Performance comparison of multi-modality MRI segmentation models

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Introduction

Medical image segmentation has clinical significance in improving workflows and aiding with diagnosis. So far, most MRI segmentation methods are feature-level models (See Fig. 1), we believe image-level models (Fig. 2) hold untapped potential. Not only can fused images offer clinicians additional visual information, but this approach also provides greater flexibility: researchers can easily experiment by swapping in state-of-the-art (SOTA) fusion or segmentation models to enhance the model performance.

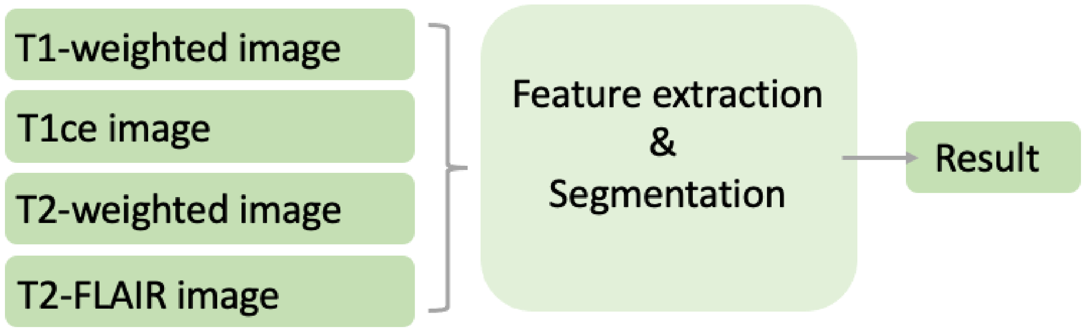


Figure 1. The general structure of feature-level models

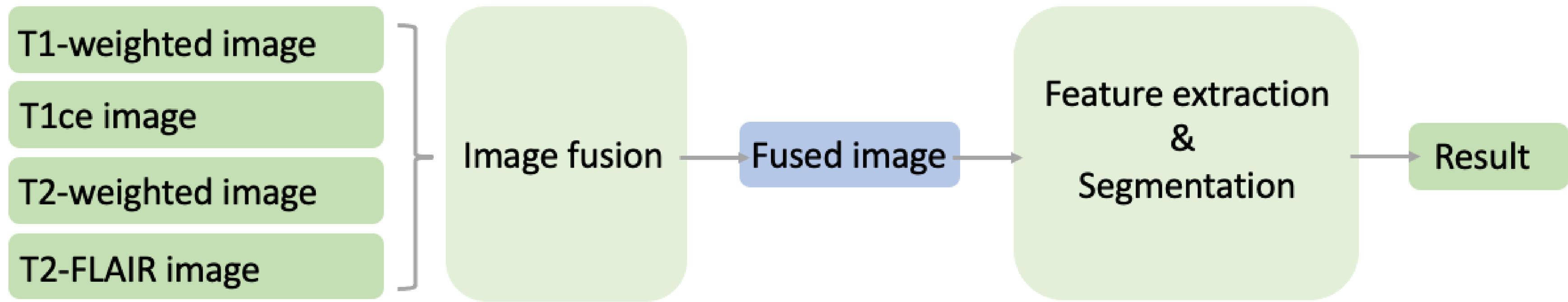
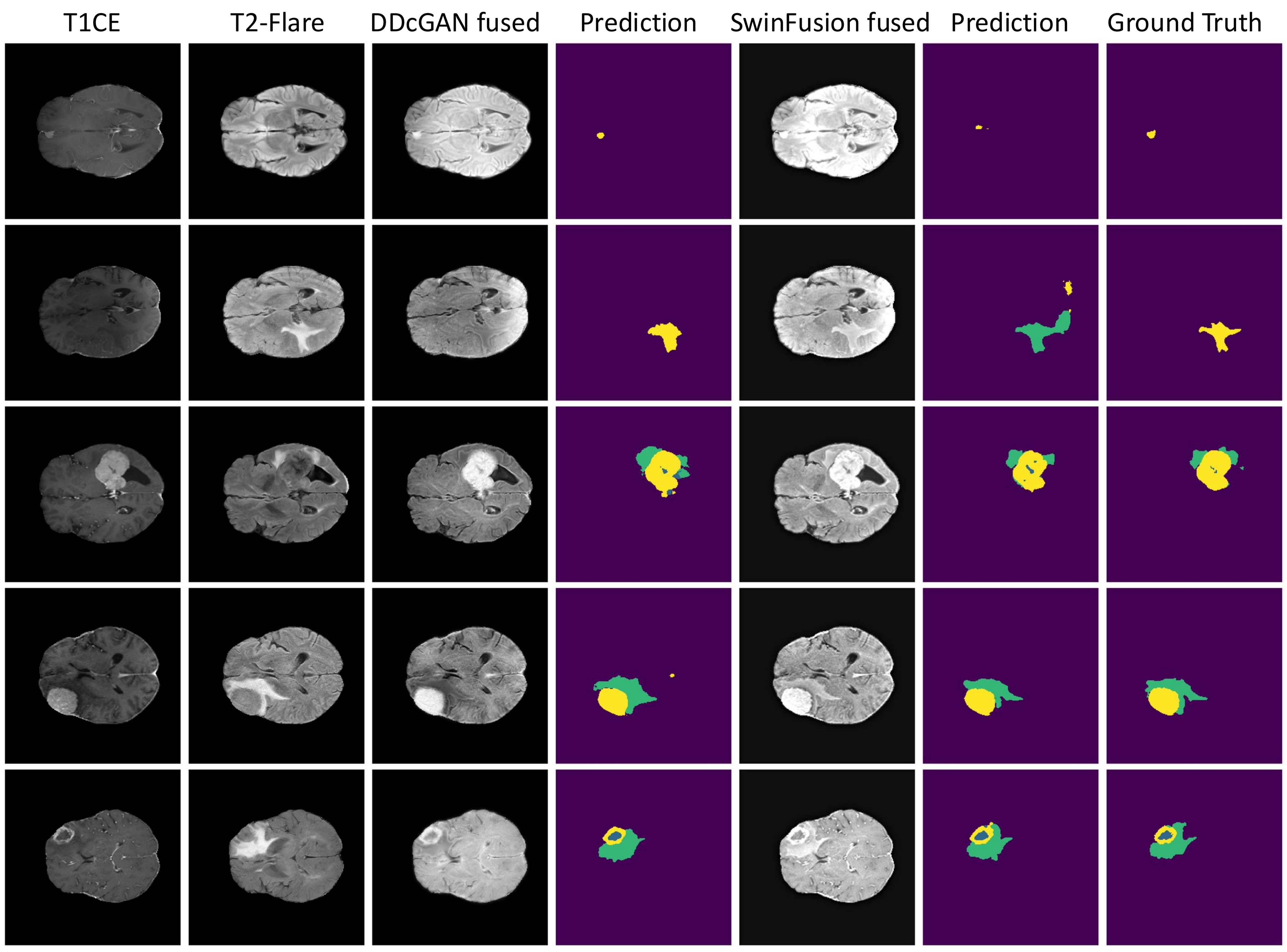


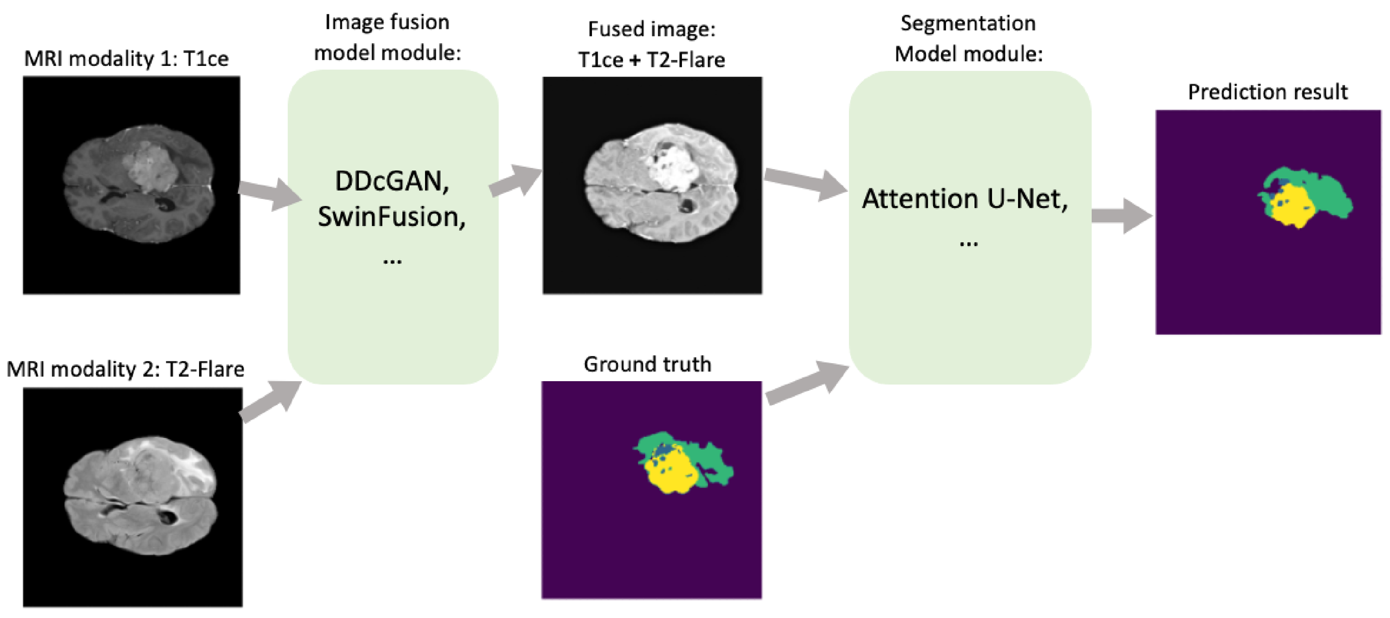
Figure 2. The general structure of pixel-level models

Experiment & Result

We experiment with two pixel-level methods: The first combines DDcGAN for image fusion with an Attention U-Net for segmentation. The second replaces DDcGAN with SwinFusion, using the same segmentation architecture. While image fusion models are traditionally evaluated using metrics like SSIM and VIF, we assess the fusion performance via downstream performance, in this instance, it's measured by Dice score and HD95.



Below is a high-level illustration of my workflow:



To ensure fair performance comparison, these selected model use the same datasets and labels (provided by the BraTS competition) and were evaluated using the same set of metrics: Dice score and 95th percentile Hausdorff distance (HD95).

Paper Title	Approach	Dataset	ET (Dice, %)	TC (Dice, %)	WT (Dice, %)	ET (HD95, mm)	TC (HD95, mm)	WT (HD95, mm)
Glioma Segmentation-Oriented Multi-Modal MR Image Fusion With Adversarial Learning	Image-level	BraTS 2019	-	-	76.9	-	-	17.51
Fuse4Seg: Image-Level Fusion Based Multi-Modality Medical Image Segmentation	Image-level	BraTS 2021	-	-	90.9	-	-	4.48
Two-Stage Cascaded U-Net: 1st Place Solution to BraTS Challenge 2019 Segmentation Task	Feature-level	BraTS 2019	83.3	83.7	88.8	2.65,	4.13	4.62
Memory-Efficient Cascade 3D U-Net for Brain Tumor Segmentation	Feature-level	BraTS 2019	77.7	82.4	90.2	5.20	7.24	5.38
E1D3 U-Net for Brain Tumor Segmentation: Submission to the RSNA-ASNR-MICCAI BraTS 2021 challenge	Feature-level	BraTS 2021	80.7	85.7	91.2	3.12	5.54	6.11
Model Ensemble for Brain Tumor Segmentation in Magnetic Resonance Imaging	Feature-level	BraTS-MEN 23	87.6	86.7	84.9	30.0	31.7	35.2
DDcGAN + Attention U-Net	**Image-level**	**BraTS-MEN 23**	**31.1**	**51.4**	**74.6**	**18.2**	**25.0**	**13.2**
SwinFusion + Attention U-Net	**Image-level**	**BraTS-MEN 23**	**35.0**	**53.3**	**57.9**	**18.9**	**24.5**	**11.8**

Datasets: BraTS 2019 (n=335), BraTS 2021 (n=200), BraTS-MEN 2023 (train = 400, val = 100, test = 100)