Distributed Deep Learning for Medical Image Denoising using U-Net and U-Net++

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OUTLINE

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- CONCLUSION AND FUTURE WORK

Distributed Deep Learning:

A subset of machine learning that involves training deep neural networks across multiple machines in parallel.

Distributed deep learning improves efficiency in the following ways;

- Huge Datasets
- Flexibility
- Large Models
- Resource Utilization
- Scalability

Credit For this Slide: Dr. Jagreet Kaur Gill (XENONSTACK)

INTRODUCTION
Traditional & Distributed Training

Traditional Training

- ✓ Involves training a model on a single machine with one or more GPUs or CPUs.
- ✓ The entire dataset is loaded onto a single node's memory.
- ✓ Training is sequential, and resources (CPU, RAM, GPU) on a single machine limit scalability.

✅ **Simplicity**
✅ **No Communication Overhead**
✅ **Efficient for Small Models**

❌ **Limited by Hardware**
❌ **Slow for Large Models**
❌ **Not Scalable.**

Distributed Training

- ✓ Involves multiple machines (nodes) working together to train a model.
- ✓ Used when a single machine is insufficient due to memory or compute demand/limitations.
- ✓ Requires a communication strategy to synchronize updates across nodes.

✅ **Scalability**
✅ **Faster Training**
✅ **Better Utilization**

❌ **Communication Overhead**
❌ **Complex Implementation**
❌ **Debugging Challenges.**

PROBLEM

- Centralized medical image training raises privacy and computational concerns.

- Hospitals and research centers face restrictions on data sharing due to patient confidentiality.

- Deep learning denoising requires large datasets but centralizing sensitive data is risky.

- Need for a distributed, privacy-conscious, and efficient denoising framework that preserves diagnostic quality.

BACKGROUND

Deep Learning

- ✓ Deep learning (U-Net, U-Net++) has improved medical image segmentation and denoising.
- ✓ Distributed Deep Learning (DDL) enables training across GPUs/nodes to reduce computation time.

Privacy-Preserving ML

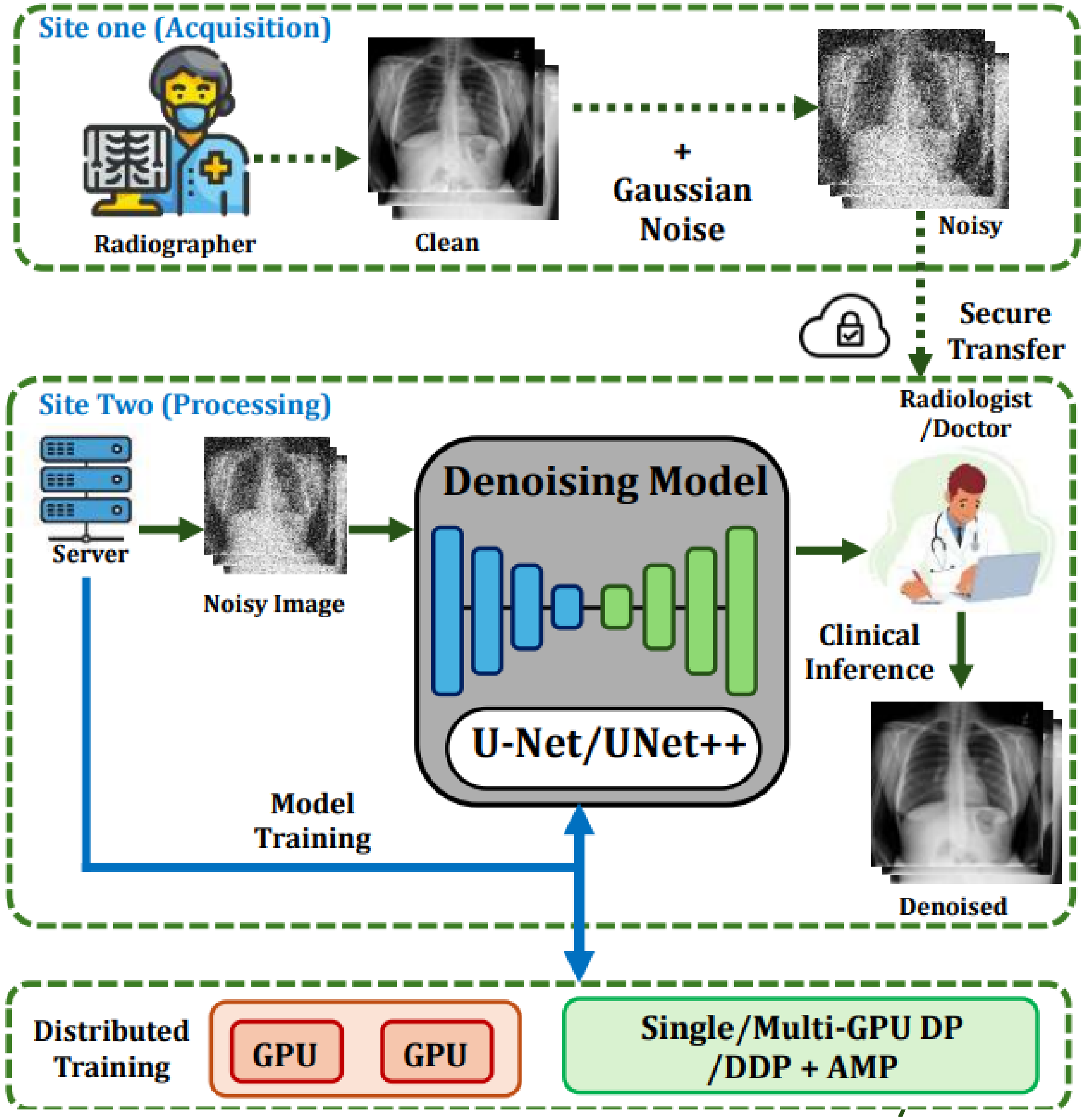
- ✓ Federated Learning, Differential Privacy, Encryption → high communication cost.
- ✓ Gaussian noise obfuscation → lightweight privacy proxy with minimal overhead.

Existing denoising filters (BM3D, TNDR, DnCNN-3) underperform compared to CNN-based methods.

METHODOLOGY

Framework Overview

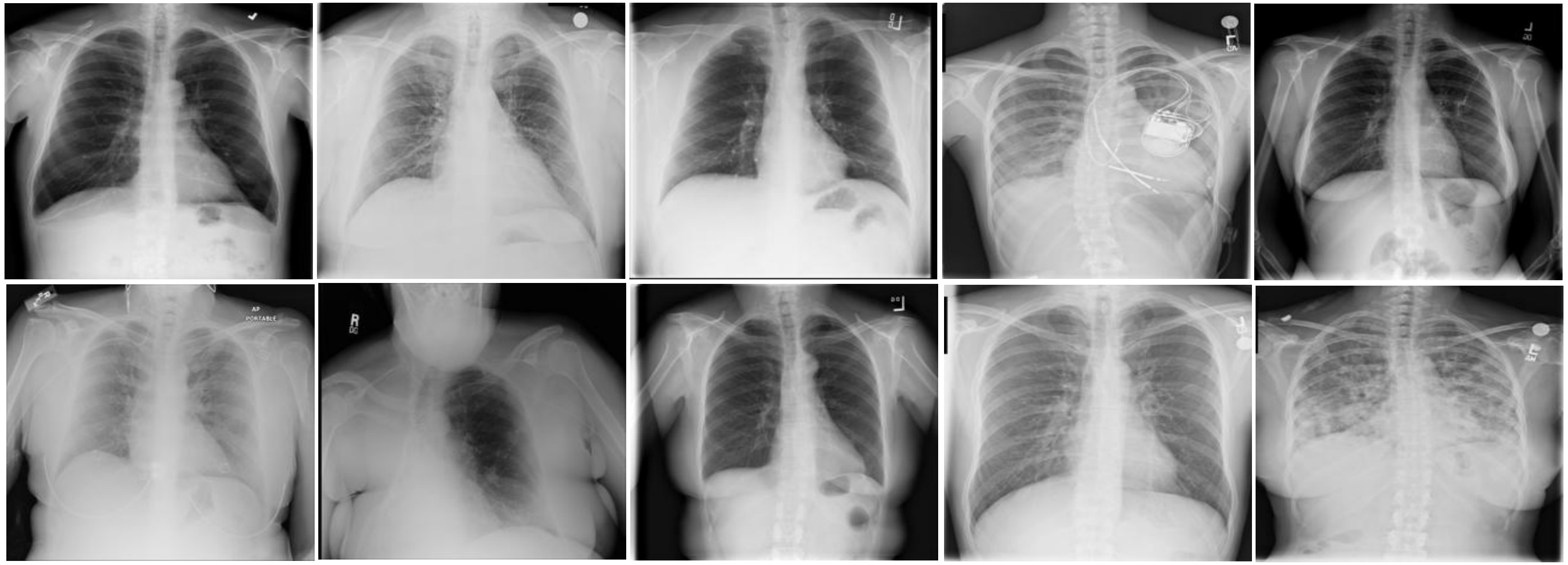
- ❖ Site 1 (Acquisition):
  Radiographer adds Gaussian noise to images → secure transfer.
- ❖ Site 2 (Processing):
  Denoising model (U-Net/U-Net++) trained on noisy-clean pairs.



METHODOLOGY
Dataset

- Chest radiographs from the NIH Chest X-ray14 dataset.
- Consists of 112,120 frontal chest X-ray images collected from 30,805 unique patients
- We sampled 15,000 images for our study.
- All images already in grayscale (single-channel) and 1024 x 1024 were resized to 256×256 pixels to standardize the input dimensions and reduce computational costs.

Samples from the dataset



SUMMARY OF U-NET AND U-NET++ ARCHITECTURES USED

Feature	U-Net	U-Net++
Input	$1 \times 256 \times 256$ grayscale image	$1 \times 256 \times 256$ grayscale image
Output	$1 \times 256 \times 256$ denoised image	$1 \times 256 \times 256$ denoised image
Depth	5 levels	5 levels with nested decoding
Param.	~ 8.6 M ($N_c = 64$)	~ 9.2 M (`base_ch=64`)
Key Features	ReLU, BatchNorm, symmetric skip connections, transposed conv upsampling	Dense skip pathways, multi-depth aggregation, multiple output heads, bilinear upsampling

Training Framework and Hardware Configuration

Training Framework and Hardware Configuration

Attribute	Details
Framework	PyTorch 1.X with `nn.DataParallel`
GPUs Used	2 $\times$ NVIDIA RTX A4500 (Each with 20470 MiB memory)
CUDA Version	12.2
Driver Version	535.171.04
GPU Utilisation	Managed by PyTorch's automatic batch splitting and gradient synchronization

METHODOLOGY
Key innovations

- Uses Gaussian noise as obfuscation instead of heavy cryptography/federated setup.
- Employs PyTorch DistributedDataParallel (DDP) + Automatic Mixed Precision (AMP) for scalability.
- Benchmarks U-Net vs U-Net++ under single-GPU, multi-GPU, and DDP setups.
- Public implementation released for reproducibility.

RESULTS AND DISCUSSION

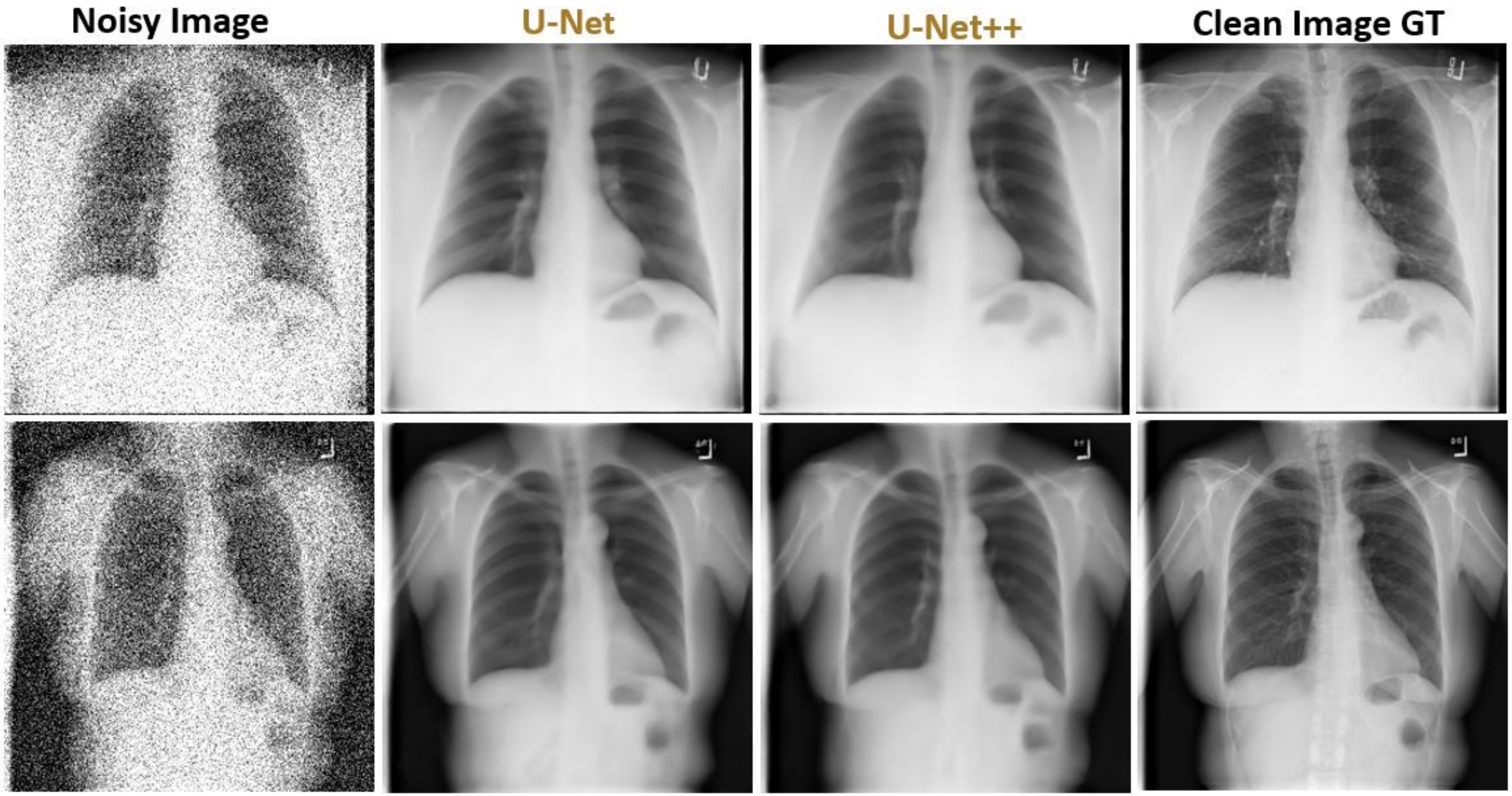
Quantitative

- ✓ U-Net++ > U-Net in PSNR/SSIM at 20–30% noise (better structure).
- ✓ U-Net > U-Net++ in LPIPS at 10% noise (better perceptual quality).

Training Speed

- ✓ DDP + AMP reduces training time by > 60 % vs single-GPU.

RESULTS AND DISCUSSION



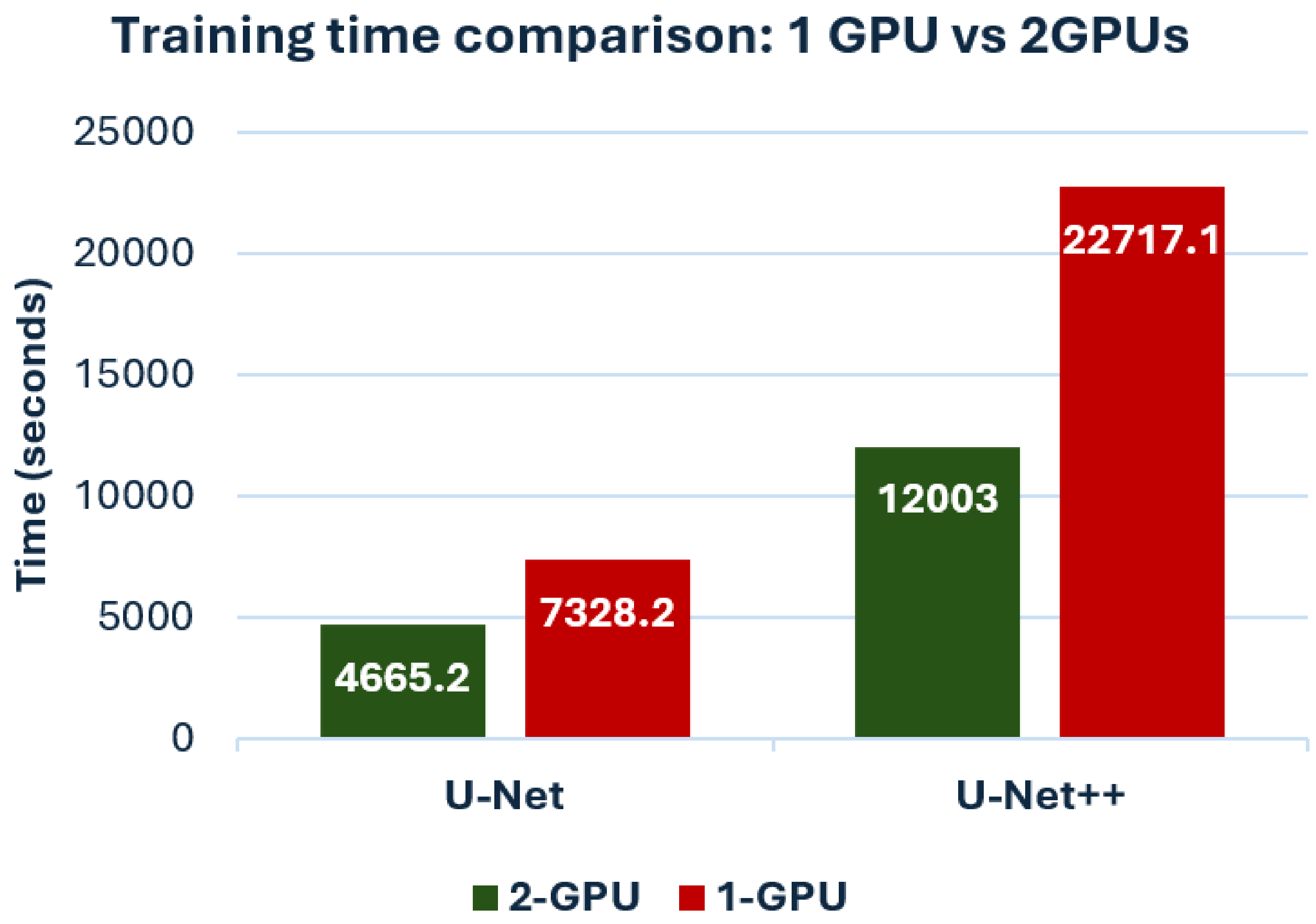
Representative qualitative comparison at 20% Gaussian noise.

RESULTS AND DISCUSSION

Noise	Model	Setup	PSNR (dB)	SSIM	LPIPS	TT (s)	TS (%)
10%	U-Net	1 GPU	34.95 ± 0.04	0.9168 ± 0.0008	0.1373 ± 0.0010	7328.2	0.00%
10%	U-Net	2 GPUs (DP)	34.034	0.9060	0.1582	4665.2	36.34%
10%	U-Net	2 GPUs (DDP+AMP)	**34.483**	**0.9067**	**0.1562**	**2737.0**	**62.68%**
10%	U-Net++	1 GPU	34.39 ± 0.05	0.9123 ± 0.0007	0.1585 ± 0.0011	22717.1	0.00%
10%	U-Net++	2 GPUs (DP)	34.089	0.9083	0.1564	12003.0	47.16%
10%	U-Net++	2 GPUs (DDP+AMP)	**33.416**	**0.8927**	**0.2175**	**8025.0**	**64.67%**
20%	U-Net	1 GPU	32.26 ± 0.04	0.8907 ± 0.0011	0.2010 ± 0.0013	7326.1	0.00%
20%	U-Net	2 GPUs (DP)	32.157	0.8906	0.2143	4648.1	36.55%
20%	U-Net++	1 GPU	32.32 ± 0.05	0.8959 ± 0.0010	0.2265 ± 0.0015	22266.0	0.00%
20%	U-Net++	2 GPUs (DP)	32.151	0.8886	0.2000	11998.5	46.11%
30%	U-Net	1 GPU	30.23 ± 0.05	0.8746 ± 0.0012	0.2498 ± 0.0016	7322.0	0.00%
30%	U-Net	2 GPUs (DP)	30.481	0.8757	0.2661	4648.2	36.52%
30%	U-Net++	1 GPU	30.76 ± 0.05	0.8840 ± 0.0011	0.2479 ± 0.0016	22343.5	0.00%
30%	U-Net++	2 GPUs (DP)	30.691	0.8830	0.2638	12015.6	46.22%

Performance (± 95% confidence interval (ci) for 1-gpu only), training time, and speedup across setups. TT = training time (s). TS = time saving (%) relative to the corresponding 1-gpu. DDP+AMP metrics/time are reported for 10% noise only.

RESULTS AND DISCUSSION
Training Time Comparison



RESULTS AND DISCUSSION
Comparison

DENOISING PERFORMANCE COMPARISON (PSNR/SSIM) ACROSS METHODS AND GAUSSIAN NOISE LEVELS.

Method	Noise Level	PSNR/SSIM	Noise Level	PSNR/SSIM
OURS (U-Net++)	20%	32.32/0.8959	30%	30.76/0.8840
OURS (U-Net)	20%	32.26/0.8907	30%	30.23/0.8746
BM3D [20]	15%	31.08/0.8722	25%	28.57/0.8017
TNDR [21]	15%	31.42/0.8826	25%	28.92/0.8157
DnCNN-3 [22]	15%	31.46/0.8826	25%	29.02/0.8190

❖Our models outperform traditional denoisers even at higher noise levels.

❖Demonstrates robustness and scalability of our models under distributed settings.

CONCLUSION

❖ Distributed Deep Learning enables efficient, privacy-aware medical image denoising.

❖ U-Net++ shows higher structural fidelity under heavy noise; U-Net performs better at low noise.

❖ DDP + AMP cuts training time by ≈ 60 % with minimal quality loss.

❖ The framework is scalable, secure, and clinically viable for real-world deployment.

Future Work

❖ Add attention and perceptual losses.
❖ Include radiologist-in-loop evaluation.
❖ Extend to federated learning for multi-site training.

THANK YOU

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