Deep Learning for Dynamic MRI Reconstruction

BME1312 Artificial Intelligence in Biomedical Imaging

ShanghaiTech University

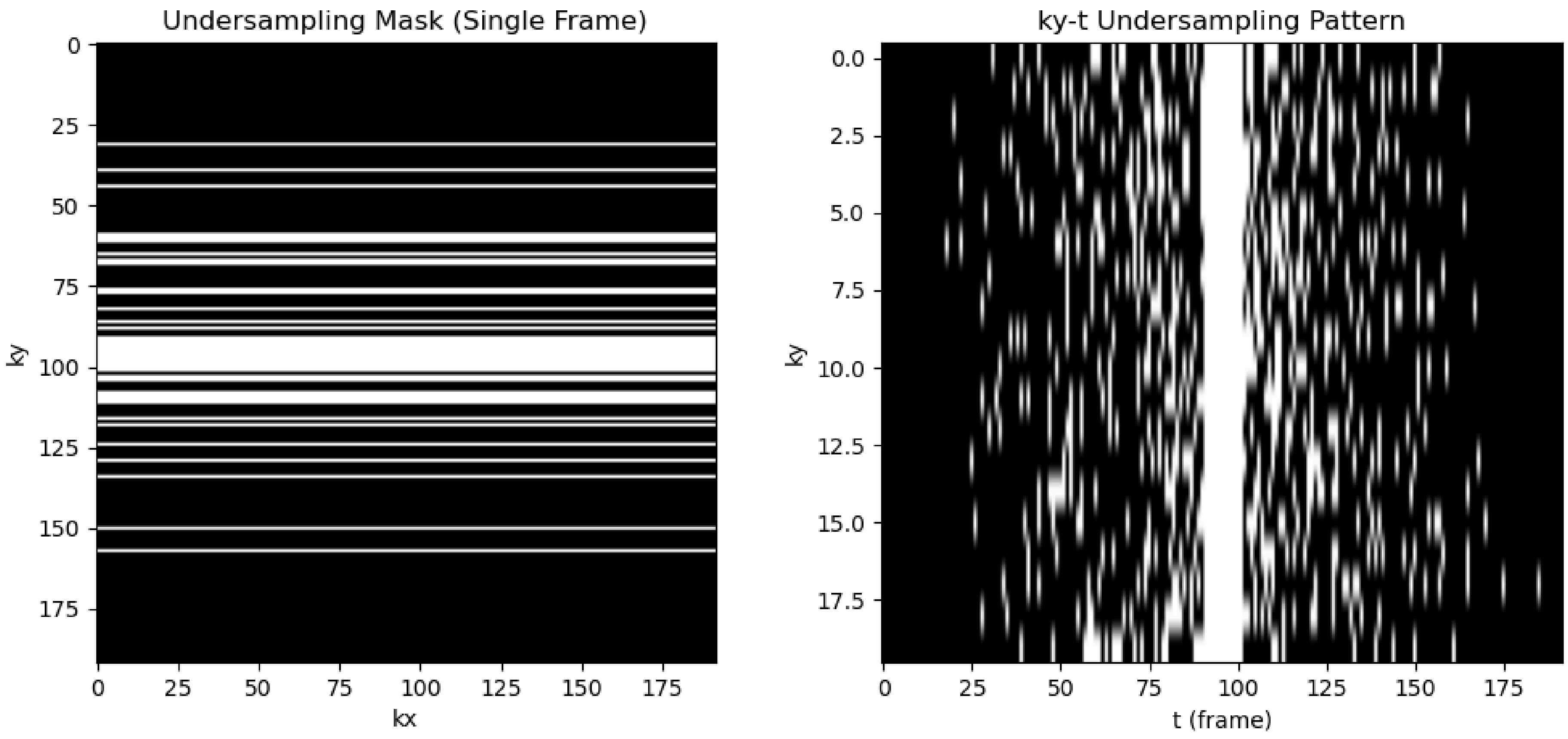
> Member: 熊闻野 夏博扬 杨人一 吴家兴 杨丰敏

Overview

- **Goal:** Reconstruct high-quality dynamic MRI images from undersampled k-space data.
- **Challenge:** Undersampling introduces aliasing artifacts.
- **Approach:** Deep learning framework combining:
- Dual 2D UNets (for real and imaginary components)
- 3D ResNet (for temporal correlation)
- **Evaluation:** PSNR and SSIM metrics.

Data & Undersampling

- **Dataset:** `cine.npz` - Fully sampled cardiac cine MRI `[nsamples, nt, nx, ny]`.
- **Mask Generation:**
- Variable density random undersampling.
- Acceleration Factor (AF) = 5.
- 11 central k-space lines preserved per frame.
- Different masks for different frames.
- **Aliasing:** $b = F^{-1} \cdot U \cdot F \cdot m$



Undersampling Mask (Single Frame)
ky
kx
0
25
50
75
100
125
150
175
ky-t Undersampling Pattern
ky
t (frame)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

Aliased Images vs. Fully Sampled (1/3)

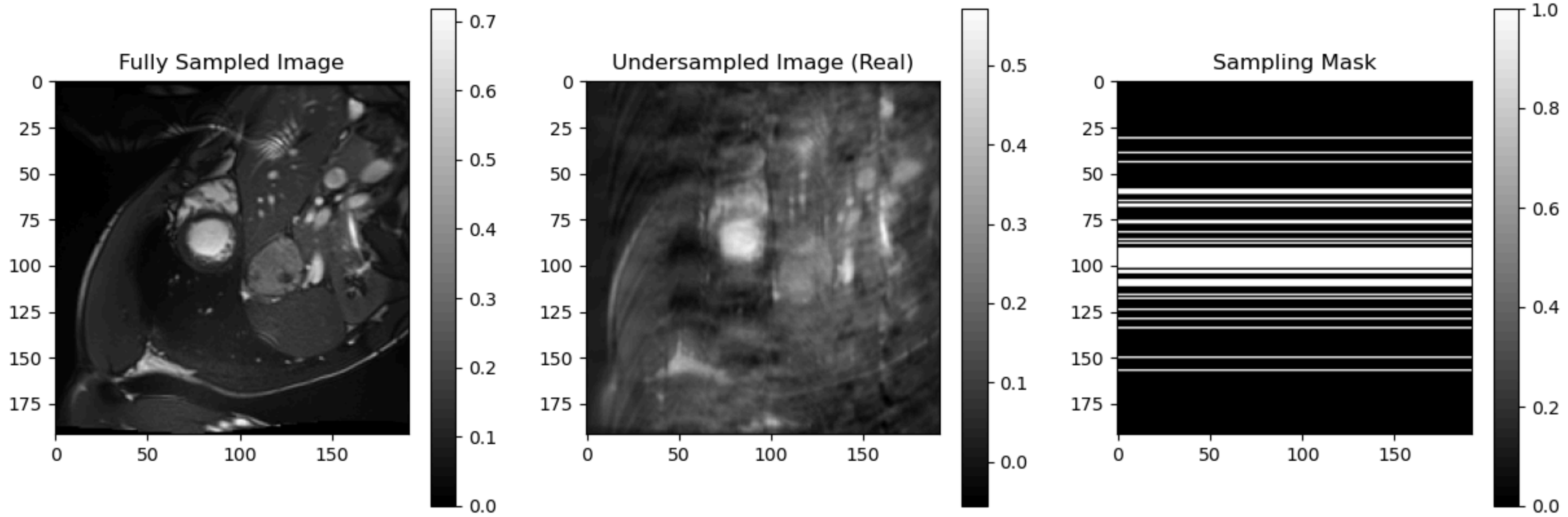


Fig: Fully sampled (left), Aliased (middle), Mask (right) - Frame 0

Aliased Images vs. Fully Sampled (2/3)

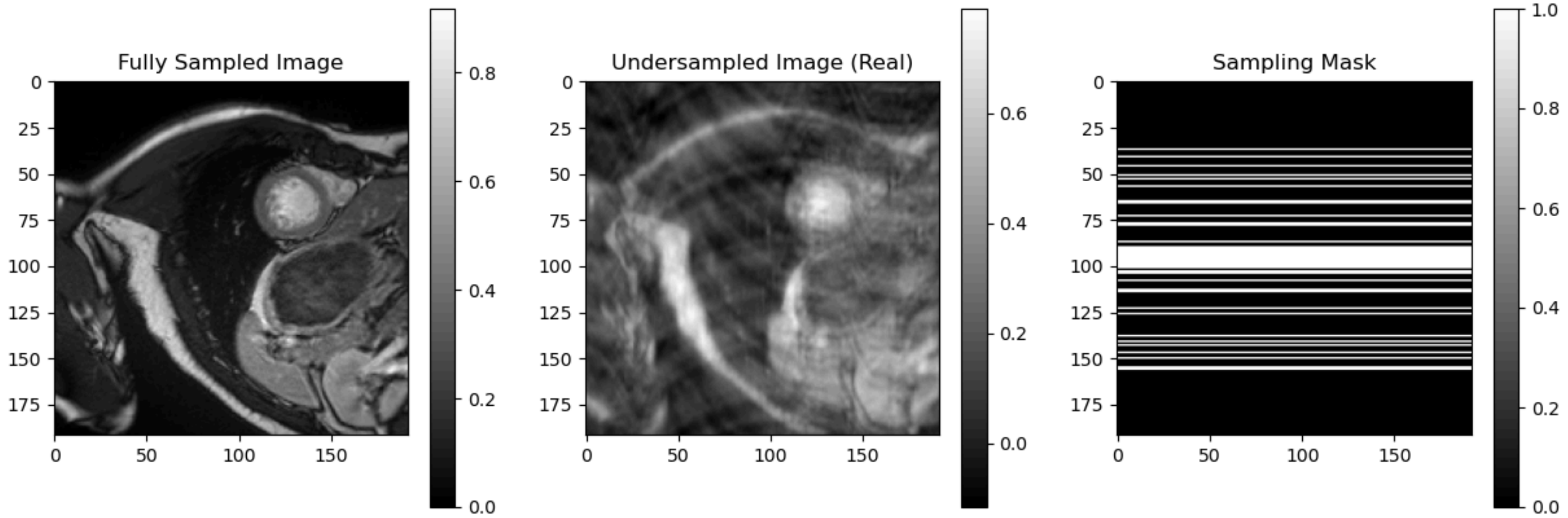


Fig: Fully sampled (left), Aliased (middle), Mask (right) - Frame 1

Aliased Images vs. Fully Sampled (3/3)

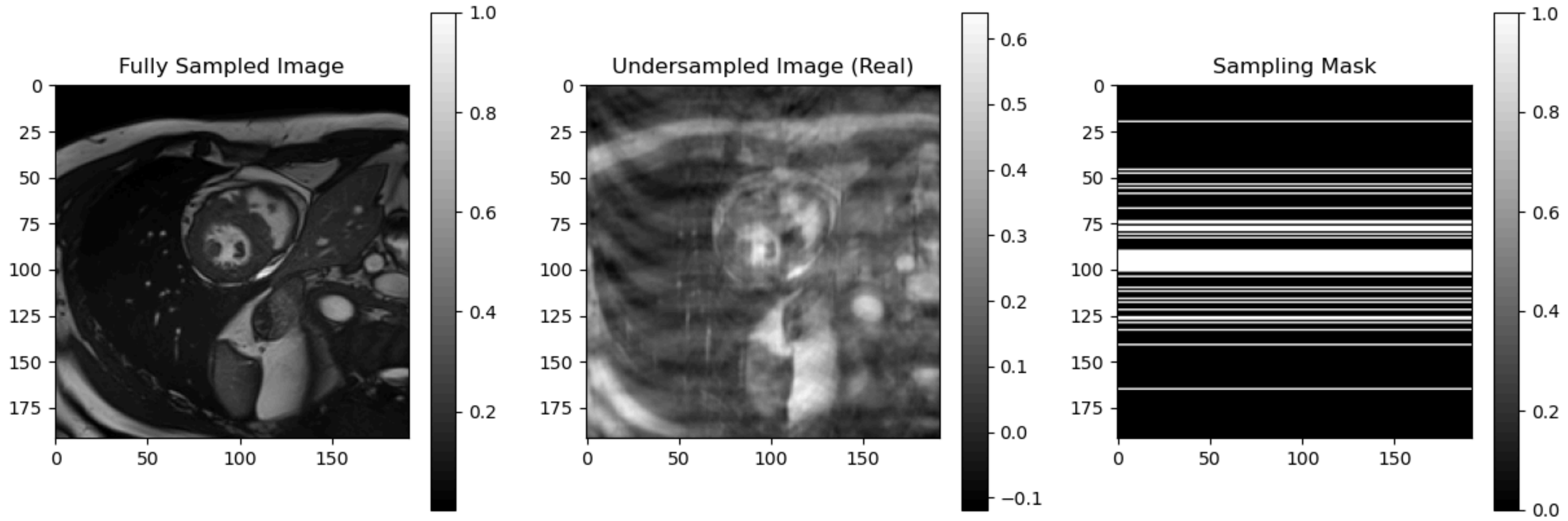
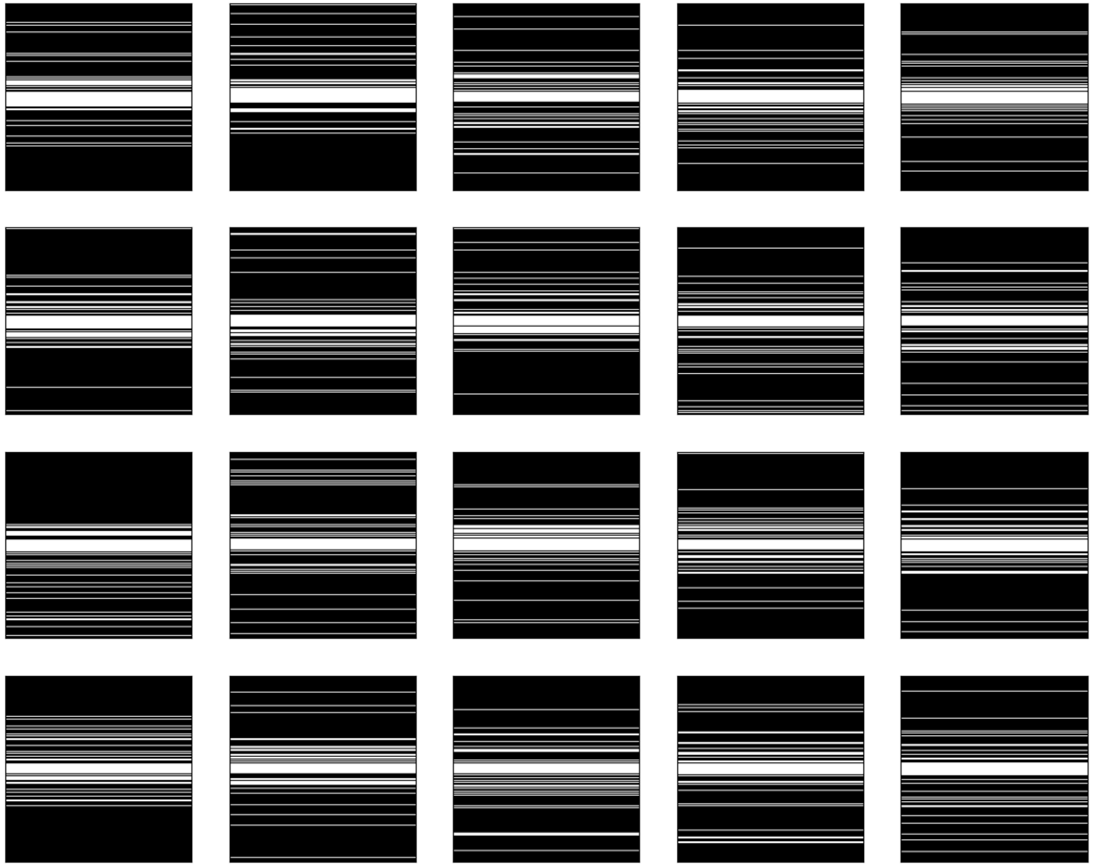


Fig: Fully sampled (left), Aliased (middle), Mask (right) - Frame 2



It is also clear to see that, for different dynamic frames, the undersampling masks are different.

Reconstruction Network: Dual UNet

- **Purpose:** Process real and imaginary parts separately.
- **Input:** Pseudo-complex images (real/imaginary as channels).
- **Features:**
- Encoder-decoder with skip connections.
- Attention mechanism (Channel & Spatial) in bottleneck.
- Dropout (p=0.3).
- LeakyReLU (negative_slope=0.1).
- Weight Regularization.

Reconstruction Network: 3D ResNet

- **Purpose:** Integrate temporal information across frames.
- **Input:** Stacked outputs from the two UNets.
- **Features:**
- 3D Convolutions.
- Residual connections (`BasicBlock`).
- Lightweight design (1 block/layer).
- Final 1x1x1 convolution.

Creativity: Addressing Challenges in Network Design

- **Challenge 1: Pseudo-Complex Input:** Stacking dynamic images along the channel dimension created issues as real/imaginary parts weren't aligned.
- **Solution 1: Dual UNet Branches:** Split input into separate real and imaginary processing branches using two UNets, concatenating them later. Added attention in bottlenecks to enhance spatial/channel correlation capture.
- **Challenge 2: Capturing Temporal Correlation:** Standard 2D UNet structures don't effectively model changes over time.
- **Solution 2: 3D ResNet Integration:** Added a 3D ResNet structure after the UNets specifically to process and fuse information across the temporal dimension (frames).

Network Architecture Detail

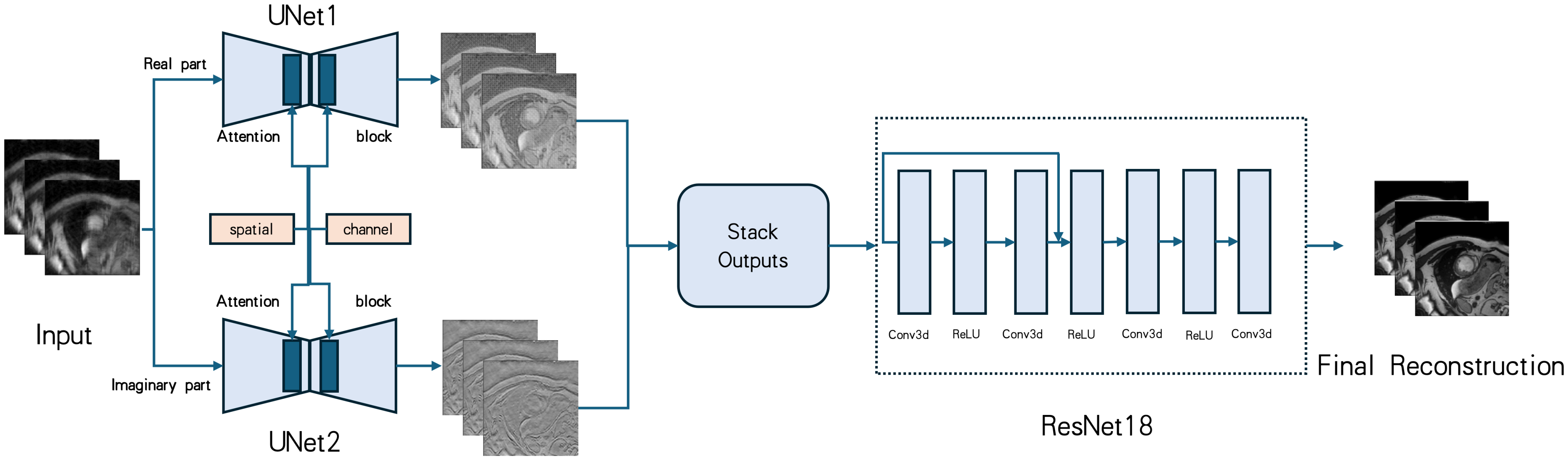
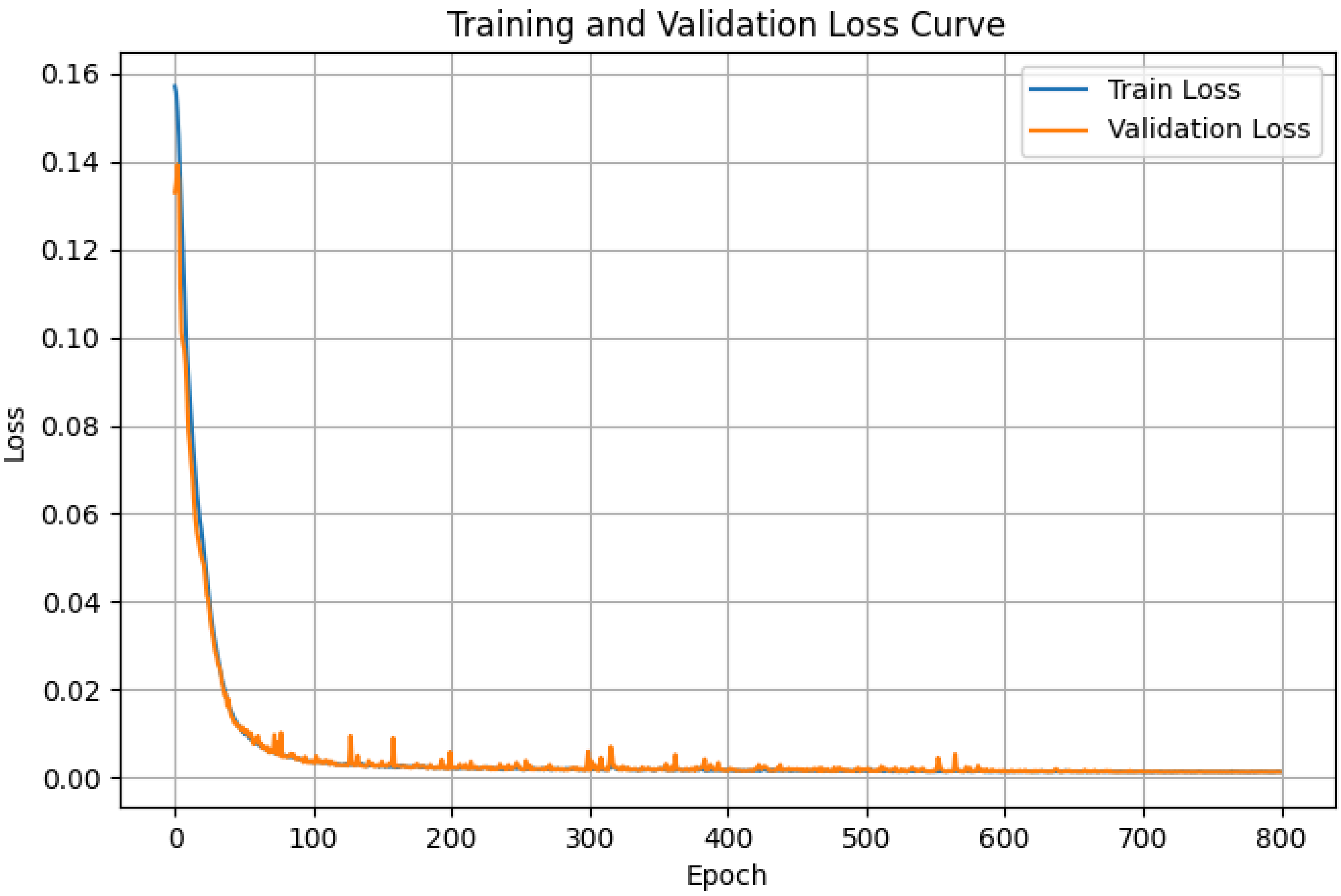


Fig: Detailed architecture showing dual UNet branches and 3D ResNet

Results: Main Model (L2 Loss)

- **Metrics:**
- Loss: mean = 0.00135 ± 0.00055
- PSNR: mean = 29.084 ± 1.932
- SSIM: mean = 0.844 ± 0.037
- Significant improvement over aliased images.


Training and Validation Loss Curve
Train Loss
Validation Loss
Loss
Epoch
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
100
200
300
400
500
600
700
800

Reconstruction Examples (1/2)

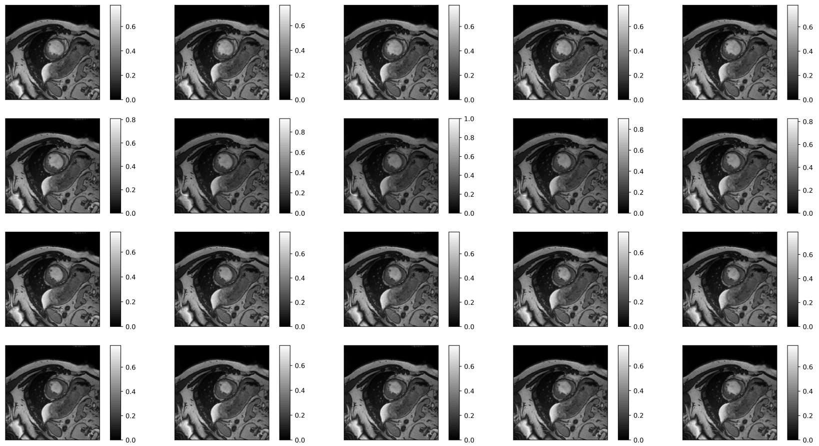


Fig: Fully Sampled (Ground Truth)

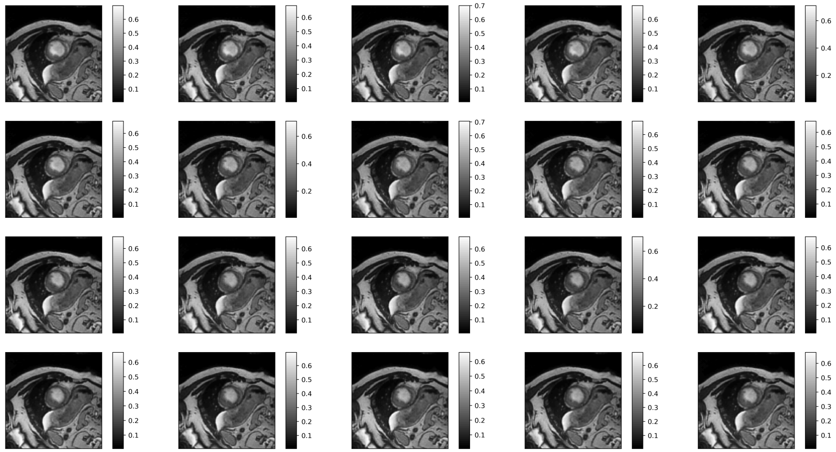


Fig: Reconstructed Image

Reconstruction Examples (2/2)

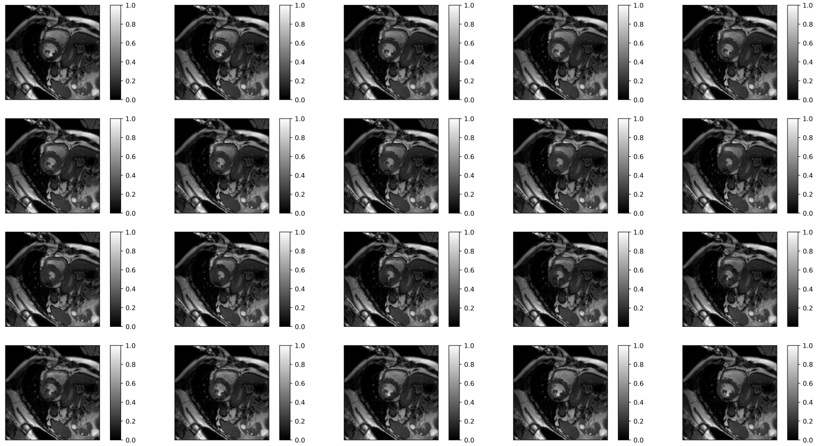


Fig: Fully Sampled (Ground Truth)

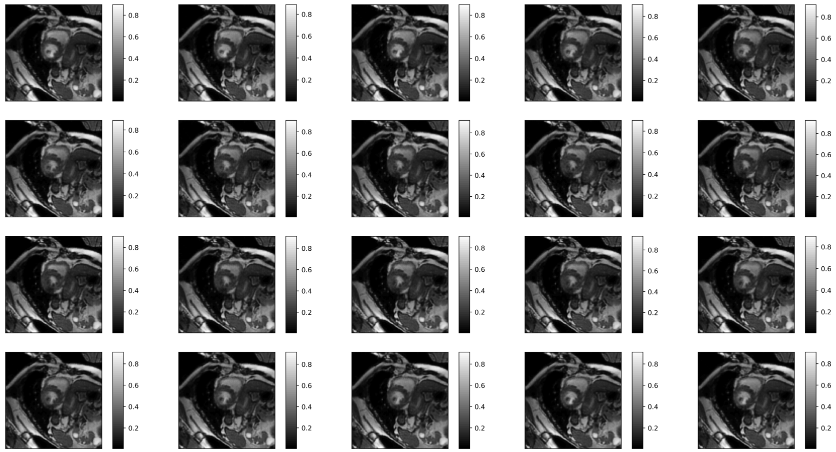
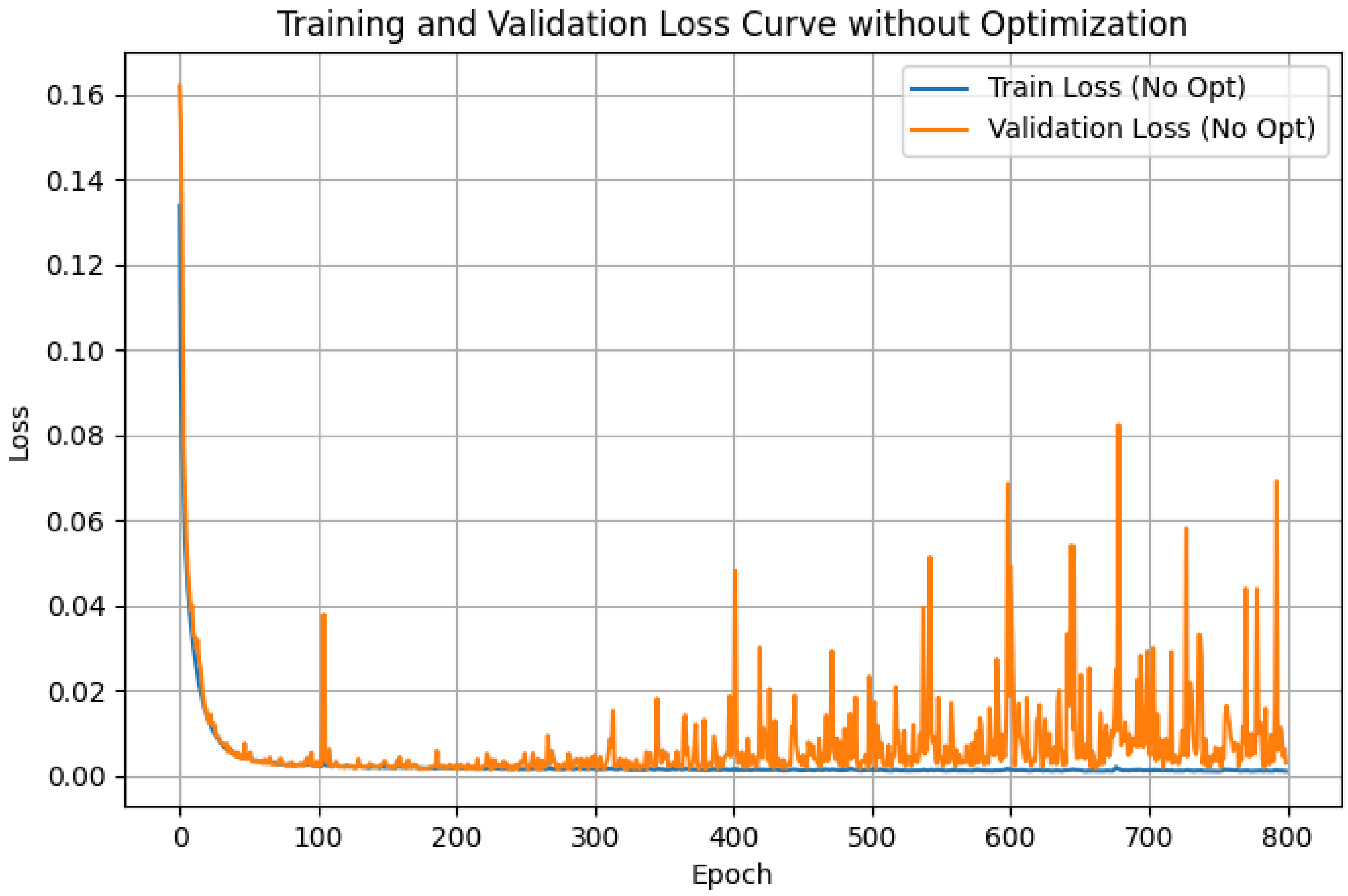


Fig: Reconstructed Image

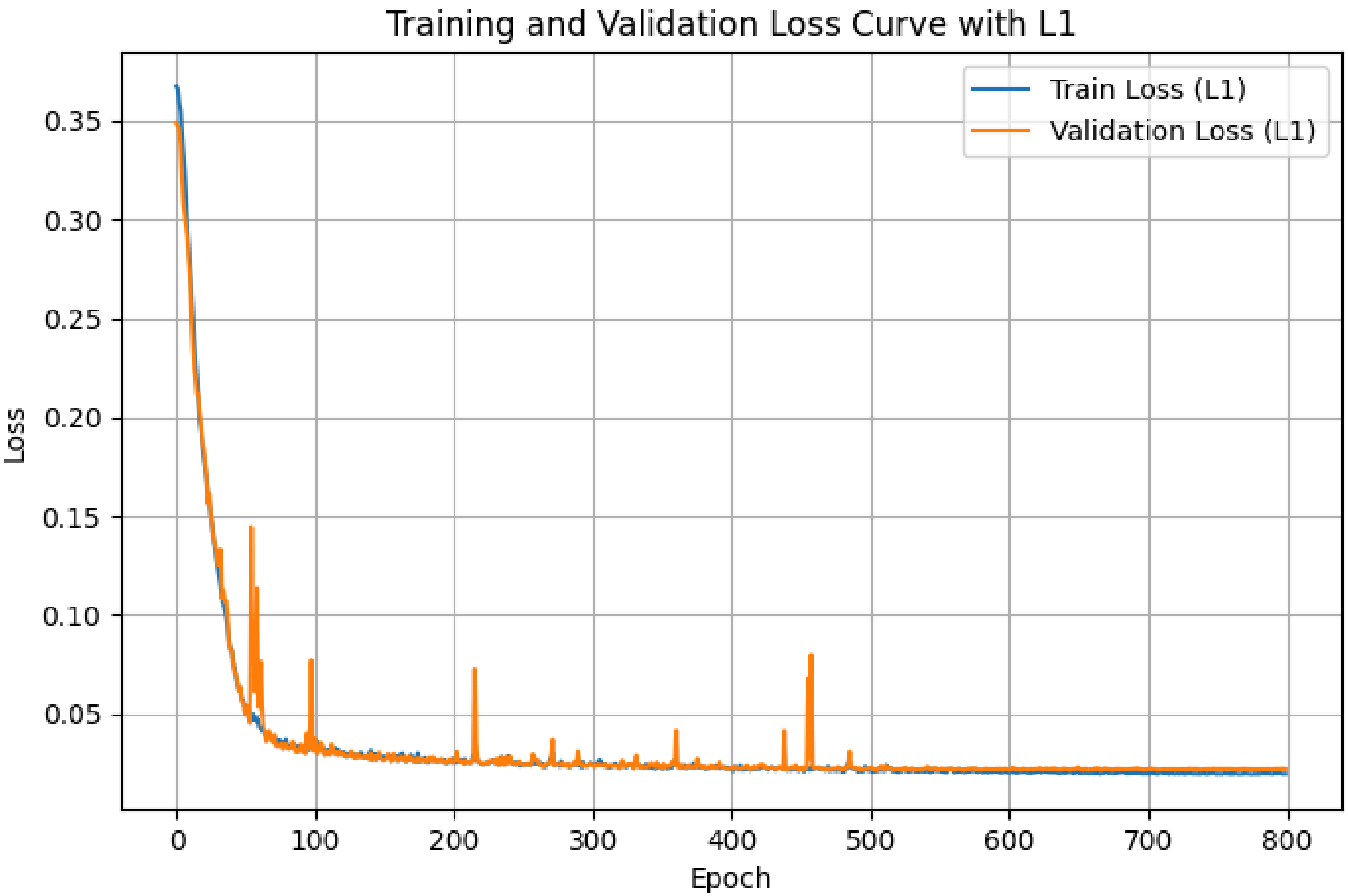
Ablation: Impact of Dropout & Dynamic LR

- **Model:** Trained without Dropout and with constant LR.
- **Results:**
- PSNR: 24.154 (vs. 29.084)
- SSIM: 0.743 (vs. 0.844)
- **Observation:** Clear signs of overfitting (validation loss). Dropout and dynamic LR are crucial for regularization and stable convergence.


Training and Validation Loss Curve without Optimization
Train Loss (No Opt)
Validation Loss (No Opt)
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Loss
0
100
200
300
400
500
600
700
800
Epoch

Ablation: Impact of L1 vs. L2 Loss

- **Results (L1):** PSNR: 29.1511, SSIM: 0.8439
- **Results (L2):** PSNR: 29.0845, SSIM: 0.8443
- **PSNR vs. SSIM Trade-off:** L1 loss can lead to higher PSNR (pixel accuracy) but potentially lower SSIM (structural similarity) because it doesn't explicitly enforce structural consistency. In this specific case, SSIM was similar for both.
- **Observations:** Both loss functions yielded high-quality reconstructions. L2 loss resulted in much lower mean loss values and slightly better metric stability (lower std dev).
- **Recommendation:** Use L1/L2 if pixel recovery is the priority; consider structure-aware losses (e.g., L1+SSIM) if perceptual quality/structural fidelity is crucial. The original L2 model was retained for stability.


Training and Validation Loss Curve with L1
Train Loss (L1)
Validation Loss (L1)
0.35
0.30
0.25
0.20
0.15
0.10
0.05
Loss
0
100
200
300
400
500
600
700
800
Epoch

Exploration: Unrolled Denoising Network

- **Concept:** Cascade base network with data consistency layers.
- **Models:** 2 Cascades (C2), 3 Cascades (C3).
- **Training:** Increased memory/time significantly. Trained only 300 epochs.

Model	Epochs	GPU Mem	PSNR	SSIM
Original	800	~10GB	29.08	0.844
Cascade 2	300	18GB	28.87	0.834
Cascade 3	300	24GB	28.96	0.807

- **Observation:** Performance did not improve over original model, possibly due to limited training data/epochs or base network complexity.

Unrolled Network Loss (Cascade 3)

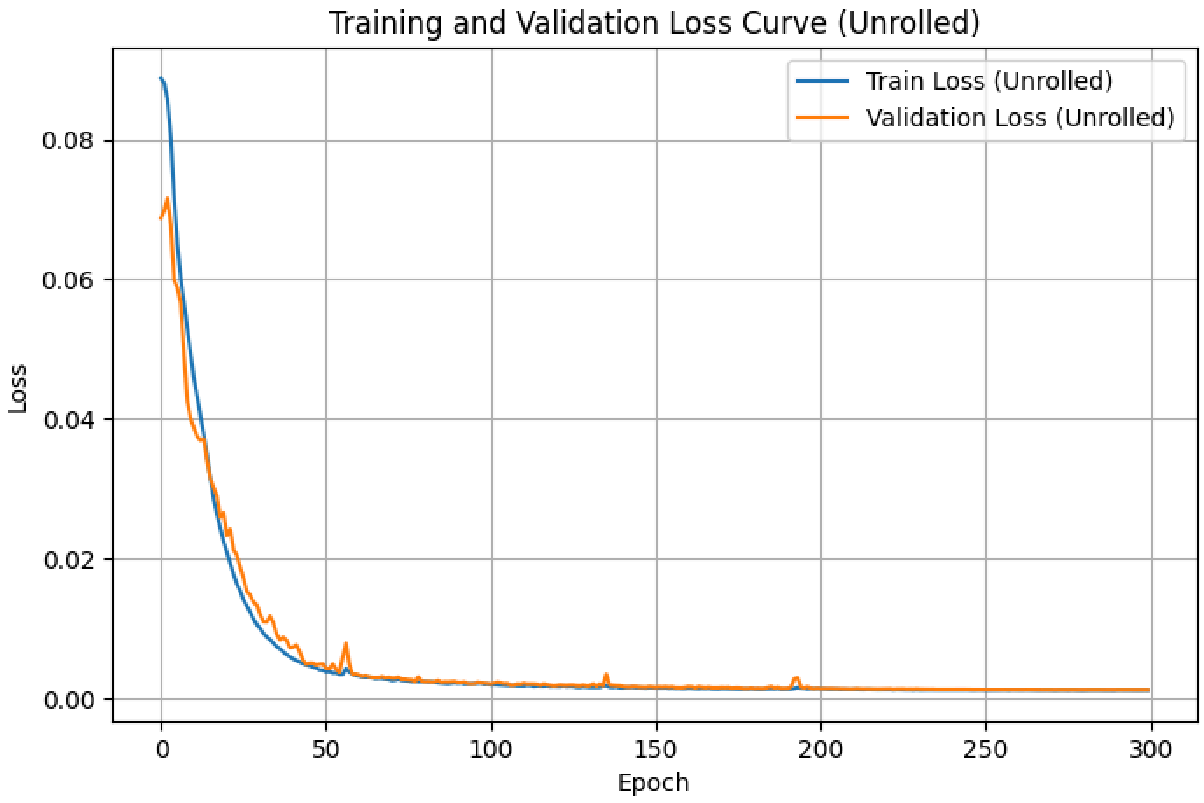


Fig: Loss Curves for 3-Cascade Unrolled Network (300 Epochs)

Conclusion

- Proposed Dual UNet + 3D ResNet architecture effectively reconstructs dynamic MRI from undersampled data (PSNR ~29.1, SSIM ~0.84).
- Dropout and dynamic learning rate are essential for optimal performance.
- L1 and L2 loss functions yield comparable results; L2 chosen for stability.
- Unrolled networks showed potential but require further investigation (more data, longer training).