Improving Spatial Resolution in fUS through ULM guided Generative Learning

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Context

- **functional UltraSound (fUS)** levrages hemodynamic signals to map brain activity
- **Ultrasound Localisation Microscopy (ULM)** provides super-resolved brain imaging
  - ➢ requires the injection of contrast agents

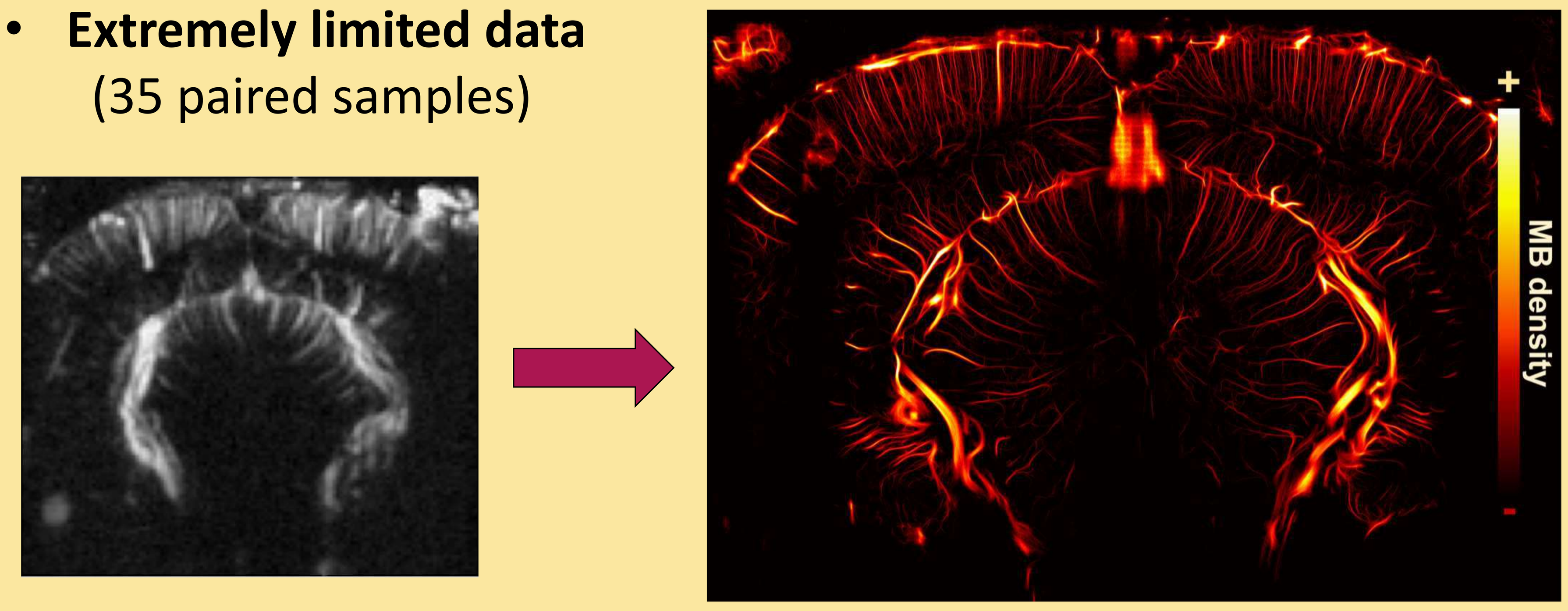
Problem

fUS → ULM translation to enhance vascular resolution

- Improve resolution of fUS by **moderate factors (×3–×5)**
- Not aiming for full ULM reconstruction
- ➢ Evaluate **modern generative models** in a data-scarce scenario

Key challenges:

- **Large resolution gap** between fUS and ULM (×2700)
- **Extremely limited data** (35 paired samples)



fUS acquisition of a rat brain

ULM acquisition of a rat brain

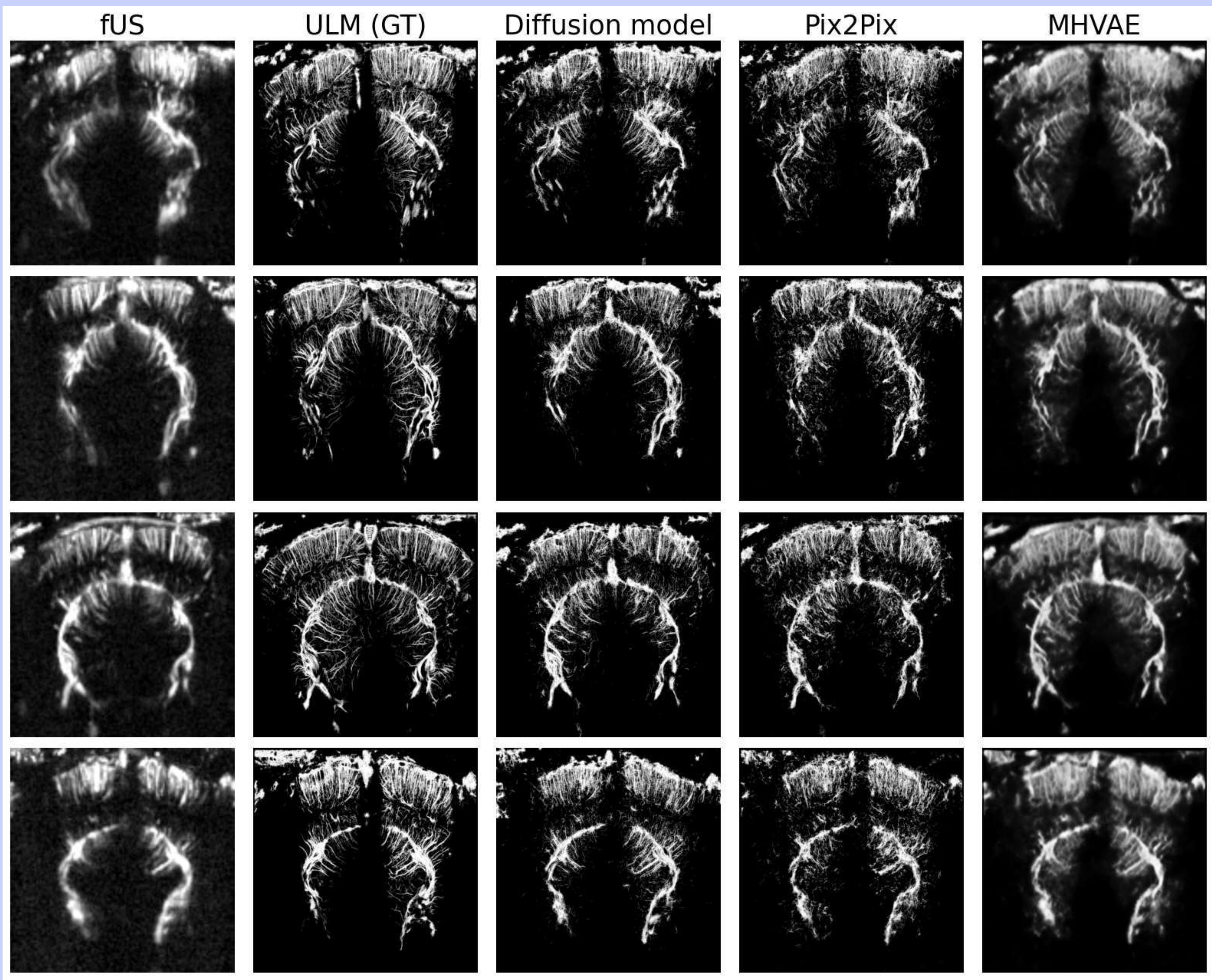
Quantitative and Qualitative Evaluation of SoA Generative Models

Models

- Pix2Pix (GAN)
- MHVAE (Multimodal VAE)
- Conditional Diffusion Model with and edge loss
  → preserves vascular structures

Dataset & Setup

- 35 paired images (rats)
  - 29 train/ 1 val/ 5 test
- Resized to **512×512**
- ULM preprocessing:
  - Grayscale + **log transformation**
- No data augmentation



Model	MSE ↓	SSIM ↑	PSNR ↑	LPIPS ↓
MHVAE	**0.0318 ± 0.0045**	0.411 ± 0.021	**15.01 ± 0.60**	0.476 ± 0.028
Diffusion Model	0.0475 ± 0.0053	**0.510 ± 0.040**	13.25 ± 0.48	**0.319 ± 0.021**
Pix2Pix	0.0476 ± 0.0038	0.476 ± 0.036	13.24 ± 0.34	0.355 ± 0.018

Results

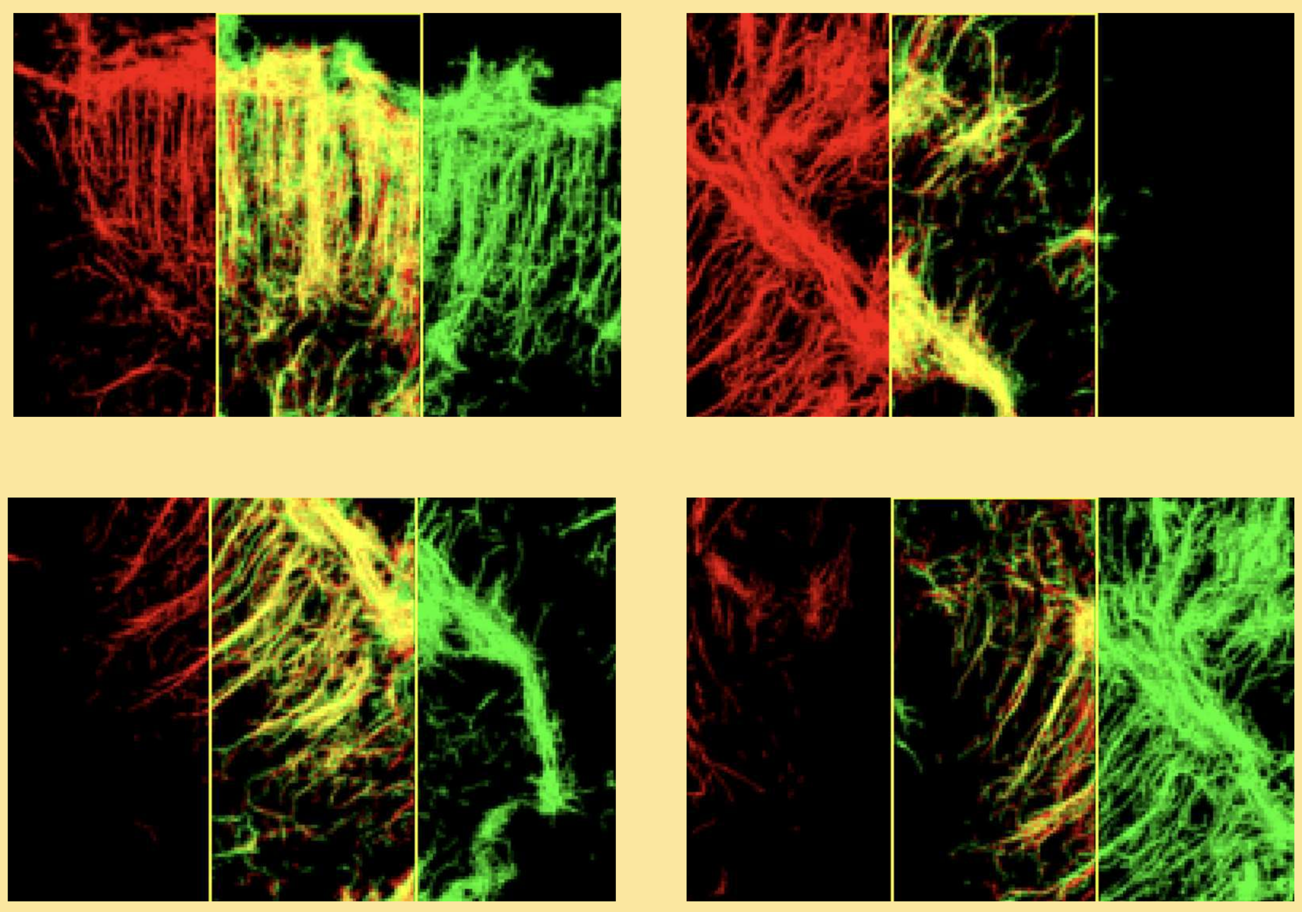
- **MHVAE**
  - ✓ Best MSE / PSNR
  - ✗ **Blurry outputs**, loss of fine vessels
- **Pix2Pix**
  - ✓ Balanced performance
  - ✗ Misses small vascular structures
- **Diffusion model**
  - ✓ **Best SSIM + LPIPS**
  - ✓ Most **realistic and detailed vascular structures**
  - ✓ Confirmed as **most anatomically coherent** by expert

Key Design for the Diffusion model

- Training on **128×128 patches**
  - → increases effective data size
- **Positional embedding** for spatial consistency
- Reconstruction:
  - Sliding window + overlap
  - Boundary artifact reduction

Spatial coherence of patch-wise predictions

- Smooth spatial continuity
- Consistent predictions across boundaries
- **Missed small vessels (false negatives) !!**



Red: left patch · Green: right patch · Yellow: overlap

Takeaway

*Diffusion models can significantly enhance fUS resolution in **extremely low-data settings**, when using the **adapted training strategy***

✓ Achieved **×5 resolution enhancement**

Critical factors:

- Patch-based training
- Edge loss
- Patch size (128×128)

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