

# Performance Analysis for Projection-Correction Methods in Motion Deblurring Problems

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- The project analyzes the performance of two **Projection-Correction** algorithms for reconstructing medical images affected by **motion blur**.
- The studied algorithms are:
  - **Diffusion Posterior Sampling (DPS)**
  - **Regularization by Denoising with Diffusion (RED-Diff)**
- Both methods are based on **pre-trained diffusion models**.
- Objective: evaluate the effectiveness of these methods in recovering degraded images.

- **Objective:** Analyze the performance of *Projection-Correction* methods **DPS** and **RED-Diff** for motion blur removal on medical images
- **Phase 1:** Dataset preprocessing (128x128)
- **Phase 2:** Data augmentation to increase dataset diversity
- **Phase 3:** Training a DDIM diffusion model on medical data
- **Phase 4:** Simulation of motion blur and its removal
- **Phase 5:** Implementation and comparison of *Projection-Correction* methods: **DPS** and **RED-Diff**
- **Phase 6:** Quantitative evaluation of performance using metrics such as **PSNR** and **SSIM**

# Dataset

- We use the "Mayo Clinic CT Dataset" of low-dose CT scans, available via the link provided in this report.
- It contains a total of 6,400 2D slices in PNG format, extracted from 20 different patients.
- The images are organized into:
  - `raw_data/train/`: 5,120 slices for training (80% of the dataset)
  - `raw_data/test/`: 1,280 slices for testing (20% of the dataset)

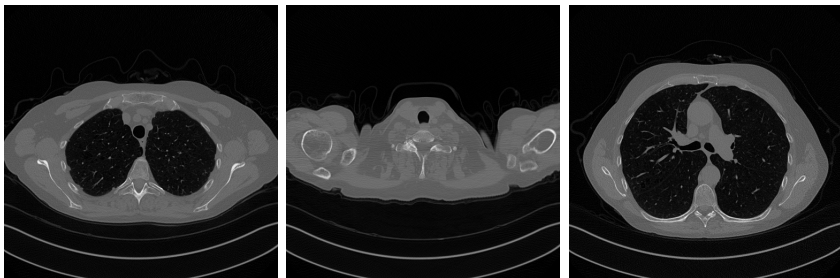


Figure: Examples of CT slices from the Mayo Clinic dataset

Before applying augmentations, each image is converted using:

- 1 **Grayscale**: single channel via `transforms.Grayscale(num_output_channels=1)`
- 2 **Resize**: to  $128 \times 128$  pixels using bicubic interpolation
- 3 **Normalization**: values scaled to  $[-1, 1]$  using mean 0.5 and std 0.5

```
base_transform = transforms.Compose([
    transforms.Grayscale(1),
    transforms.Resize((128,128), interpolation=Image.BICUBIC),
    transforms.ToTensor(),
    transforms.Normalize([0.5], [0.5]),
])
```

For each clean image, we apply the following transformations:

- **Fixed rotations:**  $\pm 5^\circ$  via `rotate_fixed()`
- **Horizontal flip:** `horizontal_flip()`
- **Gaussian noise:** mean 0, std 10 via `add_gaussian_noise()`
- **Salt-and-pepper noise:** probability 2% via `add_salt_pepper()`
- **Brightness adjustment:** factor 1.2 via `change_brightness()`
- **Contrast adjustment:** factor 1.3 via `change_contrast()`

- `raw_data/`: directory containing CT slice images (`train/`, `test/`)
- `checkpoints/`: saved model weights (`*.pth`)
- `scripts/`: main scripts for training and evaluation
- `utils.py`: module with utility functions (dataset, model, checkpoint I/O)
- `notebooks/`: exploratory and prototyping notebooks
- `result/`: output images, plots, and metrics
- `report/`: report materials (`media/`, `capitoli/`)

- **Model Type:** UNet2DModel from HuggingFace Diffusers library
- **Task:** Denoising diffusion probabilistic model for grayscale image generation
- **Input/Output:**
  - Input channels: 1
  - Output channels: 1
  - Sample size:  $128 \times 128$  pixels



- **Block Configuration:**

- Layers per block: 2
- Block output channels: (64, 128, 256)
- Dropout rate: 0.1

- **Downsampling Path:**

- DownBlock2D  $\rightarrow$  DownBlock2D  $\rightarrow$  AttnDownBlock2D
- Progressive feature extraction with attention in the deepest layer

- **Upsampling Path:**

- AttnUpBlock2D  $\rightarrow$  UpBlock2D  $\rightarrow$  UpBlock2D
- Symmetric architecture with attention mechanism

- **Training Scheduler:** DDPM Scheduler
  - Number of timesteps: 1000
  - Used for forward diffusion process during training
  - Adds noise progressively over 1000 steps
- **Inference Scheduler:** DDIM Scheduler
  - Number of timesteps: 1000
  - Deterministic sampling process
  - Used for image generation and inverse problems
  - Shares beta schedule with DDPM scheduler

- **Optimizer:** Adam
  - Learning rate:  $1 \times 10^{-4}$
  - Weight decay:  $1 \times 10^{-5}$
- **Loss Function:** Mean Squared Error *MSE*
  - Compares predicted noise with actual noise
  - Standard objective for diffusion models
- **Performance Optimizations:**
  - Model compilation with `torch.compile`
  - Mixed precision training with GradScaler
  - Cosine annealing learning rate scheduler

- **Total Parameters:** 15.722.625
- **Key Features:**
  - Attention mechanisms in deepest layers for better feature learning
  - Symmetric U-Net design for optimal information flow
  - Dropout regularization to prevent overfitting
  - Grayscale-optimized with single channel processing

- **Objective:** Train a denoising diffusion model (DDIM U-Net) on grayscale images
- **Main Components:**
  - 1 Data Augmentation
  - 2 DataLoader
  - 3 Model Compilation
  - 4 Training loop with mixed-precision

- **Base Dataset:** Dataset Mayo
  - Grayscale  $\rightarrow$  1 channel
  - Resize images to  $128 \times 128$
- **Augmentations** (8 types):
  - *None*: no transformation
  - Rotation  $\pm 5^\circ$  (rotation + centering)
  - Flip horizontal
  - Gaussian noise (mean=0, std=10)
  - Salt and pepper noise (prob=2%)
  - Brightness (factor=1.2)
  - Contrast (factor=1.3)

- **DDPMScheduler** for training diffusion process
  - Timesteps 1000
- **DDIMScheduler** for sampling
  - Timesteps 1000

- **Why:** optimize the model for better performance
- **Usage:**  

```
model = torch.compile(model)
```
- **Benefits:** improved batch throughput



- **GradScaler and autocast:**
  - GradScaler for scaling gradients
  - autocast for automatic mixed precision
- Reduce memory usage and speed up training

- ❶ Loss function: MSE
- ❷ Start the training `model.train()`
- ❸ For each epoch:
  - Move images to GPU (if available)
  - Generate noise and timesteps
  - Compute noise prediction on the input data
  - Prediction + MSE loss
  - Optimization + `scheduler.step()`
- ❹ Save validation samples to visualize the model performance during training
- ❺ Compute and log average losses
- ❻ Save model weights each epoch

- **Validation:**

- `model.eval()` to set the model to evaluation mode
- MSE loss on validation set

- **Checkpoint:**

- Save the model weights to a `.pth` file
- Update loss, PSNR and SSIM history in `history.txt`
- Monitor train vs validation loss over epochs aswell as PSNR and SSIM between the generated and original images
  - For each epoch sample 10 images from the validation set and compute the metrics

- **Metrics:**

- PSNR: Peak Signal-to-Noise Ratio
- SSIM: Structural Similarity Index

- **Sample Generation:**

- Pure noise sampling using DDIM scheduler
- Validation reconstruction:
  - Add noise to clean validation images
  - Model predicts and removes the noise

- **Quality Assessment:**

- PSNR range: 20-40 dB (higher = better reconstruction)
- SSIM range: 0-1 (closer to 1 = better similarity)
- Average metrics computed over 5-10 validation samples

- **Pure Noise Sampling:**

- Tests model's ability to generate realistic images
- Uses DDIM scheduler for iterative denoising
- Saves generated images as `generated_epoch_{epoch}.png`

- **Validation Reconstruction:**

- Adds noise to clean validation images
- Model predicts and removes the noise
- Direct assessment of denoising performance

- **History Tracking:**

- All metrics saved to `history.txt`
- Enables trend analysis and model comparison

- **Loss Monitoring:**
  - Training vs Validation Loss curves over epochs
  - MSE loss
- **Quality Metrics Visualization:**
  - PSNR trends with average values
  - SSIM trends with average values
  - Both metrics computed on validation reconstructions
  - Useful to track model performance

- **Comprehensive Monitoring:**

- Three-panel subplot: Loss, PSNR, SSIM (as shown in the Figure 2)
- Data read from `history.txt` file
- Enables performance trend analysis

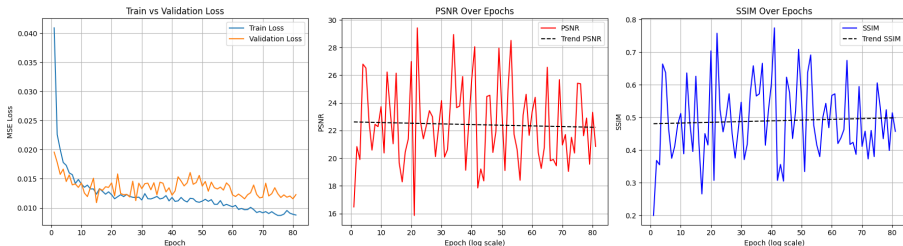


Figure: Training Loss, PSNR, and SSIM trends over epochs

- **Checkpoint Structure:**

- Model state dictionary
- Optimizer state dictionary
- Current epoch number for resuming training
- Naming: `ddim_unet_epoch81.pth`
- `load_checkpoint()` utility function



- **DPS** is a method for solving inverse problems using pre-trained diffusion models
- Key idea: combine data fidelity with diffusion model prior during reverse sampling
- Modifies the standard DDIM reverse process to incorporate measurement consistency

## Algorithm Overview:

- 1 Start with noisy initialization  $x_T \sim \mathcal{N}(0, I)$
- 2 For each timestep  $t$ : predict  $x_0$  using UNet
- 3 Apply posterior correction:  $x_0^{post} = x_0^{pred} + \gamma_t \cdot K^T (y - Kx_0^{pred})$
- 4 Continue DDIM step with corrected  $x_0^{post}$

## Posterior Correction Weight:

$$\gamma_t = \frac{\sigma_{prior}^2}{\sigma_y^2 + \sigma_{prior}^2}$$

where  $\sigma_{prior}^2 = 1 - \alpha_t$  and  $\sigma_y$  is measurement noise

## Algorithm Steps:

- 1 Initialize  $x_t$  with random noise
- 2 Predict noise  $\epsilon_\theta(x_t, t)$  using UNet
- 3 Compute  $x_0^{pred} = \frac{x_t - \sqrt{1 - \alpha_t} \epsilon_\theta}{\sqrt{\alpha_t}}$
- 4 Apply DPS correction with gradient step
- 5 Update to next timestep using DDIM

- **RED-Diff** is an optimization-based method for solving inverse problems using diffusion models
- Key idea: combine data fidelity loss with regularization from denoising diffusion priors
- Uses gradient-based optimization to reconstruct images by minimizing combined objective

## Algorithm Overview:

- 1 Initialize reconstruction  $\mu$  from adjoint operation:  $\mu = K^T(y)$
- 2 For each timestep  $t$ : sample noise and create noisy version  $x_t$
- 3 Compute data fidelity loss:  $\mathcal{L}_{obs} = \frac{1}{2\sigma_y^2} \|K(\mu) - y\|^2$
- 4 Compute regularization loss using diffusion model guidance
- 5 Update  $\mu$  using gradient descent on combined loss

## Combined Objective:

$$\mathcal{L} = \mathcal{L}_{obs} + \lambda \cdot w_t \cdot \mathcal{L}_{reg}$$

where  $w_t$  is a time-dependent weighting strategy

## Algorithm Steps:

- 1 Initialize  $\mu \leftarrow K^T(y)$  with gradient enabled
- 2 Sample noise  $\epsilon \sim \mathcal{N}(0, I)$  and create  $x_t = \sqrt{\alpha_t}\mu + \sqrt{1 - \alpha_t}\epsilon$
- 3 Predict noise  $\epsilon_\theta(x_t, t)$  using UNet
- 4 Compute regularization loss:  $\mathcal{L}_{reg} = w_t \cdot \|\epsilon_\theta - \epsilon\|^2$
- 5 Update  $\mu$  using Adam optimizer on total loss
- 6 Repeat for all timesteps in reverse order

**Weighting Strategies:** linear, sqrt, square, log, clip, const







# Conclusions

Thank you for your attention