Experimental Plan and Literature Review: Impact of Network Architecture on Noise2Inverse

Maryia Zhyrko (s4093771), Po-Kai, Chen (s4283341) Date: May 4, 2025

1 Research Question

Does the choice of CNN architecture—U-Net vs. DnCNN—significantly affect denoising quality in the Noise2Inverse self-supervised CT framework, under fixed noise and geometry settings? Subquestion: Are there differences in convergence speed?

2 Experimental Plan

We simulate a 3D human-like phantom composed of geometric primitives (spheres, ellipsoids, cuboids) representing head, torso, limbs, and embedded internal structures. The phantom is randomly generated with anatomically plausible proportions and fine-scale internal variation to test denoising and feature preservation. Using scikit-image, we simulate 360-view projections with moderate Gaussian or Poisson noise, followed by Filtered Backprojection (FBP) reconstruction.

In PyTorch, we implement the Noise2Inverse training pipeline. We compare U-Net and DnCNN architectures, keeping all other parameters fixed (loss, learning rate, epochs, etc.). Evaluation includes PSNR, SSIM, and visual inspection of denoised outputs and residuals.

3 Related Work

- Zhang et al. (2017)[3]: Introduced DnCNN with residual learning and batch norm; performs well across noise levels using a single model.
- Ronneberger et al. (2015)[2]: Proposed U-Net with encoder-decoder and skip connections; effective in preserving fine details in biomedical images.
- Geng et al. (2021)[1]: Compared U-Net and DnCNN in medical GAN denoising; both performed competitively, with differing strengths depending on modality and noise type.

References

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