Abstract #: 1274

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3D VOLUMETRIC SUPER-RESOLUTION IN RADIOLOGY USING 3D RRDB-GAN

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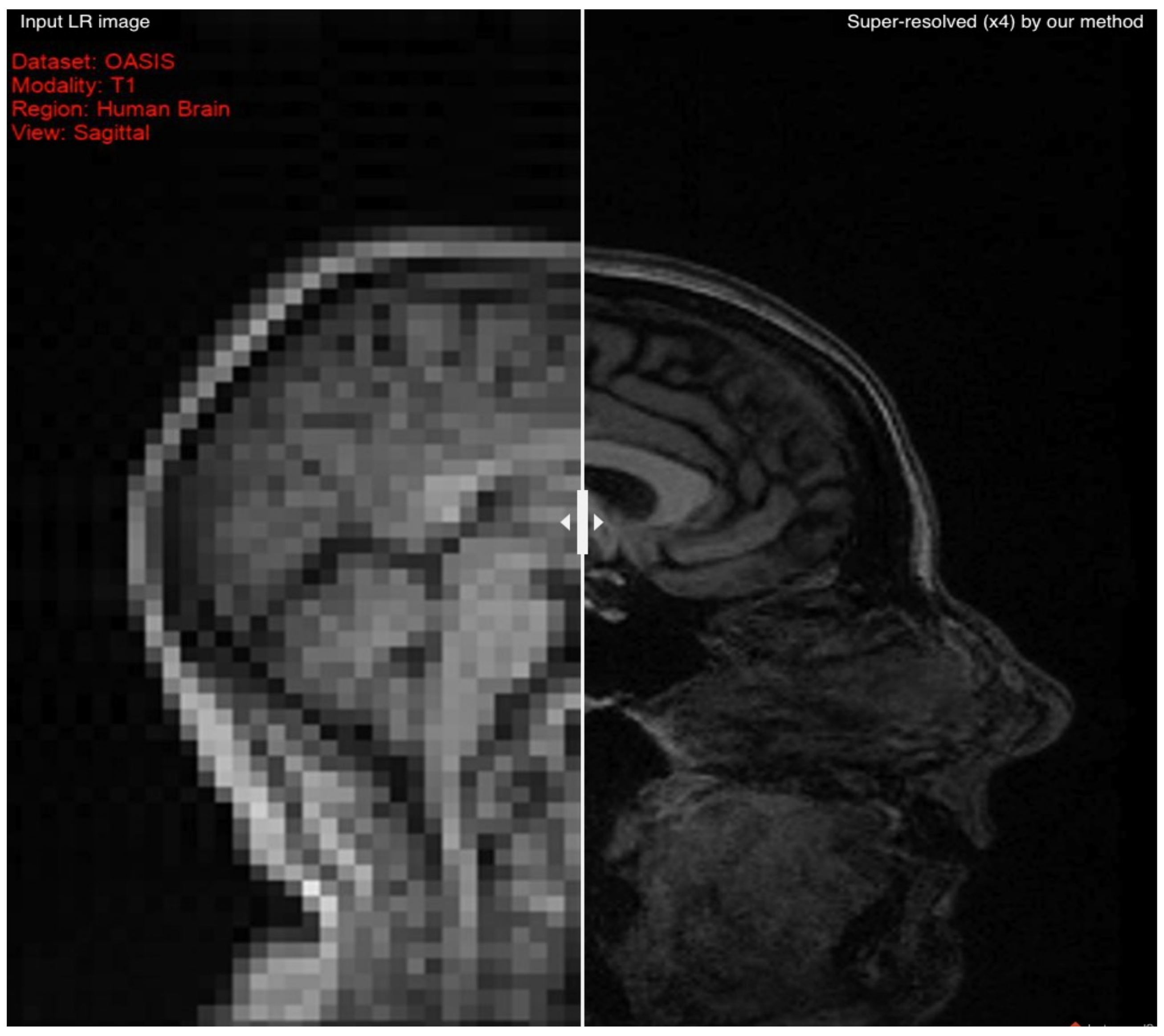
Introduction



❑ Objective

Volumetrically super-resolving medical image resolution

❑ Benefit

Faster Scans, Better Image Quality → Reducing image acquisition cost, Improving clinical practice

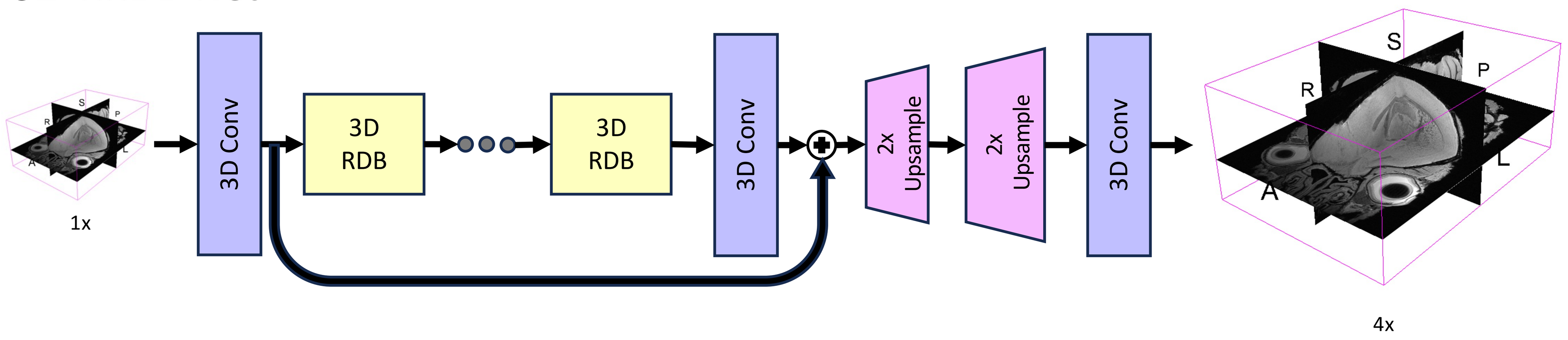
❑ Overview

We introduce 3D RRDB-GAN framework to upscale low-resolution medical image to high-resolution in scale factor of 4. Our contributions include:

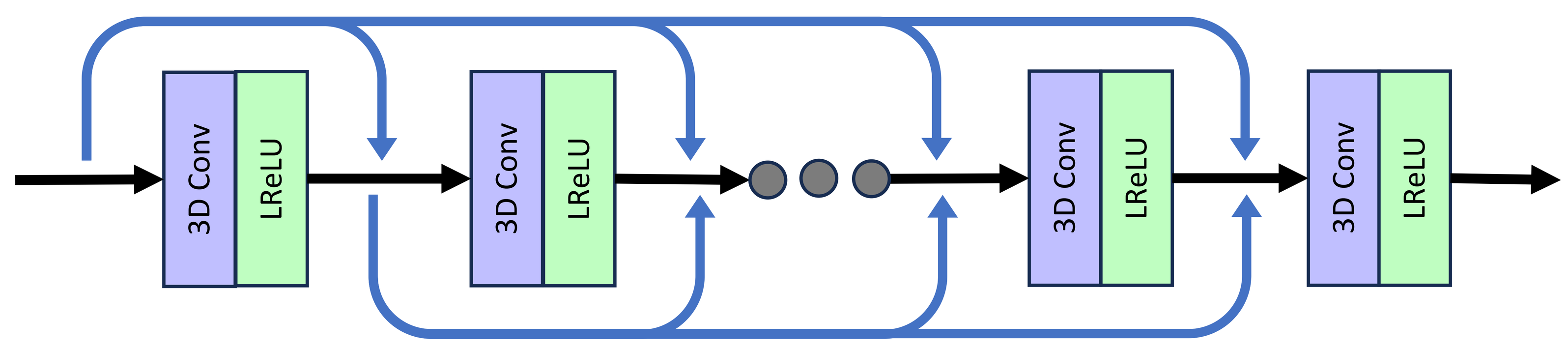
- ❑ **3D RRDB-Network**
  We introduce 3D RRDB network by scaling up 2D RRDB (SOTA super resolution model in 2D)
- ❑ **2.5D Perception Loss**
  We introduce 2.5D perception loss to apply loss from multi-view: Axial, Coronal, and Sagittal. This helps model generate more realistic volumetric medical image
- ❑ **3D U-Net Discriminator**
  We implemented 3D U-Net Discriminator for voxel-wise classification allowing more fine-level realism of output image
- ❑ **Robust Performance**
  To show the generalizability, we tested our model on four experiment settings which include: 4 modalities (T1/T2 MRIs, MRH, CT), 2 species (human, mouse), 2 body regions (brain, abdomen)

Method

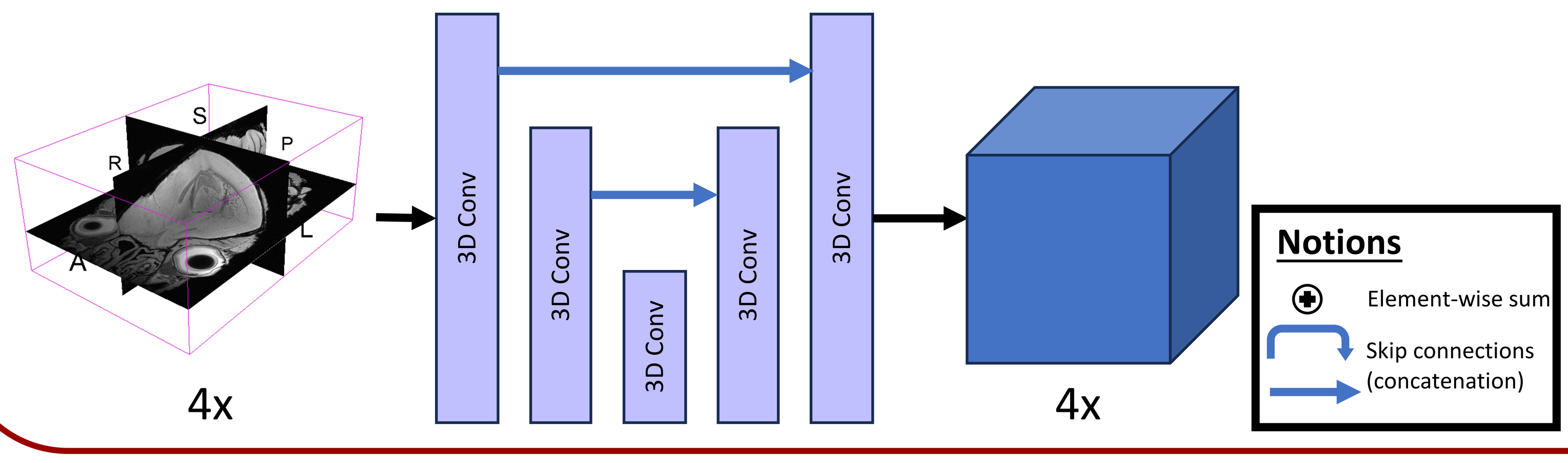
3D RRDB-Net



Residual-Dense-Block (3D RDB)



3D U-Net Discriminator



❑ Loss formulation

$$L = L_{gen} + L_{disc}$$

$$L_{gen} = \lambda_1 L_{pixel} + \lambda_2 L_{perc} + \lambda_3 L_{adv}$$

$\lambda_1 = 1$
$\lambda_2 = 1$
$\lambda_3 = 0.01$

$$L_{perc} = \sum_{view}^{a,c,s} |VGG(I_{SR}) - VGG(I_{HR})|$$

a: axial-view
c: coronal-view
s: sagittal-view

Dataset

Dataset	Modality	Subject	Region
Oasis	T1 MRI	Human	Brain
HCP1200	T2 MRI	Human	Brain
MSD-Task 6	CT	Human	Abdomen
Mice Brain	Magnetic resonance histology (MRH)	Mice	Brain

Results

Dataset	Method	SSIM ↑	PSNR ↑	LPIPS ↓	FID ↓
Mice Brain MRH	Trilinear	0.79	29.38	0.32	6.69
	3D SRResNet [4]	**0.85**	**33.30**	0.18	4.07
	3D DCSRN [5]	0.82	32.34	0.22	4.29
	3D RCAN [3]	0.84	32.73	0.12	1.91
	Ours	0.82	32.21	**0.06**	**0.35**
OASIS	Trilinear	0.79	26.55	0.25	6.89
	3D SRResNet	0.88	31.95	0.12	4.17
	3D DCSRN	0.82	29.96	0.17	5.41
	3D RCAN	**0.89**	**32.27**	0.11	3.69
	Ours	0.82	29.50	**0.04**	**0.18**
HCP1200	Trilinear	0.77	26.94	0.29	4.67
	3D SRResNet	0.92	33.74	0.10	1.85
	3D DCSRN	0.86	31.06	0.17	3.07
	3D RCAN	**0.93**	**34.09**	0.10	1.60
	Ours	0.88	31.61	**0.04**	**0.09**
MSD Task 6	Trilinear	0.80	28.82	0.27	3.94
	3D SRResNet	**0.93**	**37.89**	0.08	1.70
	3D DCSRN	0.88	33.88	0.14	2.72
	3D RCAN	0.92	37.79	0.07	1.38
	Ours	0.89	36.01	**0.03**	**0.18**