TAI4H Workshop

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Computer Graphics and Visualization

FusionINN: Decomposable Image Fusion for Brain Tumor Monitoring

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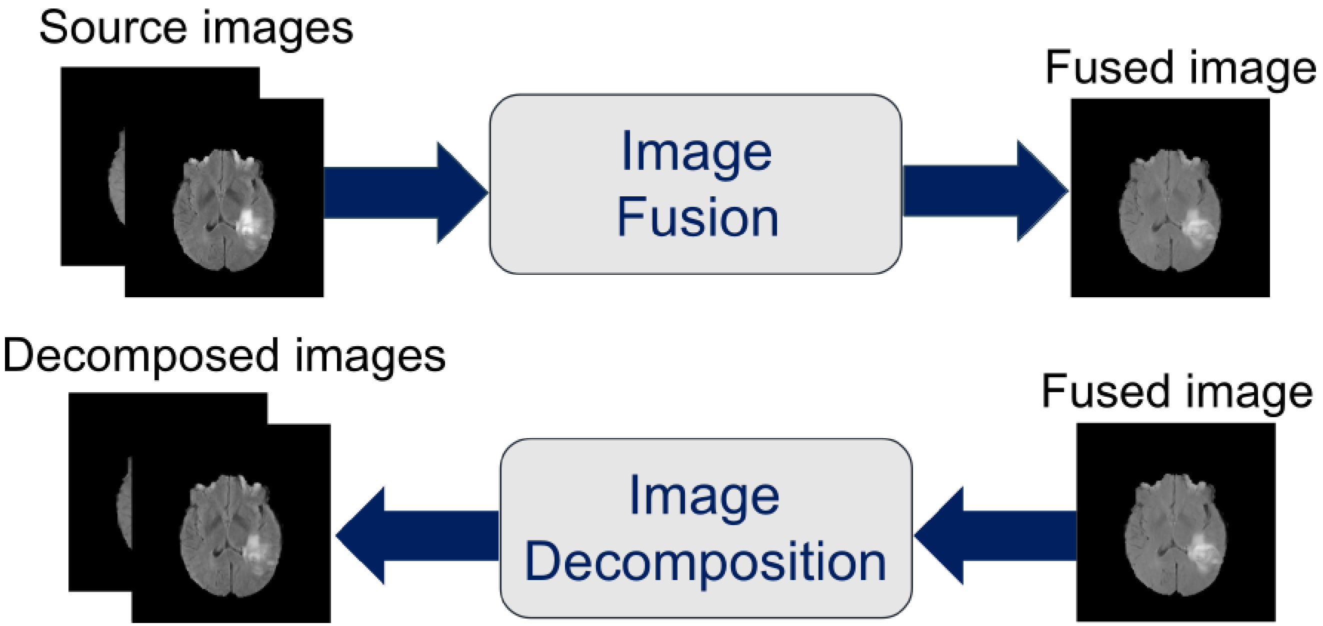
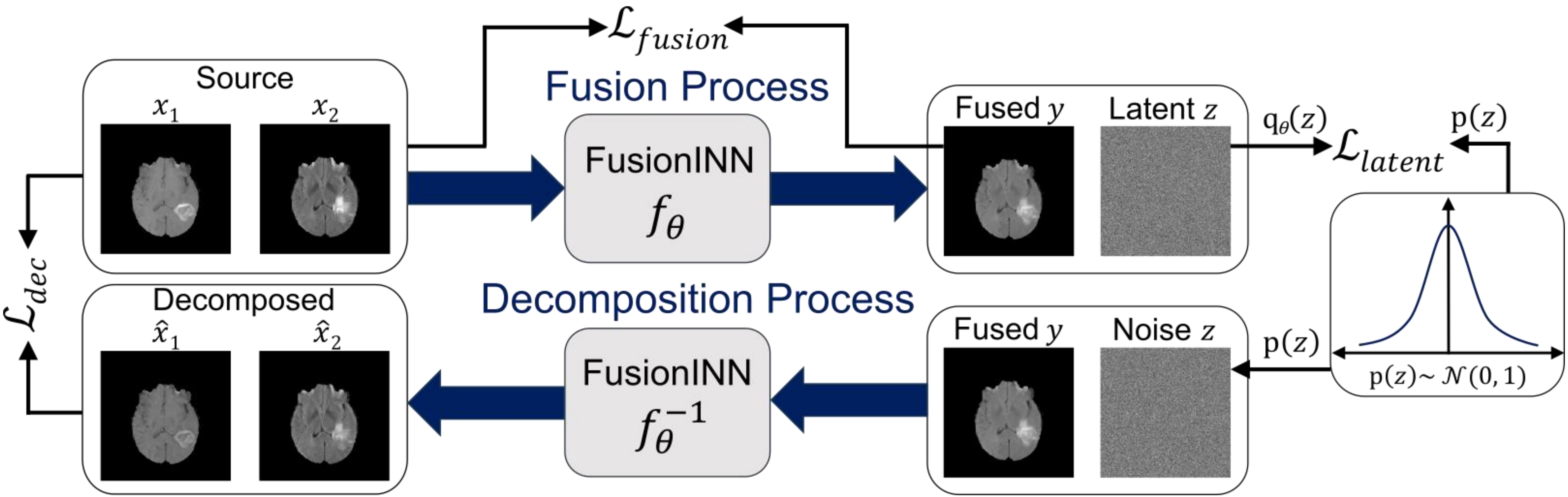
DRESDEN concept

Motivation

- ❑ Fused images aid in visualizing clinical features from multiple sources.
- ❑ Merging grayscale values can obscure salient features.
- ❑ Prior work use non-invertible neural networks to perform image fusion.
- ❑ Decomposability of fused images is therefore not explored.



Method



$\mathcal{L}_{fusion}$
Source
x_1
x_2
Fusion Process
FusionINN
f_θ
Fused y
Latent z
$q_\theta(z)$
$\mathcal{L}_{latent}$
$p(z)$
$\mathcal{L}_{dec}$
Decomposed
$\hat{x}_1$
$\hat{x}_2$
Decomposition Process
FusionINN
f_θ^{-1}
Fused y
Noise z
$p(z)$
$p(z) \sim \mathcal{N}(0,1)$

Loss Functions

Fusion Loss

- $L_{SSIM} = \left(1 - \mathrm{Q}_{SSIM}(x_1, y)\right) + \left(1 - \mathrm{Q}_{SSIM}(x_2, y)\right)$
- $L_{l2} = ||y - x_1||_2^2 + ||y - x_2||_2^2$
- $L_{fusion} = \lambda\, L_{SSIM} + (1 - \lambda)\, L_{l2}$

Decomposition Loss

- $L_{dec}^{SSIM} = \left(1 - \mathrm{Q}_{SSIM}(x_1, \hat{x}_1)\right) + \left(1 - \mathrm{Q}_{SSIM}(x_2, \hat{x}_2)\right)$
- $L_{dec}^{l2} = ||\hat{x}_1 - x_1||_2^2 + ||\hat{x}_2 - x_2||_2^2$
- $L_{dec} = \lambda\, L_{dec}^{SSIM} + (1 - \lambda)\, L_{dec}^{l2}$

Latent Loss

- $L_{latent} = MMD(q_\theta(z)||p(z))$

Total Loss

- $L_{total} = \alpha\, (L_{fusion} + L_{latent}) + (1 - \alpha)\, L_{dec}$

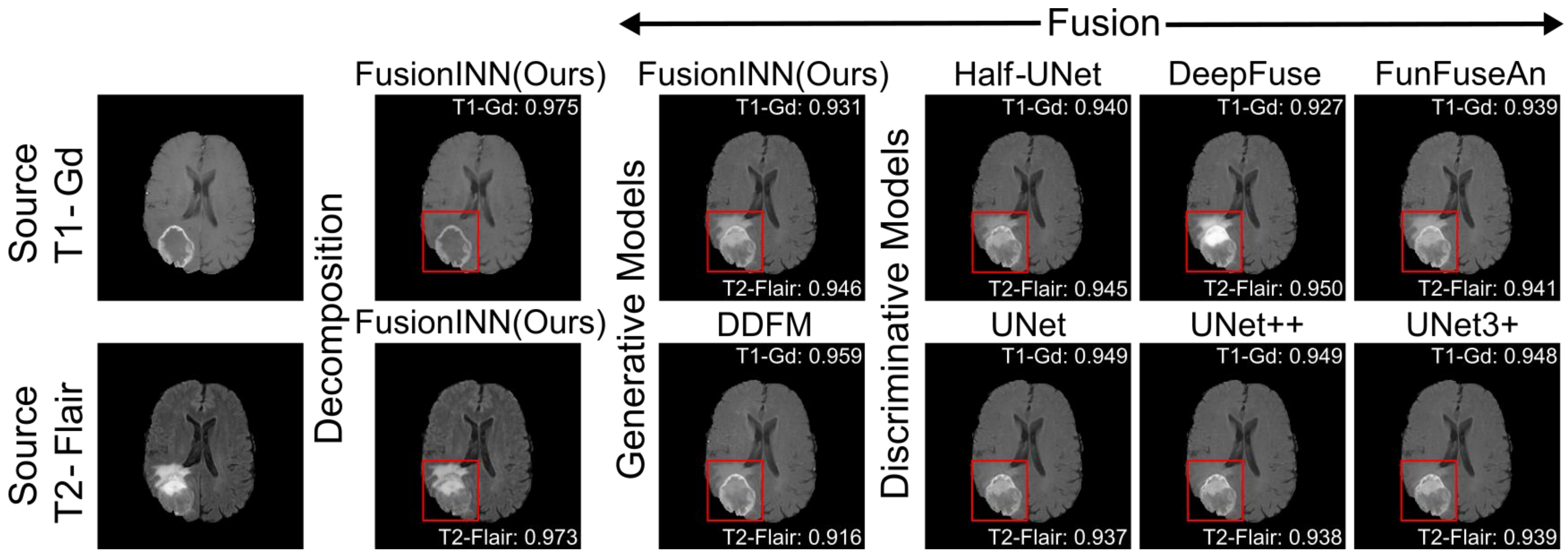
Experiments - Main Results

- BraTS-2018 data ⟶ T1-Gd and T2-Flair modalities ⟶ 8500 training + 1153 validation images.

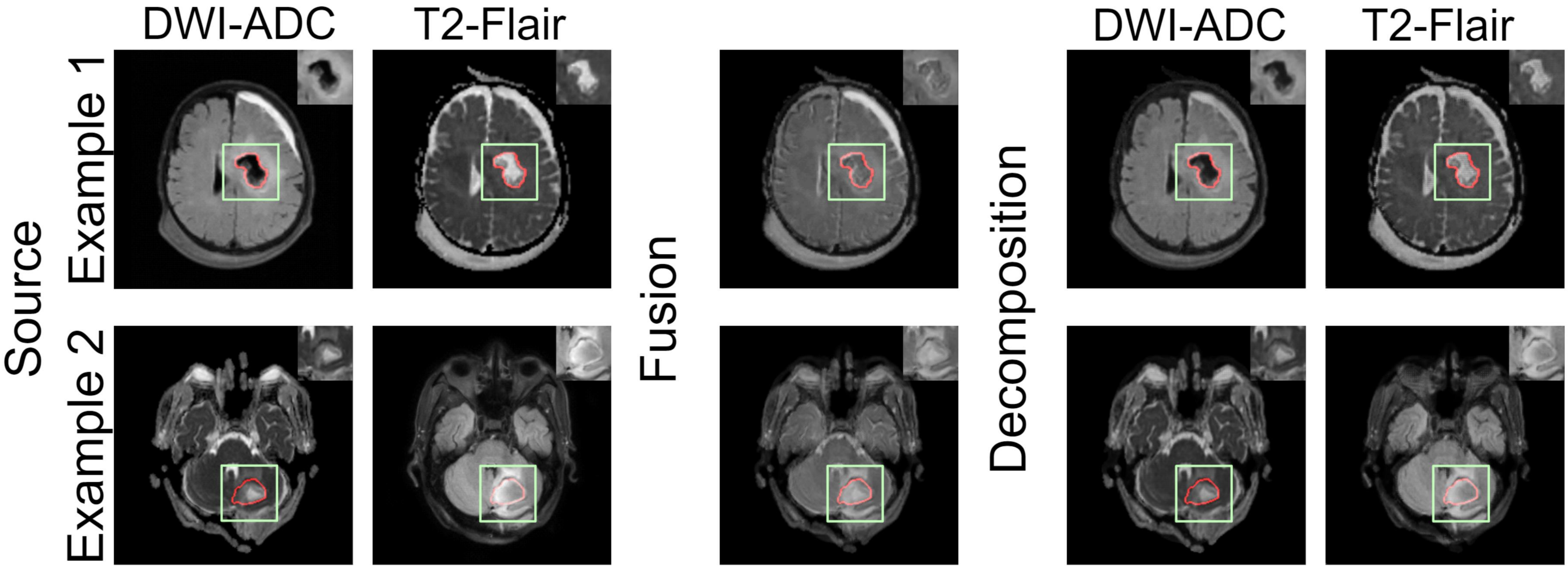
Averaged results on the validation dataset of our pre-processed BraTS-2018 images.

Model Type	Model Name	$Q_{SSIM} \uparrow$	$Q_{FMI} \uparrow$	$Q_{NCIE} \uparrow$	$Q_{XY} \uparrow$	$Q_{P} \uparrow$
Discriminative (Equal Dimension)	DeepFuse [3]	0.927	0.791	0.806	0.449	0.766
	FunFuseAn [5]	0.930	0.845	0.806	0.481	0.781
Discriminative (Dimension Reduction)	Half-UNet [17]	0.933	0.850	0.805	0.464	0.774
	UNet [18]	0.934	0.835	0.805	0.420	0.711
	UNet++ [19]	**0.937**	0.849	0.805	0.433	0.739
	UNet3+ [20]	0.937	0.849	0.805	0.434	0.742
Generative	DDFM [10]	0.921	**0.861**	0.806	0.472	0.702
	FusionINN (Ours)	0.927	0.835	**0.806**	**0.493**	**0.783**

Experiments - Main Results



Experiments - Clinical Results



Conclusion

- ❑ FusionINN integrates the image decomposition task into the fusion problem.
- ❑ Showcases its capability for clinically relevant fusion and decomposition images.

Future work

- ❑ Learning latent space not as random noise, but for tasks like image segmentation.
- ❑ Incorporating feedback from clinicians may help enhance the learning scheme.

Thanks for Listening!

Questions?