Segmentation of Late Gadolinium-Enhanced Cardiac Magnetic Resonance Images Based on Residual Attention Mechanisms

Background: Magnitude (MAG) and Phase-Sensitive Inversion Recovery (PSIR) images are routinely co-acquired for cardiovascular diagnosis and left ventricular myocardium (Myo) segmentation. However, previous automated models primarily rely on a single modality. This forces researchers to manually select higher-quality scans or run multiple segmentation attempts, which is time-consuming and wastes complementary data. Given the strict computational limits and scarce annotated data in clinical environments, there is a critical need for an efficient dual-modality model capable of leveraging both sequences automatically.

Method: To address this, we developed a Gated U-Net that utilizes a quality-aware, asymmetric feature-fusion strategy for Myo segmentation. Our architecture designates one scan as the primary modality, using stage-wise gating to dynamically integrate auxiliary features when they provide local benefit. This approach fully utilizes the strengths of both modalities, achieving high segmentation accuracy with significantly less computational overhead. We utilized 56 imaging pairs from Beijing Anzhen Hospital (44 training, 12 testing).

Results: Overall, our Gated U-Net achieved an 81.5% Dice score in only 10 training epochs, demonstrating rapid convergence and superior accuracy. In contrast, the advanced single-modality model nnUNet v2 required twice as many epochs (20) yet achieved lower Dice scores of 80.4% (MAG alone) and 81.3% (PSIR alone). Furthermore, our method reduced training time by 60.3% compared to obtaining the optimal result from single-modality training. Even with sufficient training (100 epochs), our method (82.4%) still outperformed single-modality methods (MAG: 81.6%, PSIR: 81.5%).

Conclusion: Overall, the proposed Gated U-Net provides a highly efficient and accurate solution for dual-modality cardiac segmentation, successfully overcoming the computational and data-utilization limitations of single-modality approaches. Furthermore, the adaptive fusion weights learned by the network can be extracted to generate high-quality fused MAG-PSIR images. This provides clinicians with enhanced visual clarity for precise diagnostic assistance, extending the model's clinical utility well beyond pure segmentation tasks.