Brain tumor MRI synthesis using GAN aggregation

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Motivation

- MRI is a powerful non-invasive tool for obtaining location and growth of tumor
- Lack of medical imaging data along with high class imbalance due to resource constraints and privacy concerns
- Traditional data augmentation generates highly correlated images with less variance resulting in poor generalization
- Generative Adversarial Networks (GAN) have shown promising results with good generalization on a large variety of images. It serves as an anonymization tool and reduces data handling risks
- We evaluate 5 GAN models individually, then run an aggregation algorithm followed by style transfer
- This allows our model to capture both the unique and shared features in the latent representation. Style transfer allows us to capture localized information
- We aim to perform an ablation study to measure the contribution of fake images produced by the Aggregate GAN (AGGrGAN) model [1] to a basic classification network

Related Work

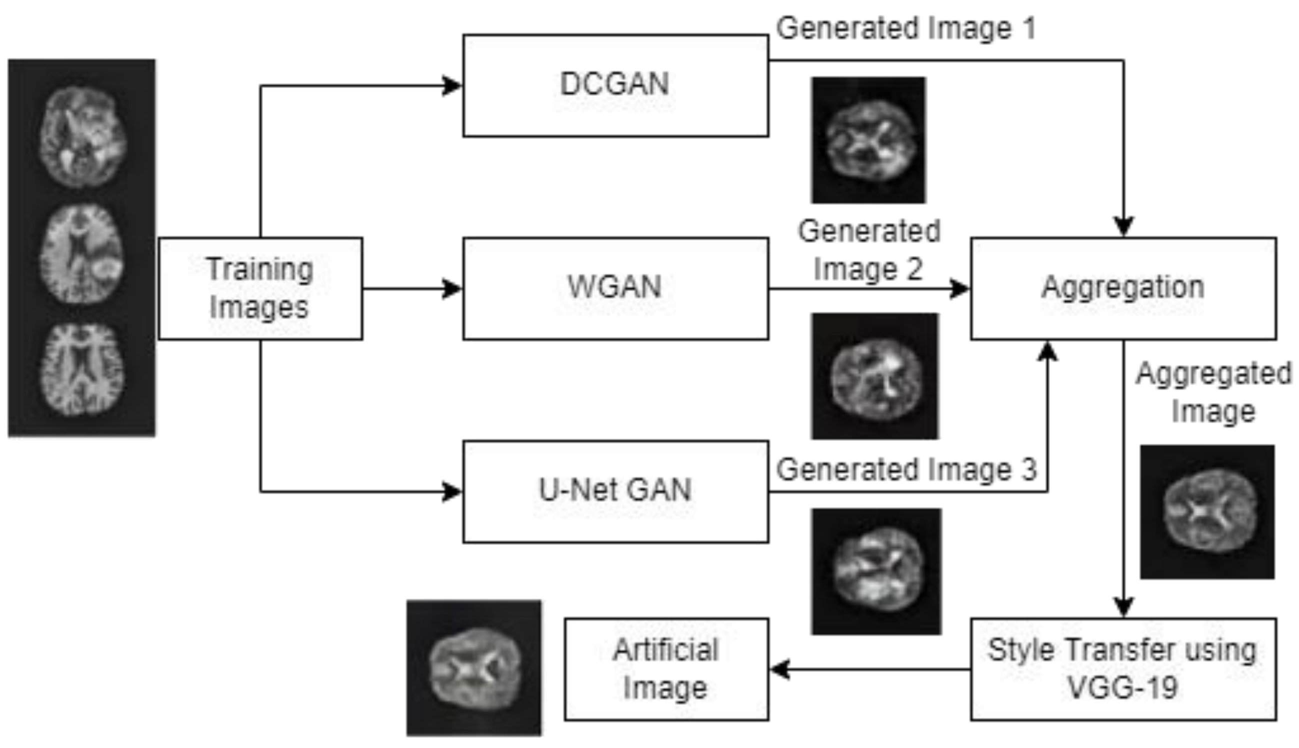
- Debadyuti et al. proposed aggregation of GANs for medical image synthesis
- Improved classification performance with augmented data on BraTS 2020 dataset
- Han et al. applied DCGAN and WGAN separately on the BraTS 2016 dataset
- Conducted visual turing test with 53% accuracy for WGAN
- Shin et al., segmented images from ADNI and BraTS dataset into brain anatomy, tumor using pix2pix
- Sarkar et al., created a CNN model to detect type of brain tumor using MRI scans to classify meningioma, glioma and pituitary tumors.

References

[1] Mukherjee et al., Brain tumor image generation using aggregation of GAN, Scientific Reports, 2022
[2] Schonfeld, Schiele, Khoreva, U-Net based discriminator for GAN, CVPR, 2020
[3] Radford, Metz, Chintala, Deep Convolutional Generative Adversarial Network, ICLR 2016

New Technique

- We added a UNet-GAN whose discriminator is a UNet. A UNet discriminator provides region-specific feedback to the generator for improved image synthesis.
- UNet-GAN was added to the aggregation process of AGGrGAN in addition to DCGAN and WGAN
- We also enhanced the aggregation logic to process all images instead of top 3 images based on PSNR/SSIM metric
- We performed style transfer using three intermediate layers of VGG-19 and then used Adam optimizer on content + style loss
- Flow chart of AGGrGAN model



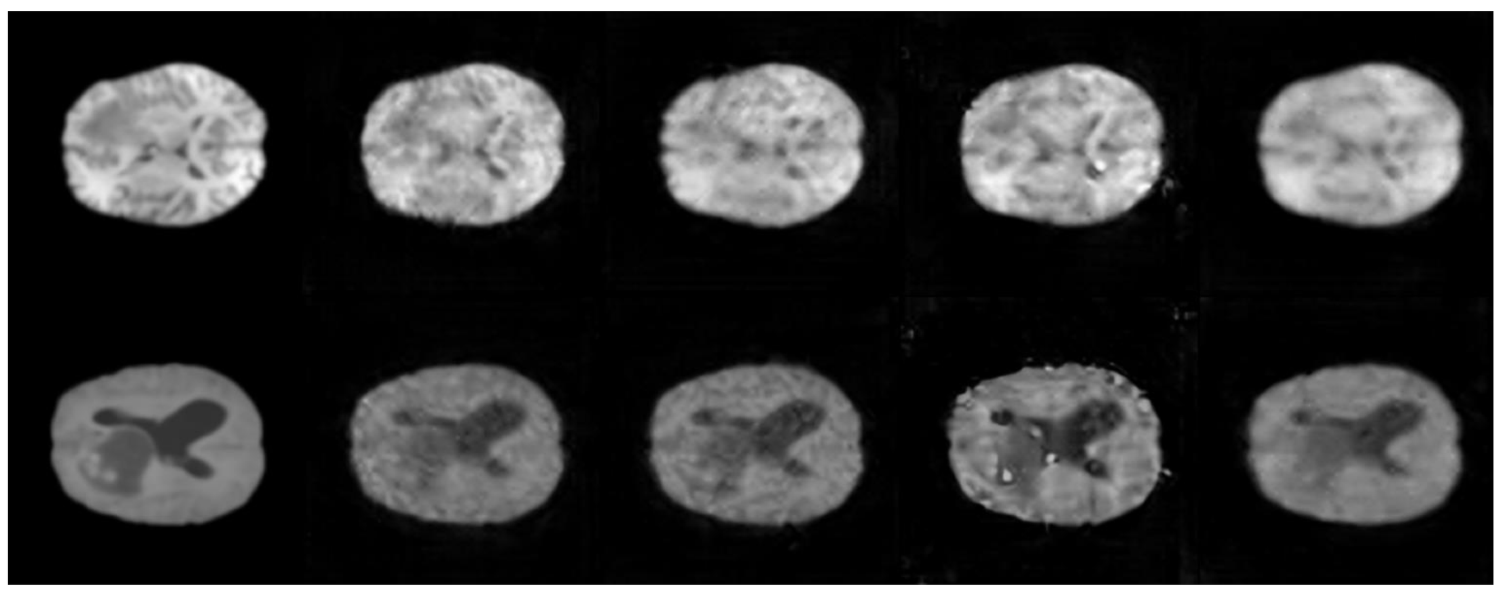
Experimental Results

We present the images from individual GANs and the AGGrGAN followed by the PSNR and SSIM scores of both T1 and T1 ce modalities from the BraTS 2020 dataset

Real DCGAN WGAN-GP UNET GAN AGGR GAN

T1

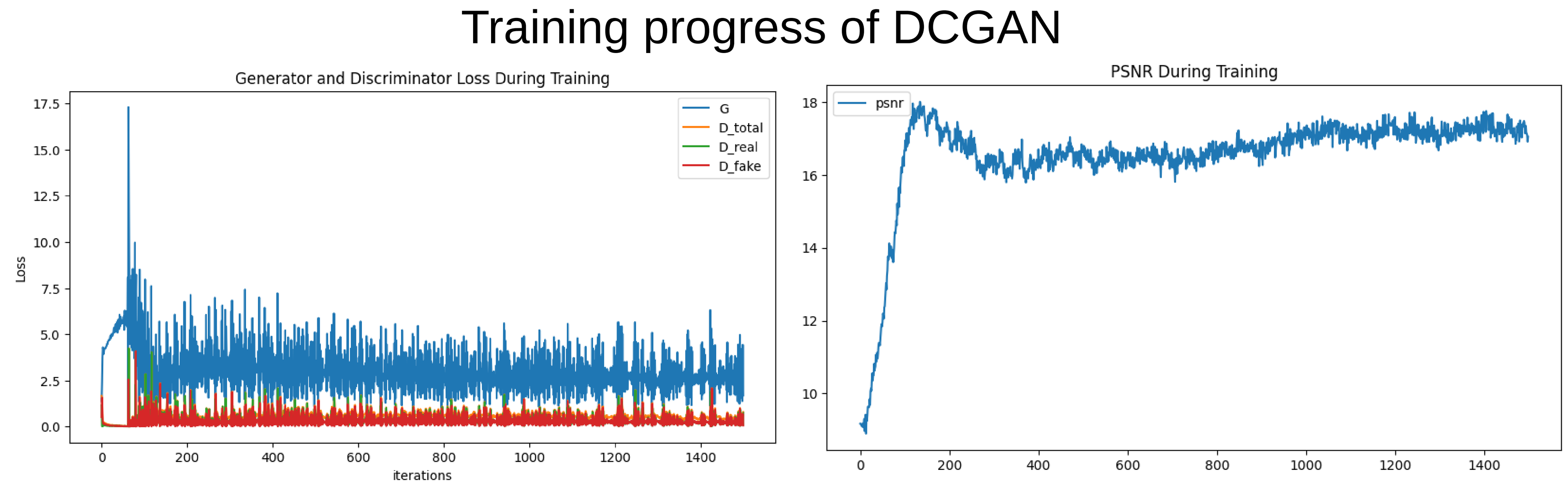
T1ce



Method	T1_PSNR	T1_SSIM	T1CE_PSNR	T1CE_SSIM
DCGAN	21.3	0.69	25.57	0.7
DCGAN+style transfer	**29.64**	**0.87**	**32.46**	**0.86**
WGAN	19.43	0.63	21.4	0.36
WGAN+style transfer	28.49	0.85	30.74	0.76
WGAN-GP	21.26	0.73	25.14	0.71
WGAN-GP+style transfer	28.88	0.85	32.27	0.85
UNetGAN (normal weight init)	15.79	0.63	12.77	0.29
UNetGAN (normal weight init)+style transfer	25.21	0.69	19.9	0.31
UNetGAN (ortho weight init)	17.88	0.71	20.4	0.66
UNetGAN (ortho weight init)+style transfer	27.63	0.79	26.91	0.79
AGGrGAN (total agg)	19.42	0.67	20.01	0.38
AGGrGAN (total agg)+style transfer	28.08	0.81	28.45	0.6
AGGrGAN (top 3 PSNR)	19.12	0.69	22.85	0.58
AGGrGAN (top 3 PSNR)+style transfer	28.62	0.84	31.1	0.8

Ablation study of GANs and style transfer

Training progress of DCGAN



Model losses decrease rapidly initially leading to a steady mean with high variance. PSNR increases rapidly followed by a steady increase.