Healthcare Technology Innovation Centre

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Ministry of Science and Technology

# *Recon-GLGAN*
# *A Global-Local context based Generative Adversarial Network for MRI Reconstruction*


**Balamurali Murugesan**, Vijaya Raghavan S, Kaushik Sarveswaran, Keerthi Ram, Mohanasankar Sivaprakasam

Healthcare Technology Innovation Centre
Indian Institute of Technology Madras, India


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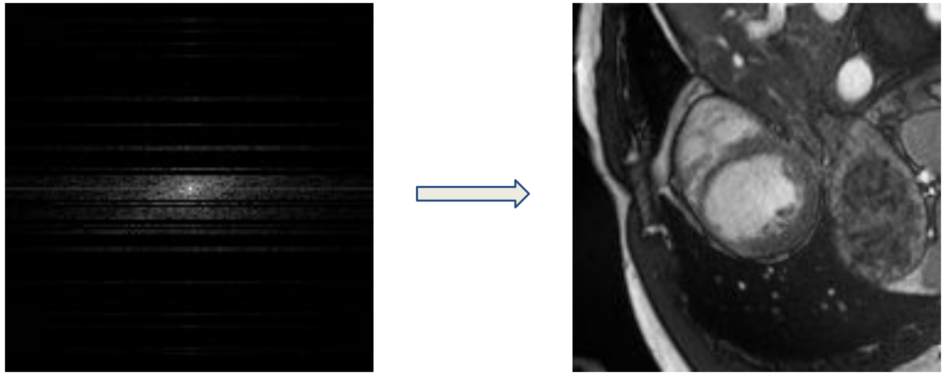
# Magnetic Resonance Imaging (MRI)

- Diagnostic modality - Excellent spatial resolution, Soft tissue contrast, Non-invasive nature, Lack of ionizing radiation
- Long data acquisition time - Patient discomfort, Higher scan cost
- Undersampling k-space to accelerate acquisition process.
- Zero-filled k-space results in aliasing artifacts.
- Deep learning - Reduce the aliasing artifacts.

# Deep learning based approaches

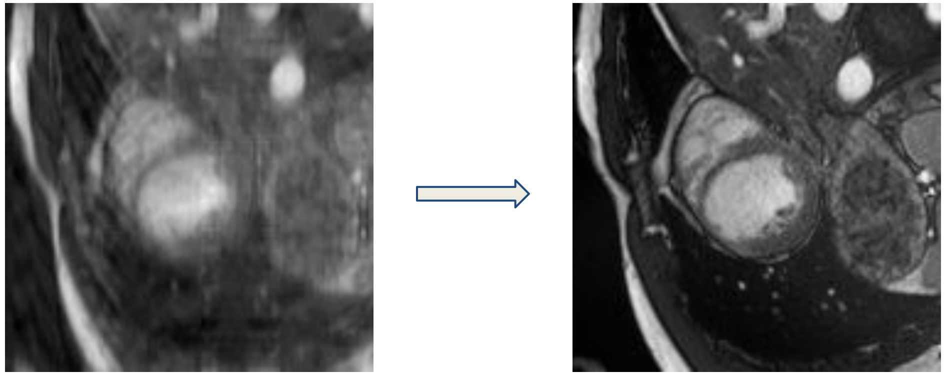
K-space to Image methods:



- Image reconstruction by domain-transform manifold learning (Nature 2018)
- Translation of 1D Inverse Fourier Transform of K-space to an Image Based on Deep Learning for Accelerating Magnetic Resonance Imaging  (MICCAI 2018)

# Deep learning based approaches

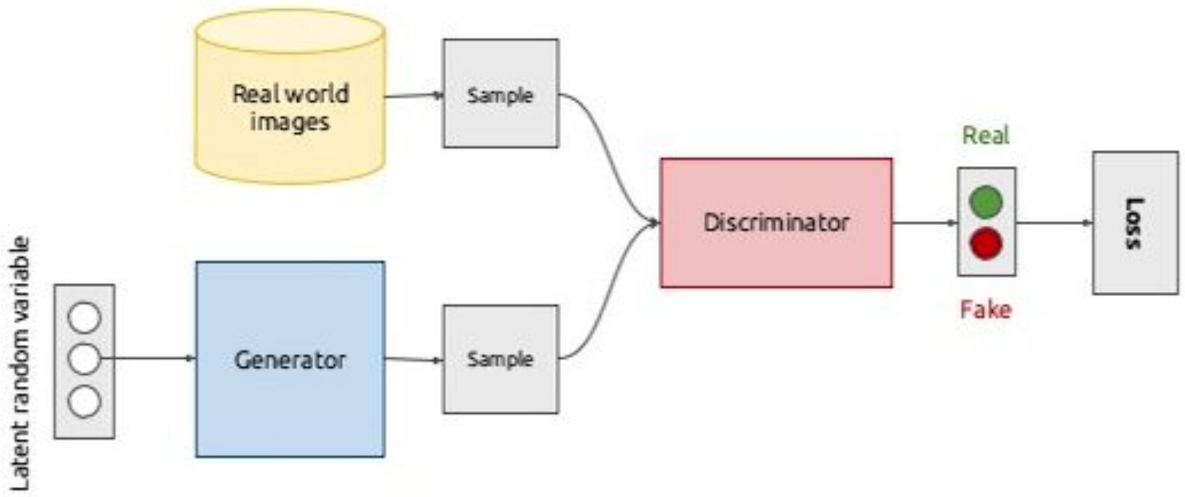
Image to Image methods:



- Accelerating magnetic resonance imaging via deep learning (ISBI 2016)
- Generative adversarial network (GAN) based approaches (Our interest)

# GAN background

1. GAN consists of generator (G) and discriminator (D) networks.
2. The goal of the G is to map a latent variable to the distribution of the given true data that we are interested in imitating in order to fool the D.
3. The D aims to distinguish the true data from the synthesized data.



# GAN based approaches

| Network | Generator | Discriminator | Loss function |
|---|---|---|---|
| GANCS[1] | U-Net with residual connections | DL classifier | MSE (img) + Adv |
| ReconGAN[2] | MS U-Net with residual connections | DL classifier | MSE (img) + Adv + MSE (freq) |
| DAGAN[3] | U-Net with residual connections | DL classifier | MSE (img) + Adv + MSE (freq) + VGG |
| SEGAN[4] | U-Net with multi-scale filterss | DL classifier | MSE (img) + Adv + SSIM |
| ComGAN[5] | U-Net with residual connections | DL classifier | MSE (img) + Adv + MSE (Freq) + SSIM |

[1]Deep generative adversarial neural networks for compressive sensing (TMI 2019)
[2]Compressed sensing mri reconstruction using a generative adversarial network with a cyclic loss (TMI 2018)
[3]Dagan: Deep de-aliasing generative adversarial networks for fast compressed sensing mri reconstruction (TMI 2018)
[4]SEGAN: structure-enhanced generative adversarial network for compressed sensing MRI reconstruction (AAAI 2019)
[5]Complex fully convolutional neural networks for mr image reconstruction (MLMIR 2018)

# Motivation

## Application driven MRI

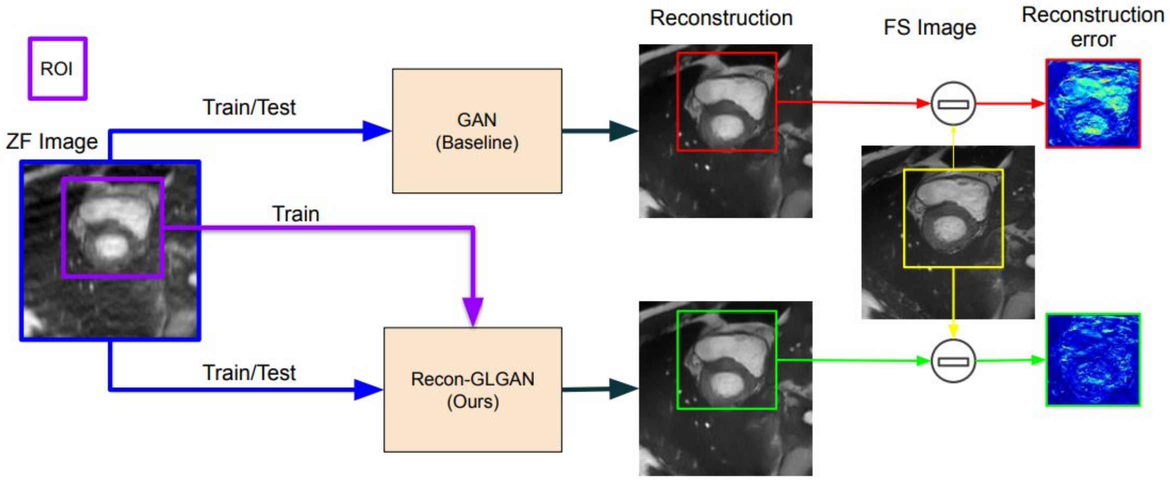
Incorporating prior information about the end goal in the MRI reconstruction process would likely result in better performance.[6]

- Prior - Region of Interest (ROI)
- End goal - Segmentation
- Better performance - Reconstruction and segmentation

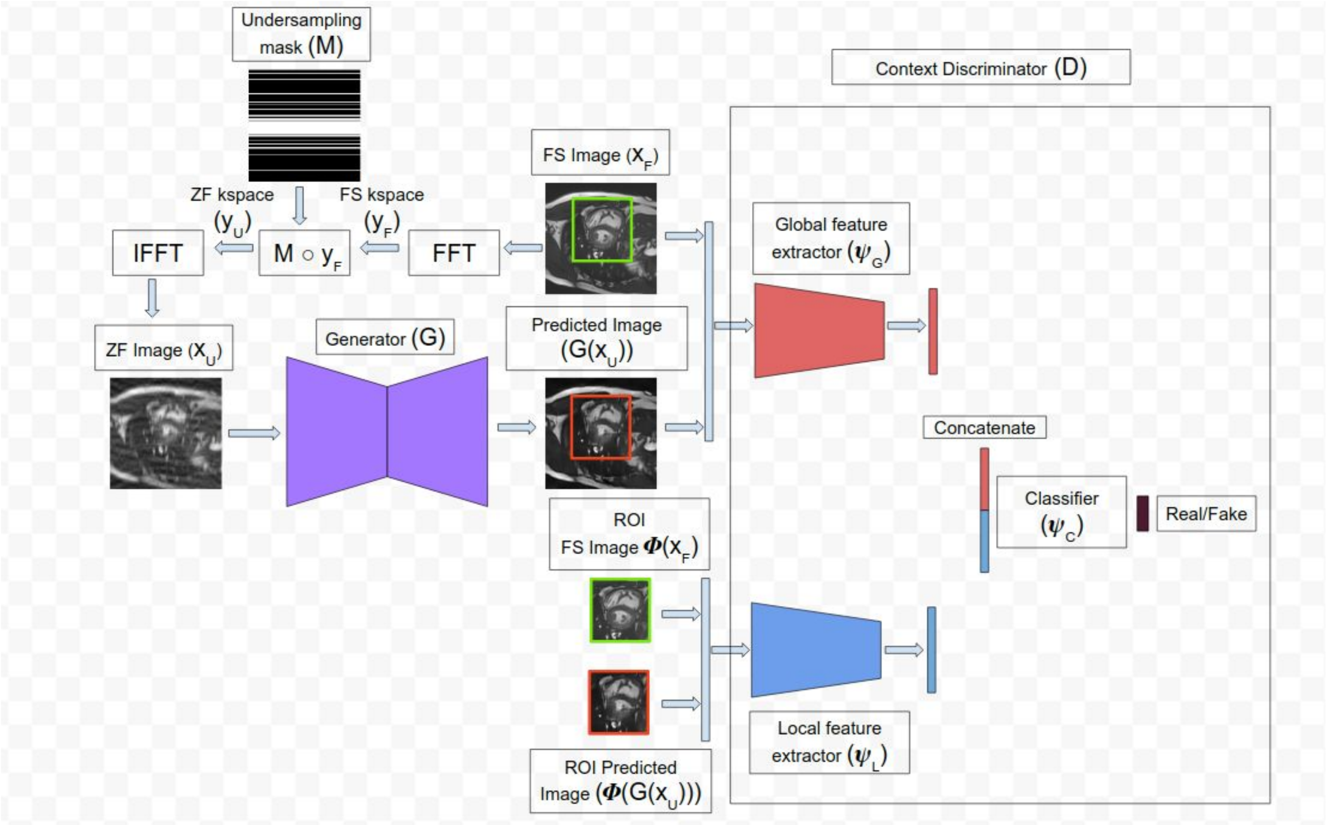
[6]Application-driven mri: Joint reconstruction and segmentation from undersampled mri data. (MICCAI 2014)

# Motivation

- Cardiac MRI: ROI - Heart region
- Limitation: Previous GAN based reconstruction methods does not specifically use ROI information.
- Proposed Recon-GLGAN: MRI reconstruction with emphasis on ROI.



# Proposed architecture - Recon-GLGAN




**Generator** : U-Net

**Context Discriminator** :

1) Global feature extractor
   a) 3 Conv layers + 2 FC
   b) Activation function: ReLU.
   c) Output - 64d vector.
2) Local feature extractor
   a) 3 Conv layers + 2 FC
   b) Activation function: ReLU.
   c) Output - 64d vector.
3) Classifier
   a) 128d vector
   b) FC layer ( 128 x 1 )

# Loss function

$$L_{total} = \lambda_1 L_{imag} + \lambda_2 L_{context} \quad (3)$$

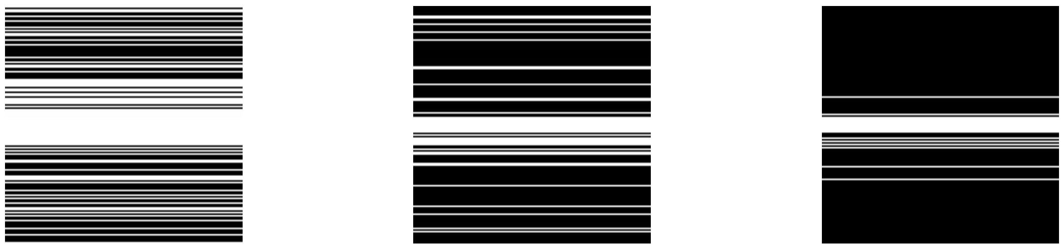
$$L_{imag} = E_{x_u, x_f}[||x_f - G(x_u)||_1] \quad (4)$$

$$L_{context} = E_{x_f}[log(D(x_f))] + E_{x_u}[-log(D(G(x_u)))] \quad (5)$$

where $L_{imag}$ is the L1 loss between predicted and target fully sampled image, $L_{context}$ is the context adversarial loss.

# Dataset

- Automated Cardiac Diagnosis Challenge (ACDC)[6]
- Training: 1841 and Validation: 1076 2D slices.
- Dimensions: Image (160 x 160), ROI (60 x 60).
- Fixed cartesian undersampling masks for 2x, 4x and 8x accelerations.
- Sampling pattern : Ten lowest spatial frequencies, Remaining frequencies follow a zero-mean Gaussian distribution.



2x 4x 8x

[7]Deep learning techniques for automatic mri cardiac multi-structures segmentation and diagnosis: Is the problem solved? (TMI 2018)

# Experiments and results

## Experiment 1: Quantitative comparison of Recon-GLGAN with baseline GAN for 2x, 4x and 8x accelerations for the whole image (FI) and region of interest (ROI).

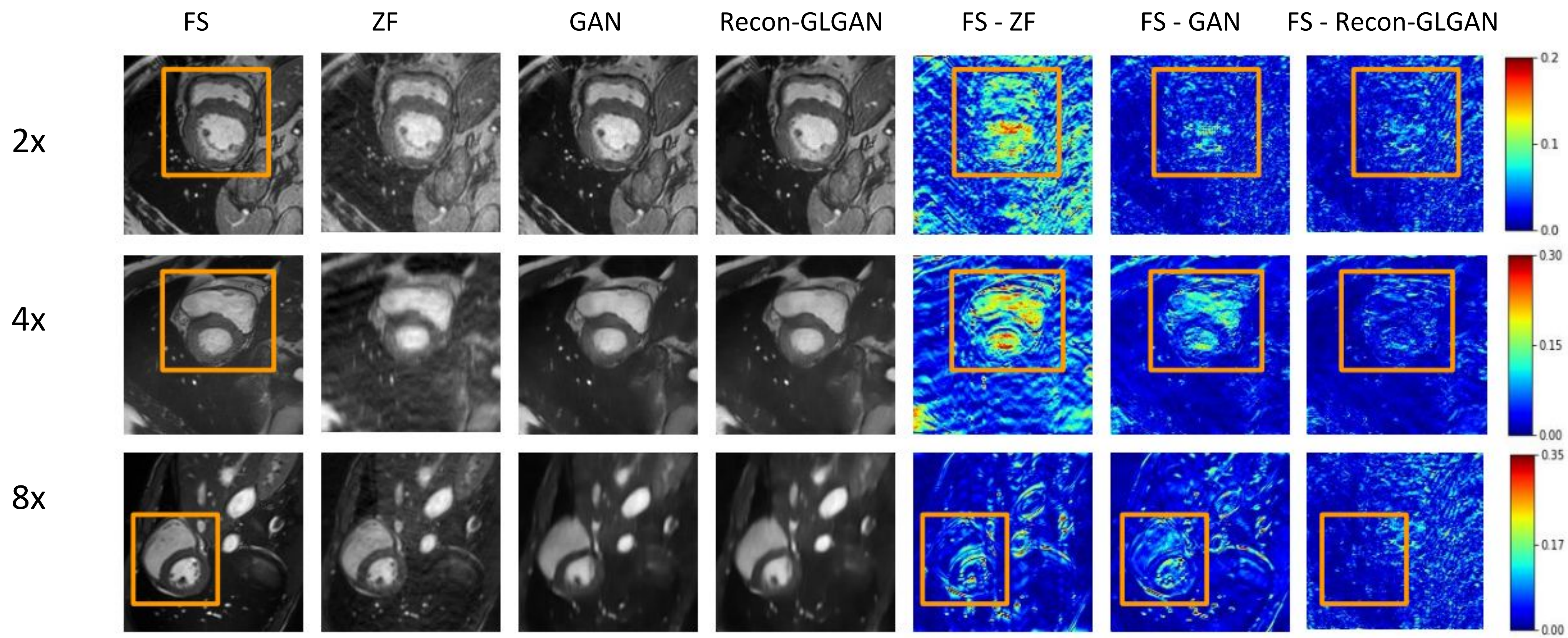
| | | | NMSE | PSNR | SSIM |
|---|---|---|---|---|---|
| 2x | FI | Zero-filled | 0.01997 ± 0.01 | 26.59 ± 3.19 | 0.8332 ± 0.06 |
| | | UNet | 0.00959 ± 0.00 | 29.7 ± 2.97 | 0.9069 ± 0.03 |
| | | GAN | 0.00958 ± 0.01 | 29.72 ± 3.03 | 0.9083 ± 0.03 |
| | | Recon-GLGAN | **0.00956 ± 0.00** | **29.74 ± 3.0** | **0.9108 ± 0.03** |
| | ROI | Zero-filled | 0.01949 ± 0.02 | 25.48 ± 3.73 | 0.859 ± 0.05 |
| | | UNet | 0.00952 ± 0.01 | 28.48 ± 3.03 | 0.9036 ± 0.04 |
| | | GAN | **0.00942 ± 0.00** | 28.53 ± 3.12 | 0.904 ± 0.04 |
| | | Recon-GLGAN | 0.00944 ± 0.01 | **28.54 ± 3.19** | **0.9065 ± 0.04** |

| | | | NMSE | PSNR | SSIM |
|---|---|---|---|---|---|
| 4x | FI | Zero-filled | 0.03989 ± 0.03 | 23.65 ± 3.38 | 0.7327 ± 0.08 |
| | | UNet | 0.01962 ± 0.01 | 26.62 ± 3.209 | 0.8419 ± 0.05 |
| | | GAN | 0.01934 ± 0.01 | 26.68 ± 3.08 | 0.8465 ± 0.05 |
| | | Recon-GLGAN | **0.01905 ± 0.01** | **26.8 ± 3.25** | **0.8497 ± 0.05** |
| | ROI | Zero-filled | 0.03886 ± 0.04 | 22.63 ± 3.87 | 0.7514 ± 0.07 |
| | | UNet | 0.01931 ± 0.01 | 25.46 ± 3.35 | 0.8242 ± 0.06 |
| | | GAN | 0.01925 ± 0.02 | 25.52 ± 3.38 | 0.8301 ± 0.06 |
| | | Recon-GLGAN | **0.01878 ± 0.02** | **25.66 ± 3.26** | **0.8327 ± 0.06** |

| | | | NMSE | PSNR | SSIM |
|---|---|---|---|---|---|
| 8x | FI | Zero-filled | 0.08296 ± 0.06 | 20.46 ± 3.24 | 0.6443 ± 0.09 |
| | | UNet | 0.03353 ± 0.02 | 24.26 ± 2.71 | 0.7547 ± 0.07 |
| | | GAN | 0.03359 ± 0.02 | 24.25 ± 2.71 | 0.7557 ± 0.07 |
| | | Recon-GLGAN | **0.03286 ± 0.02** | **24.32 ± 2.68** | **0.7562 ± 0.07** |
| | ROI | Zero-filled | 0.07943 ± 0.08 | 19.47 ± 3.82 | 0.6435 ± 0.07 |
| | | UNet | 0.03147 ± 0.02 | 23.31 ± 2.88 | 0.72 ± 0.07 |
| | | GAN | 0.03129 ± 0.02 | 23.33 ± 2.92 | **0.7294 ± 0.07** |
| | | Recon-GLGAN | **0.03102 ± 0.02** | **23.34 ± 2.82** | 0.7293 ± 0.07 |

# Experiments and results

## Experiment 1: Qualitative comparison of Recon-GLGAN with baseline GAN for 2x, 4x and 8x acceleration.



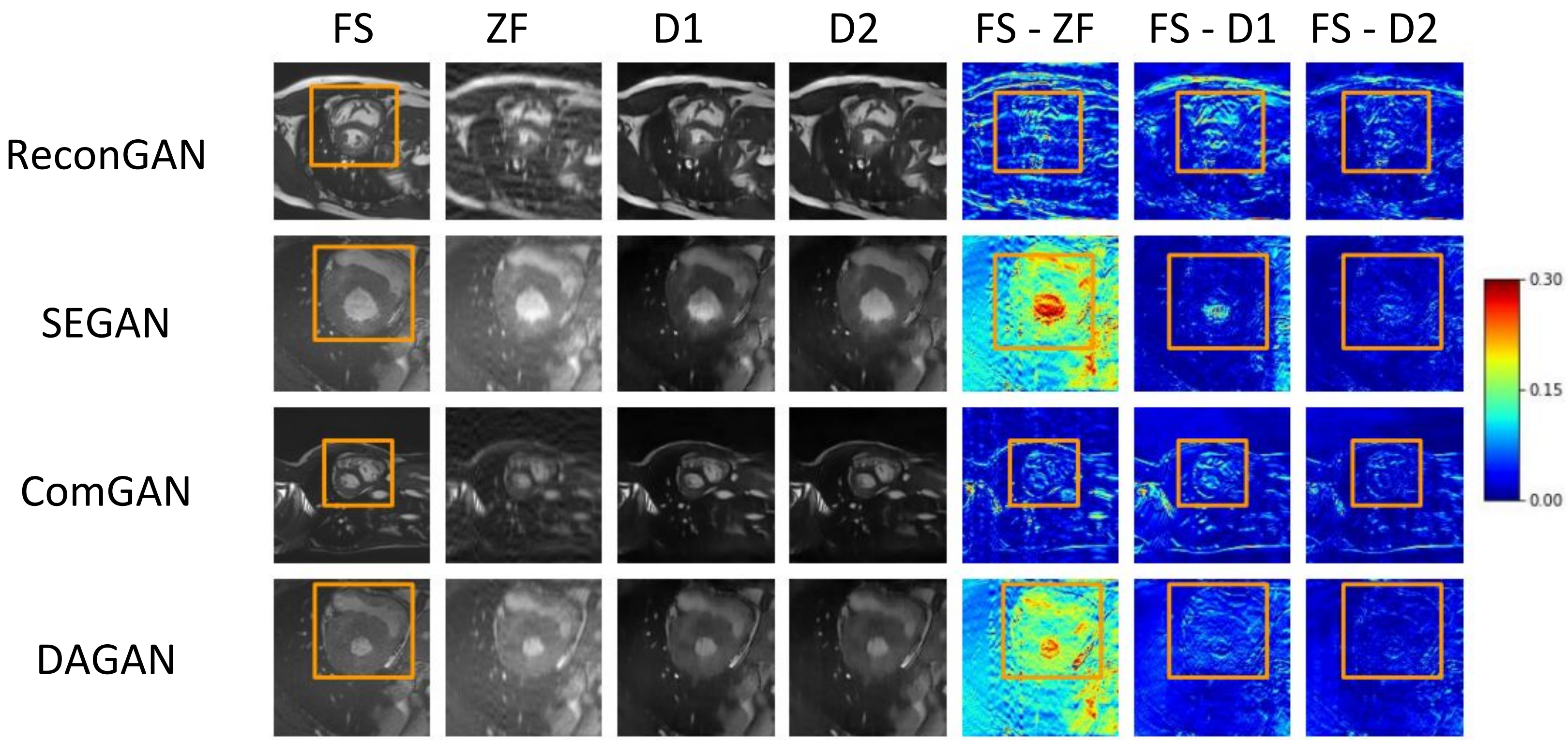
# Experiments and results

## Experiment 2: Quantitative comparison of reconstruction GAN architectures with context and normal discriminator for 4x acceleration

| | | | NMSE | PSNR | SSIM |
|---|---|---|---|---|---|
| ReconGAN | FI | - | 0.01857 ± 0.01 | 26.82 ± 2.89 | 0.8485 ± 0.05 |
| | | GL-ReconGAN | **0.01844 ± 0.01** | **26.91 ± 3.12** | **0.8498 ± 0.05** |
| | ROI | - | **0.018 ± 0.01** | **25.76 ± 3.06** | 0.832 ± 0.06 |
| | | GL-ReconGAN | 0.01836 ± 0.01 | 25.72 ± 3.24 | **0.8336 ± 0.06** |
| SEGAN | FI | - | 0.01862 ± 0.01 | 26.84 ± 3.10 | 0.8483 ± 0.06 |
| | | GL-SEGAN | **0.01817 ± 0.01** | **27.02 ± 3.4** | **0.8545 ± 0.05** |
| | ROI | - | 0.0185 ± 0.01 | 25.64 ± 3.19 | 0.8308 ± 0.07 |
| | | GL-SEGAN | **0.01793 ± 0.01** | **25.87 ± 3.56** | **0.838 ± 0.06** |
| ComGAN | FI | - | 0.01899 ± 0.01 | 26.78 ± 3.14 | 0.8481 ± 0.05 |
| | | GL-ComGAN | **0.01789 ± 0.01** | **27.06 ± 3.26** | **0.8505 ± 0.05** |
| | ROI | - | 0.01872 ± 0.01 | 25.64 ± 3.28 | 0.8315 ± 0.06 |
| | | GL-ComGAN | **0.01766 ± 0.02** | **25.91 ± 3.25** | **0.834 ± 0.06** |
| DAGAN | FI | - | 0.01903 ± 0.01 | 26.75 ± 3.06 | 0.8452 ± 0.06 |
| | | GL-DAGAN | **0.01851 ± 0.01** | **26.87 ± 3.03** | **0.845 ± 0.06** |
| | ROI | - | **0.01838 ± 0.01** | **25.68 ± 3.04** | 0.8272 ± 0.07 |
| | | GL-DAGAN | 0.01858 ± 0.01 | 25.62 ± 3.016 | **0.8277 ± 0.07** |

# Experiments and results

## Experiment 2: Qualitative comparison of reconstruction GAN architectures with context and normal discriminator for 4x acceleration.




ZF - Zero-filled

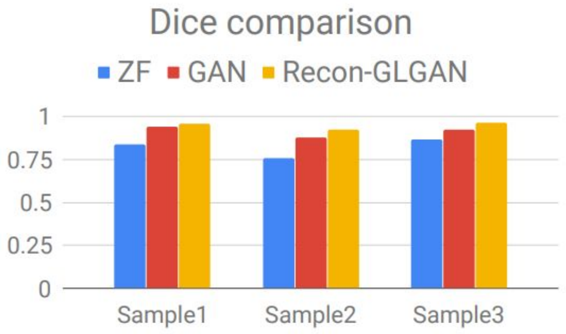
FS - Fully sampled

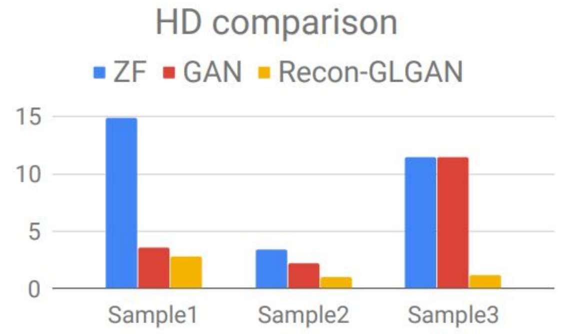
D1 - Normal discriminator

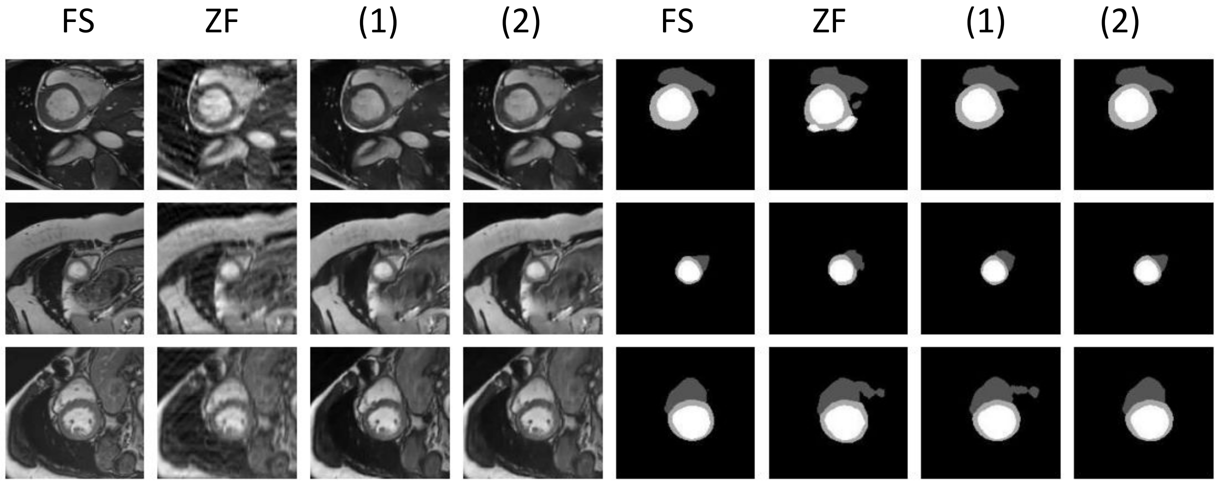
D2 - Context discriminator

# Experiments and results

## Experiment 3: Quantitative and Qualitative comparison of segmentation architecture for ZF, GAN (1), Recon-GLGAN (2)



# Conclusion and Future work

- We proposed a novel GAN architecture, Reconstruction Global-Local GAN (Recon-GLGAN) with a U-Net generator and a context discriminator.
- We showed that the concept of a context discriminator can be easily extended to existing GAN based reconstruction architectures

- Recon-GLGAN works only for fixed square/rectangular ROI.
- Does using GAN in image-to-image translation tasks generate artifacts ? If so how to tackle it.

# Thank you

Paper

https://arxiv.org/abs/1908.09262

Code

https://github.com/Bala93/Recon-GLGAN.git

Contact

balamurali@htic.iitm.ac.in