AUSGAN: Attention UNet Spectral GAN for Generalizable MRI Reconstruction with Tissue-Specific Evaluation

Sarah Anjum[a], Hamed Akbari[b], David C. Anastasiu[a]

[a] Department of Computer Science and Engineering, [b] Department of Bioengineering , Santa Clara university

Abstract

AUSGAN is an attention-based spectral GAN for accelerated MRI reconstruction from undersampled k-space data. Validated on brain and prostate datasets, AUSGAN outperforms existing methods across undersampling rates and enhances tissue-specific feature learning. Bhattacharya distance analysis confirms improved tissue discrimination and clinical robustness

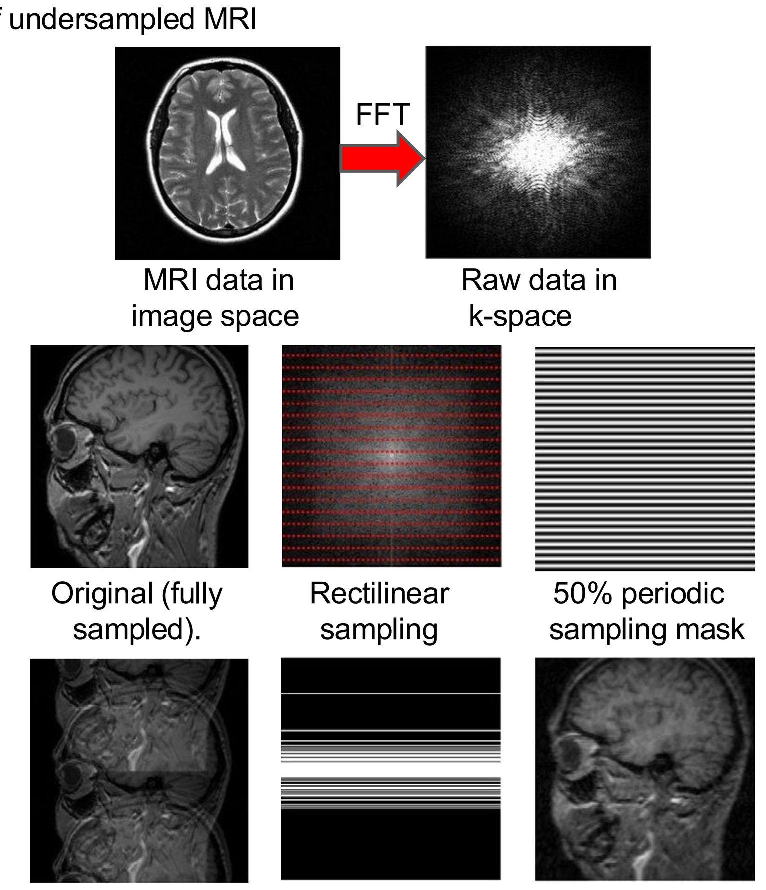
Introduction

MRI is a non-ionizing diagnostic tool, but its long acquisition time can cause motion artifacts and patient discomfort. While accelerated scanning methods address this, they often compromise spatial resolution.

Motivation:

- ❑ Reconstruct high-fidelity MRI from undersampled data that are perceptually like the fully-sampled images with accuracy quantified by structural similarity index metric (SSIM) and peak signal-to-noise ratio (PSNR).
- ❑ Enhance tissue contrast in the reconstructed images as compared to the original images measured as Bhattacharya distances between region of interest segmentation voxel intensities.

Overview of undersampled MRI



Materials and Methods

Datasets:

- ❑ BraTS-GBM[1] Glioblastoma brain MRI images with four different acquisition protocols T1, T1GD, T2 and FLAIR. The manual segmentation include edema (ED), enhancing tumor (ET) and necrotic core (NC) volumes.
- ❑ QIN-Prostate[2] MRI images with biopsy proven prostate cancer along with manual segmentations outlining the whole prostate gland and tumor volumes.

Dataset Demographics and Acquisition Parameters

Dataset	Brain GBM[1]	Prostate[2]
Subjects	135	15
Training slices	20,200	180
Validation slices	10,100	36
Testing slices	10,100	45
Scanner strength	1.5 Tesla	3 Tesla

Problem formulation:

$$\Phi = \arg\min_{\varphi} L(|F^{H}(G(K_p;\phi))|, I_o)$$

G : Generative model defined by a set of unknown parameters ϕ
$L(.)$: Loss function, I_o, K_p : Desired real signal, complex k-space signal
F^H: Orthonormal 2D IFT operation

Loss function:

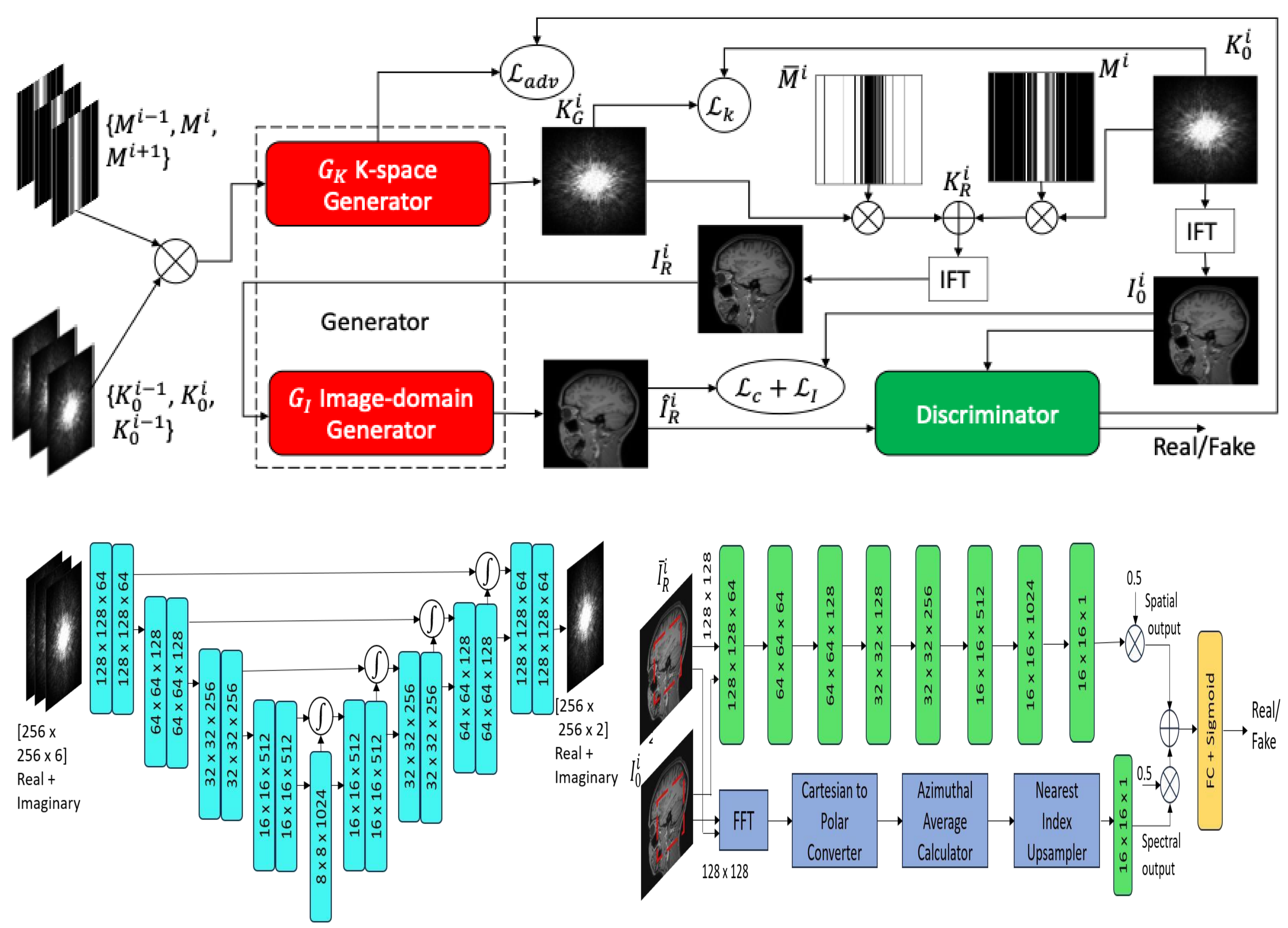
$$L = L_{adv} + L_I + L_K + L_C$$

L_{adv} : Adversarial loss (BCE), L_I : Image space loss (MSE), L_K : K-space loss (MSE), L_C : Content loss

Content loss:

- ❑ Euclidean distance between the feature map representations of reconstructed and fully sampled images is content loss.
- ❑ Features are extracted using the first 35 layers of a VGG19 network, ignoring the last few fully connected layers.

Network Architecture



- ❑ K-space generator input is 3 adjacent slices; each has 2 channels, real and imaginary, to reconstruct the middle slice. IFT of the k-space generator output is passed through the image generator, which is a single channel k-space generator.
- ❑ Discriminator uses both spatial-based features, obtained from PatchGAN discriminator and spectral-based features, obtained from a frequency aware classifier focusing on high-frequency content, to distinguish the realness of the reconstructed image.

Experiments

Comparison of Structural Similarity Index Metric and Peak Signal-to-Noise-Ratio across all the models and undersampling rates. Bold indicates best and underline shows the second-best performing model. AUGAN results are highlighted. SD = Standard Deviation

Dataset	Method	Undersampling Rates					
		20%		30%		50%	
		SSIM ± SD	PSNR ± SD	SSIM ± SD	PSNR ± SD	SSIM ± SD	PSNR ± SD
Brain	CS-MRI	0.176 ± 0.009	32.49 ± 0.94	0.201 ± 0.010	35.37 ± 0.93	0.220 ± 0.031	39.47 ± 0.94
	AdaDiff	0.375 ± 0.019	23.20 ± 3.55	0.379 ± 0.030	23.25 ± 4.15	0.381 ± 0.132	18.47 ± 1.82
	ADMMNet	0.520 ± 0.025	30.15 ± 2.10	0.580 ± 0.020	33.20 ± 1.85	0.600 ± 0.031	35.48 ± 1.73
	Zero-filled	0.709 ± 0.018	26.58 ± 1.73	0.748 ± 0.019	29.30 ± 1.81	0.769 ± 0.019	32.04 ± 1.69
	Dual GAN	0.841 ± 0.110	45.02 ± 0.17	0.887 ± 0.130	49.02 ± 0.45	0.912 ± 0.210	50.02 ± 0.76
	AUSGAN	**0.989 ± 0.000**	**46.29 ± 0.09**	**0.994 ± 0.001**	**49.75 ± 0.24**	**0.997 ± 0.001**	**52.52 ± 0.07**
Prostate	AdaDiff	0.347 ± 0.016	16.38 ± 0.43	0.347 ± 0.016	16.27 ± 0.41	0.344 ± 0.015	16.10 ± 0.40
	CS-MRI	0.579 ± 0.027	**35.71 ± 1.08**	0.590 ± 0.026	36.27 ± 1.08	0.644 ± 0.027	37.83 ± 1.08
	ADMMNet	0.720 ± 0.020	34.50 ± 1.20	0.750 ± 0.018	35.80 ± 1.10	0.763 ± 0.016	36.02 ± 0.35
	Zero-filled	0.854 ± 0.017	29.72 ± 1.24	0.869 ± 0.015	30.44 ± 1.22	0.903 ± 0.011	32.43 ± 1.18
	Dual GAN	0.937 ± 0.002	34.62 ± 0.29	0.947 ± 0.002	35.78 ± 0.40	0.959 ± 0.073	**40.37 ± 1.09**
	AUSGAN	**0.951 ± 0.007**	35.52 ± 0.21	**0.963 ± 0.001**	**37.98 ± 1.14**	**0.973 ± 0.001**	39.87 ± 0.58

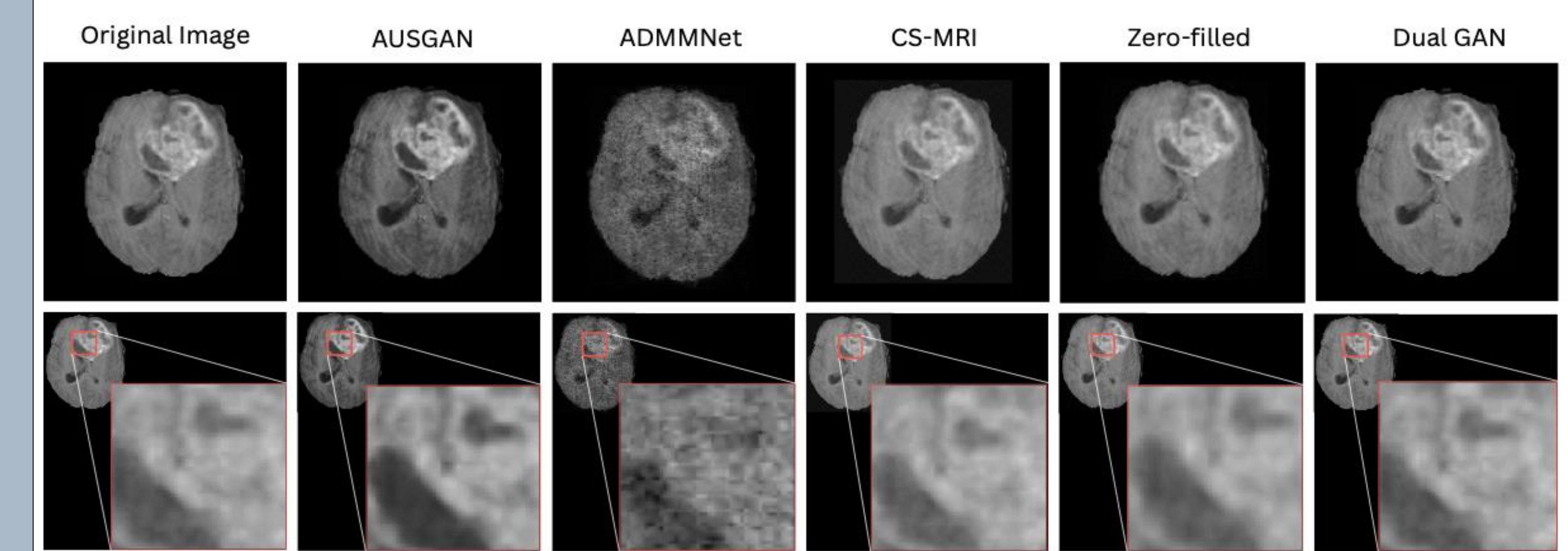
Bhattacharya distances in Brain Glioblastoma MRI for tissue discrimination for AUSGAN against original image. Bold indicates percentage improvement. ET = enhancing tumor, ED = edema, NC = necrotic core, SD = standard deviation

Method	Contrast Comparison ± SD		
	ET Vs ED	ET Vs NC	NC Vs ED
Original Image	2.598 ± 0.081	2.543 ± 0.084	2.535 ± 0.087
AUSGAN	3.065 ± 0.096	2.856 ± 0.085	2.964 ± 0.091
Improvement ($p < 10^{-2}$)	**17.98%**	**12.31%**	**16.92%**

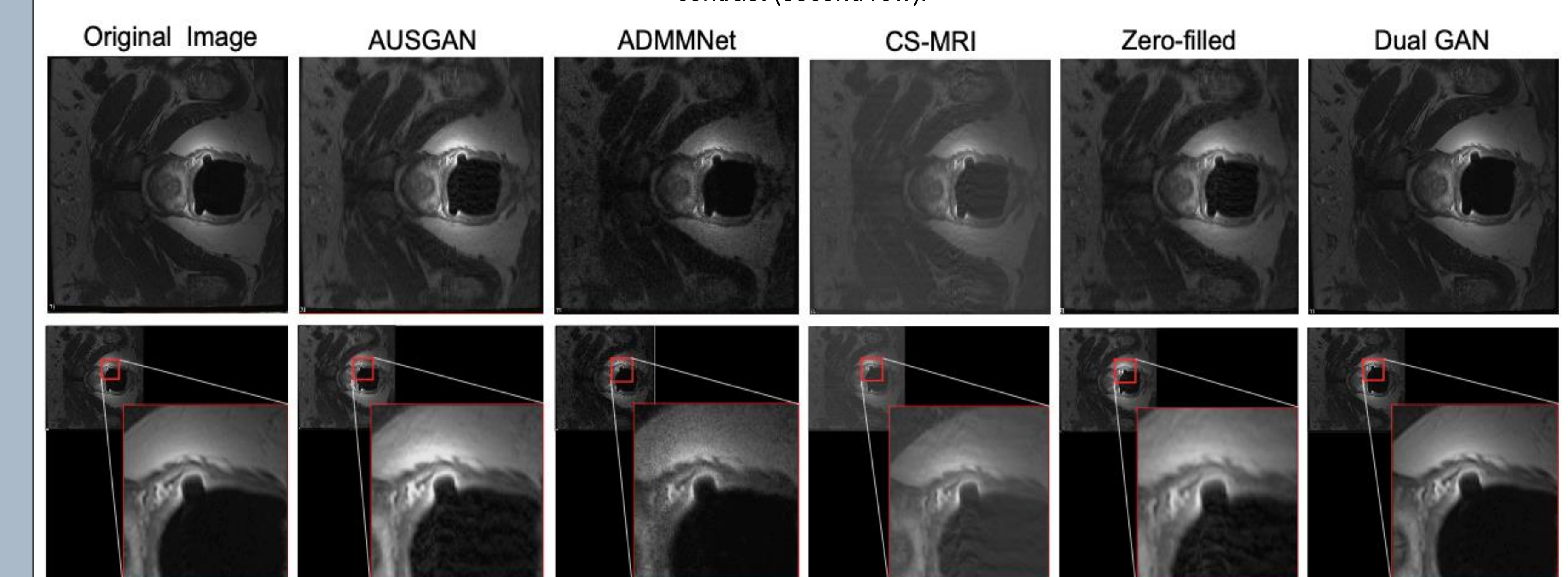
Bhattacharya distances in Prostate MRI for tissue discrimination for AUSGAN against original image. Bold indicates percentage improvement.

Method	Contrast Comparison ± SD
	Prostate gland - Periphery
Original Image	4.528 ± 0.359
AUSGAN	4.548 ± 0.378
Improvement (p = 0.0119)	**0.44%**

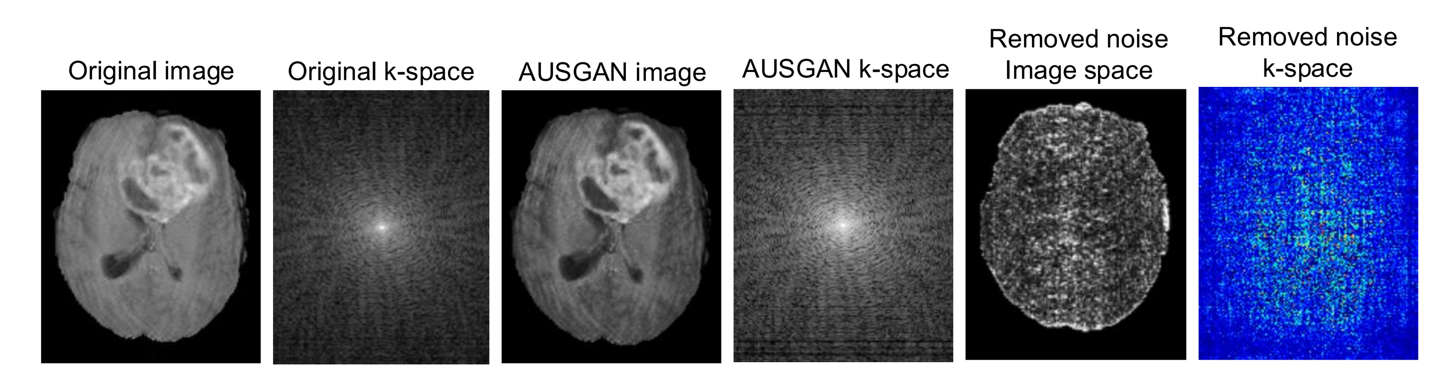
Results



Reconstructed images for 50% undersampled Brain Glioblastoma MRI (first row). Zoom-in images further showcase enhanced tissue contrast (second row).



Reconstructed images for 50% undersampled Prostate MRI (first row). Zoom-in images further showcase enhanced tissue contrast (second row).



Removed noise by AUSGAN from original image in image and k-space for representative image

Conclusions and Future Work

- ❑ AUSGAN demonstrates consistent improvements over baseline, with **SSIM enhancement of 9-18% and PSNR gains of 1-5%** across all acceleration factors (20-50% sampling) for **Brain** Glioblastoma images.
- ❑ AUSGAN model demonstrates consistent improvements over baseline, with **SSIM enhancement of 1.5-4.9% and PSNR gains of 0.3-6.2%** across all acceleration factors for **Prostate** MRI.
- ❑ AUSGAN significantly **improved brain tumor tissue contrast by 12-18%** across all region comparisons, while exhibiting modest **contrast improvement of 0.44%** for **prostate gland vs periphery** differentiation.
- ❑ AUSGAN also demonstrates high reconstruction performance with improved tissue contrast in breast MRI, confirming its effectiveness across multiple anatomical domains.

References

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Contact Information: sanjum2@scu.edu, danastasiu@scu.edu