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A COMPARATIVE ANALYSIS OF GAN ARCHITECTURES FOR BRAIN TUMOR SEGMENTATION ON MRI IMAGES

Abstract
This study compares several GAN architectures (CycleGAN, SegGAN, U-Net GAN, WGAN-GP, Attention GAN) for brain tumor segmentation on MRI images using the BraTS 2020 dataset. Results show that Attention GAN and SegGAN provide the most accurate segmentation, highlighting the effectiveness of GANs in medical image analysis.
Keywords: Brain tumor segmentation; Magnetic resonance imaging (MRI); Generative adversarial networks (GAN); Attention mechanism, CycleGAN; WGAN-GP; U-Net GAN; Segmentation accuracy; Deep learning in medical imaging; BraTS dataset.

Introduction. Brain tumor segmentation on MRI images is a critical task in neuroradiology, directly affecting the quality of diagnosis and treatment planning. Traditional methods, including U-Net and SVM, often struggle with tumor heterogeneity and poorly defined boundaries. Generative Adversarial Networks (GANs) have proven effective in medical image segmentation, improving accuracy and compensating for the lack of annotated data. However, the wide variety of GAN architectures and their comparative effectiveness in brain tumor segmentation remain insufficiently explored. This study analyzes CycleGAN, SegGAN, U-Net GAN, WGAN-GP, and Attention GAN using the clinically annotated BraTS 2020 dataset, employing metrics such as Dice, IoU, and Hausdorff distance to identify optimal solutions for practical use.

Methods. This study presents a comparative analysis of GAN architectures for brain tumor segmentation on MRI images using the BraTS dataset, which includes annotated regions such as edema, necrosis, and enhancing tumor. The evaluated models include: CycleGAN (for unpaired data), SegGAN (with perceptual mask discrimination), U-Net GAN (with a U-Net-based generator), WGAN-GP (using gradient penalty for training stability), and Attention GAN (incorporating attention mechanisms for finer focus). Training was conducted in RStudio using the Keras and TensorFlow libraries. All 3D data were converted into normalized 2D slices of 128×128 pixels. Model evaluation was performed using segmentation quality metrics: Dice coefficient, IoU, Precision, Recall, F1-score, and Hausdorff distance, along with assessments of training stability, convergence time, and visual segmentation quality.

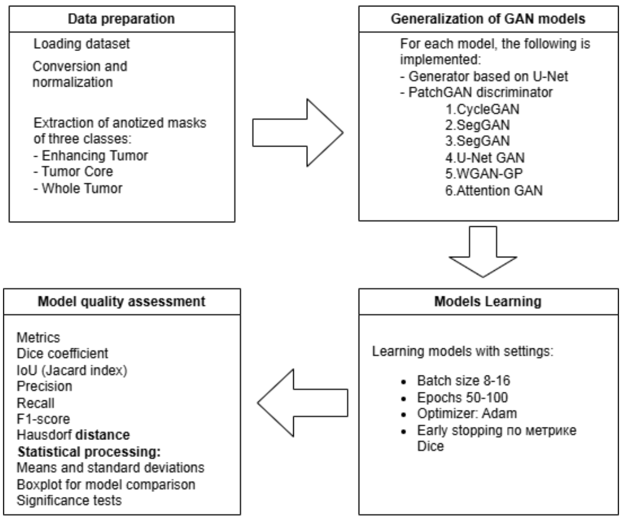

Figure 1. Block diagram of GAN architecture analysis for brain tumor segmentation on MRI images

Conclusions. The results showed that models incorporating attention mechanisms (Attention GAN) and using a combined loss function (Dice + BCE) achieved the highest segmentation accuracy, particularly in cases with complex tumor morphology. SegGAN demonstrated strong performance in delineating precise tumor boundaries but exhibited high sensitivity to training parameters. U-Net GAN provided balanced segmentation quality with minimal implementation complexity. CycleGAN had limited applicability in the absence of paired annotations but proved effective for generating additional training data. WGAN-GP showed high robustness to overfitting and noise, though it required longer training time.

Table 1 – Statistical segmentation performance of GAN models

Model	Dice Coefficient	IoU (Jaccard)	Precision	Recall	F1-score	Hausdorff Distance
Attention GAN	0,91	0,85	0,93	0,9	0,91	3,2
SegGAN	0,88	0,81	0,86	0,91	0,88	4,5
U-Net GAN	0,85	0,78	0,84	0,86	0,85	5
WGAN-GP	0,83	0,76	0,85	0,81	0,83	5,3
CycleGAN	0,74	0,62	0,68	0,72	0,69	7,1

The obtained results confirm that the use of GAN models significantly improves the quality of automatic brain tumor segmentation compared to traditional methods. This study opens up prospects for further integration of deep generative models into clinical practice to enhance diagnostic accuracy and treatment planning.

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