INTRODUCTION

Background

- PVS as a Biomarker:** Enlarged perivascular spaces (PVS) are increasingly recognized as a crucial neuroimaging biomarker
- Current Limitations:** Visual Rating Scores (VRS) are widely used in clinical practice but suffer from inherent subjectivity and coarse granularity.
- Technical Challenges:** Automated methods (e.g., Frangi filtering) are highly sensitive to image resolution. This spatial heterogeneity in multi-site data hinders accurate quantification.
- Objective:** To evaluate whether deep learning-based SR can serve as a resolution harmonization strategy to reduce resolution-dependent variability and improve the reliability of automated PVS quantification.

Dataset

- T2-weighted MRI (T2WI) scans from:
- SNU dataset (n=324): Used for SR model training, Frangi parameter optimization, and internal validation with visual rating scores.
 - High in-plane resolution: $0.215 \times 0.215\text{mm}^2$ (n=146).
 - Mid in-plane resolution: $0.246 \times 0.246\text{mm}^2$ (n=124).
 - Low in-plane resolution: $0.625 \times 0.625\text{mm}^2$ (n=54).
 - ADNI4 dataset (n=631): Used for external clinical validation.
 - Approximately $1.0 \times 1.0\text{mm}^2$ in-plane resolution.
 - Includes White Matter Hyperintensity (WMH) volume data.

Key Takeaway

- ✓ Noise augmentation improves the robustness of SR-based PVS quantification.
- ✓ Resolution harmonization enhances agreement with expert visual ratings.
- ✓ SR-harmonized PVS measures show stronger associations with WMH burden in an external cohort.

METHODS

SR-Based Resolution Harmonization

- Model:** Utilized A-LIIF (Adaptive Local Implicit Image Function) to enable 2D arbitrary-scale SR, ensuring resolution harmonization across heterogeneous datasets.
- Preprocessing:** A-LIIF was retrained on high-resolution SNU T2-weighted slices using synthetic multi-scale degradation. A-LIIF-MRI incorporated Gibbs and Rician noise augmentation to improve robustness.
- Resolution Harmonization:** All images were upsampled to a uniform $0.215 \times 0.215\text{mm}^2$ target resolution.

PVS Segmentation & Optimization

- Automated Segmentation:** PVS were quantified using a Frangi filter-based algorithm.
- Experimental Conditions:** Five image conditions were compared in the SNU cohort: 1 mm downsampling, original resolution, bicubic upsampling, A-LIIF, and A-LIIF-MRI, a noise-augmented variant of A-LIIF.
- VRS-Guided Tuning:** Frangi filter parameters were rigorously optimized for each resolution group by maximizing the correlation with the VRS.
- Validation:** Once optimized, parameters were fixed and applied to independent datasets to validate the robustness of the SR-enhanced quantification.

Clinical Validation

- ADNI4 Cohort Analysis:** SNU-locked pipeline was applied to original-resolution, bicubic-upsampled, and A-LIIF-MRI images.
- Clinical Validation:** Investigated the clinical relevance by examining the association between BG PVS-VF and log-transformed WMH volume, a marker of vascular burden.

RESULTS

Scale	Method	PSNR (mean $\pm$ SD)	SSIM (mean $\pm$ SD)
Mid (1.14x)	Bicubic	58.24 $\pm$ 2.16	0.9995 $\pm$ 0.0001
	A-LIIF	60.99 $\pm$ 2.11	0.9997 $\pm$ 0.0001
	A-LIIF-MRI	58.60 $\pm$ 1.98	0.9991 $\pm$ 0.0005
Low (2.91x)	Bicubic	42.16 $\pm$ 2.13	0.9838 $\pm$ 0.0041
	A-LIIF	44.39 $\pm$ 1.78	0.9881 $\pm$ 0.0029
	A-LIIF-MRI	44.03 $\pm$ 1.74	0.9866 $\pm$ 0.0037
ADNI-like (4.65x)	Bicubic	34.50 $\pm$ 2.32	0.9278 $\pm$ 0.0207
	A-LIIF	36.64 $\pm$ 2.02	0.9475 $\pm$ 0.0161
	A-LIIF-MRI	36.52 $\pm$ 2.02	0.9463 $\pm$ 0.0164

Table 1. Image-level SR reconstruction performance.

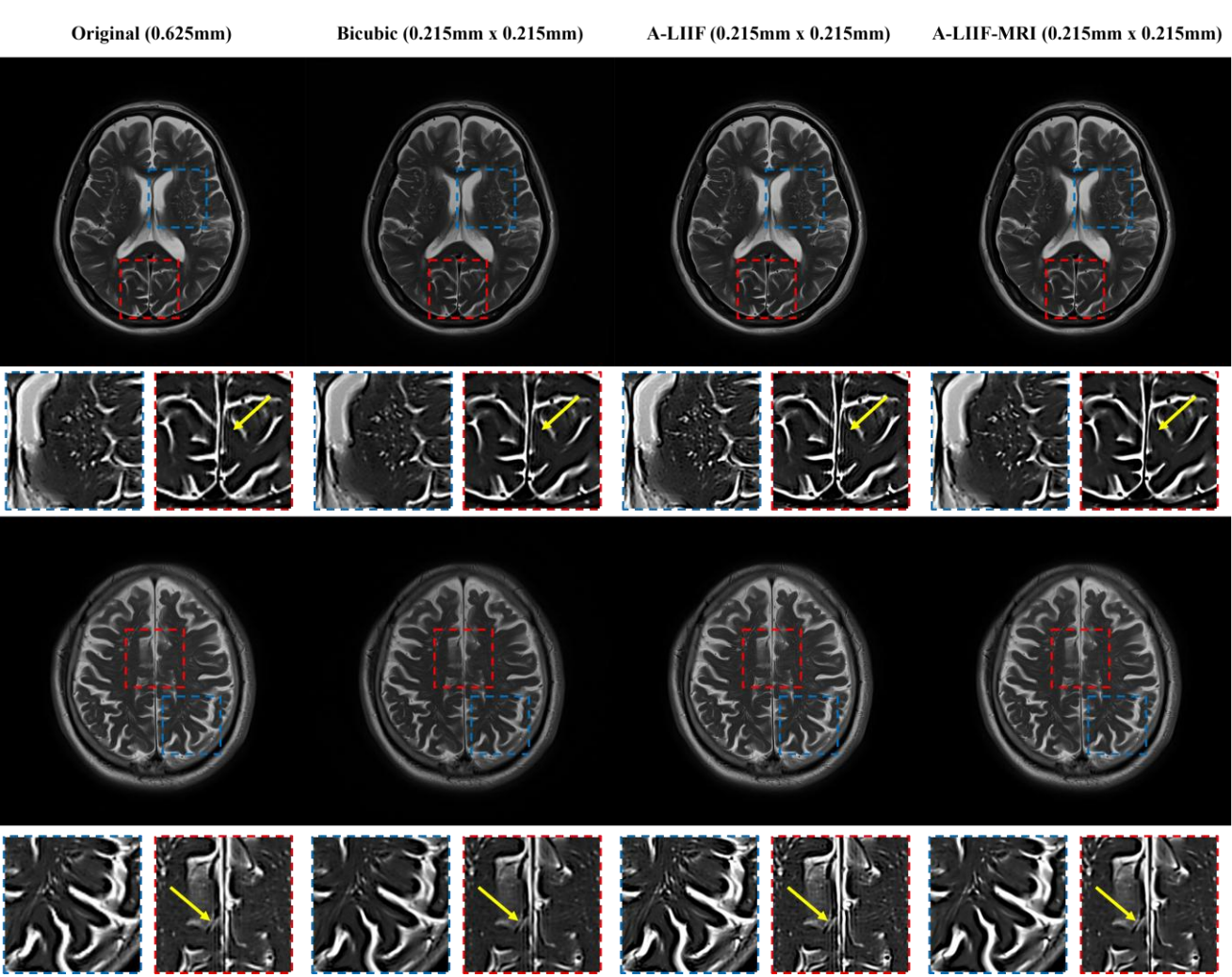


Figure 1. Qualitative comparison of resolution harmonization methods applied to low-resolution T2-weighted MRI scans. Enlarged views highlight differences in vessel-like structures and noise-related pseudo-structures.

Condition	BG ρ [95% CI]	CSO ρ [95% CI]
Downsampled	0.416 [0.337, 0.519]	0.452 [0.394, 0.570]
Original	0.479 [0.405, 0.556]	0.569 [0.487, 0.639]
Bicubic Upsampling	0.540 [0.437, 0.610]	0.614 [0.535, 0.676]
A-LIIF	0.553 [0.448, 0.622]	0.621 [0.541, 0.679]
A-LIIF-MRI	0.553 [0.454, 0.623]	0.628 [0.547, 0.683]

Table 2. Agreement between automated PVS volume fraction and visual rating scores.

- Image-level reconstruction:** A-LIIF achieved the highest PSNR/SSIM (Table 1), while A-LIIF-MRI slightly reduced image-level scores but suppressed noise-related pseudo-structures, improving downstream robustness (Figure 1).
- SNU internal validation:** Resolution harmonization improved the agreement between automated PVS volume fraction and expert visual rating scores (Table 2). A-LIIF-MRI showed the best overall downstream performance.
- ADNI4 external validation:** In the independent ADNI4 cohort, BG PVS volume fraction showed stronger association with WMH burden after harmonization (Table 3). The adjusted partial correlation was strongest for A-LIIF-MRI, followed by bicubic upsampling and original-resolution images, supporting the clinical relevance of resolution-harmonized PVS quantification.

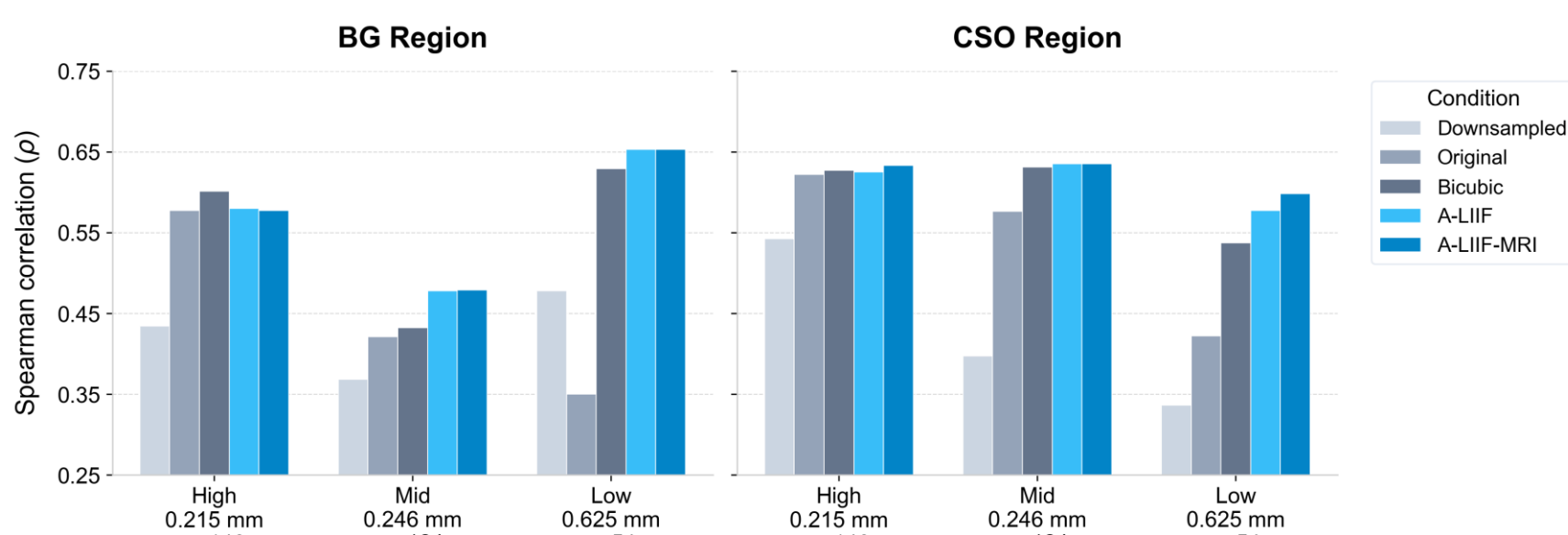


Figure 2. Resolution-specific agreement between automated PVS volume fraction and visual rating scores. Resolution harmonization improved agreement across all resolution groups, with the largest gains observed in the low-resolution (0.625 mm) group.

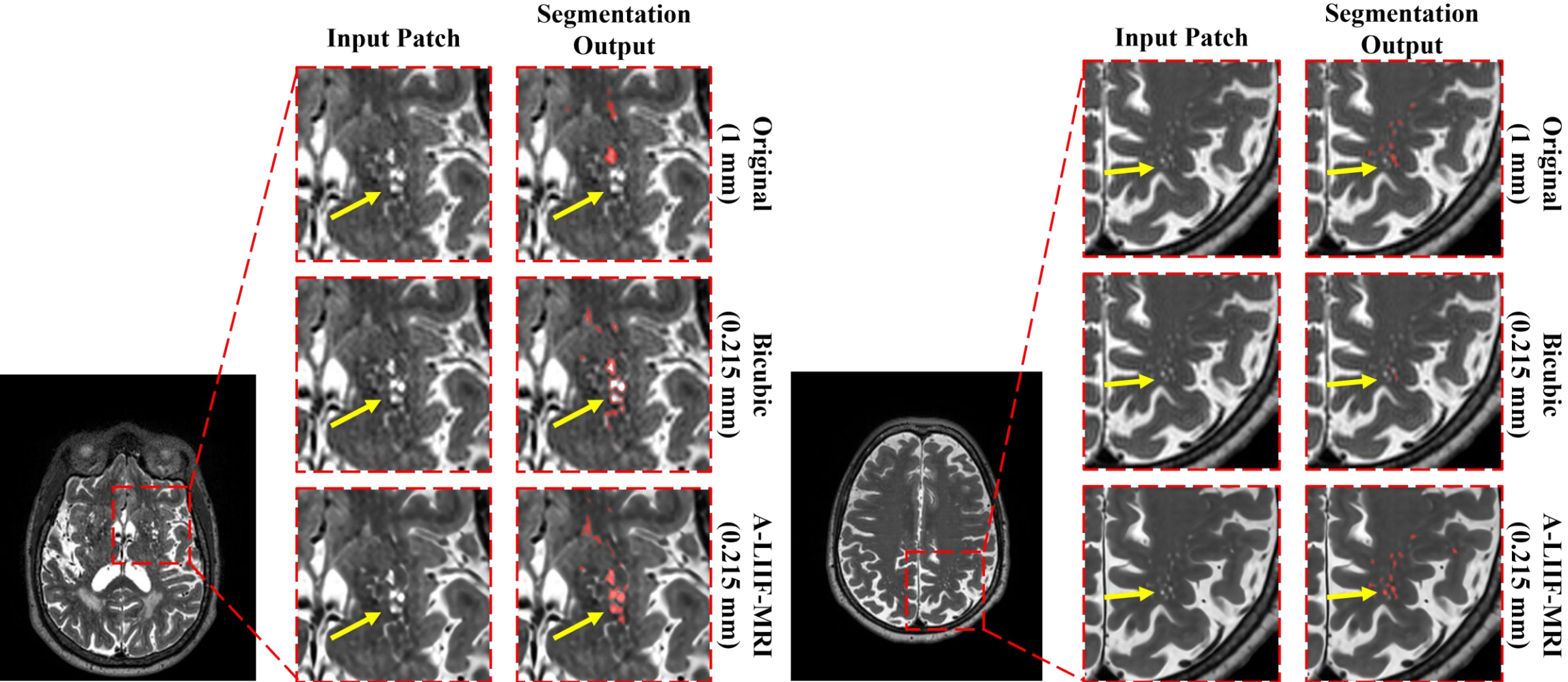


Figure 3. Representative examples demonstrating the effect of SR-based resolution harmonization on Frangi-based PVS segmentation. Yellow arrows indicate vessel-like structures that became more clearly distinguishable after SR harmonization.

Image Condition	r	95% CI	p
Original	0.274	[0.20, 0.35]	<.001
Bicubic	0.300	[0.23, 0.37]	<.001
A-LIIF-MRI	0.385	[0.32, 0.45]	<.001

Table 3. Age-, sex-, and education-adjusted partial correlation between BG PVS volume fraction and log-transformed WMH burden in the ADNI4 cohort.

CONCLUSION

- Resolution Harmonization:** Deep learning-based SR served as a resolution harmonization strategy, improving the reliability of automated PVS quantification across heterogeneous T2-weighted MRI scans.
- Clinical Relevance:** The SNU-locked A-LIIF-MRI pipeline strengthened the association between BG PVS burden and log-transformed WMH volume in ADNI4.
- Impact:** This framework supports resolution harmonization as a practical preprocessing strategy for robust PVS biomarker analysis in large-scale retrospective and multi-site MRI cohorts.