Report on Combining Denoising Diffusion Probabilistic Models (DDPM) and Deep Image Priors (DIP)

GitHub link: https://github.com/jli40858/GAI_Project_4

Introduction

This report details the experimental findings on the effectiveness of integrating Denoising Diffusion Probabilistic Models (DDPM) with Deep Image Priors (DIP). The goal is to enhance image reconstruction quality and speed by leveraging the unique strengths of both models.

Theoretical Background

The combination of DDPM and DIP aims to use the quick high-level feature capture ability of DIP to provide an advanced initial state for DDPM. This could potentially accelerate the convergence and efficiency of the DDPM process, which typically requires gradual denoising of an image and is computationally intensive.

Experimental Setup

Model Description

- **Architecture**: Simple U-Net-like model with two convolutional layers in the encoder and corresponding deconvolutional layers in the decoder.
- **Framework**: Implemented using PyTorch.
- **Optimizer**: Adam.
- **Loss**: Mean Squared Error (MSE).

Training Procedure

Three sets of experiments were conducted:

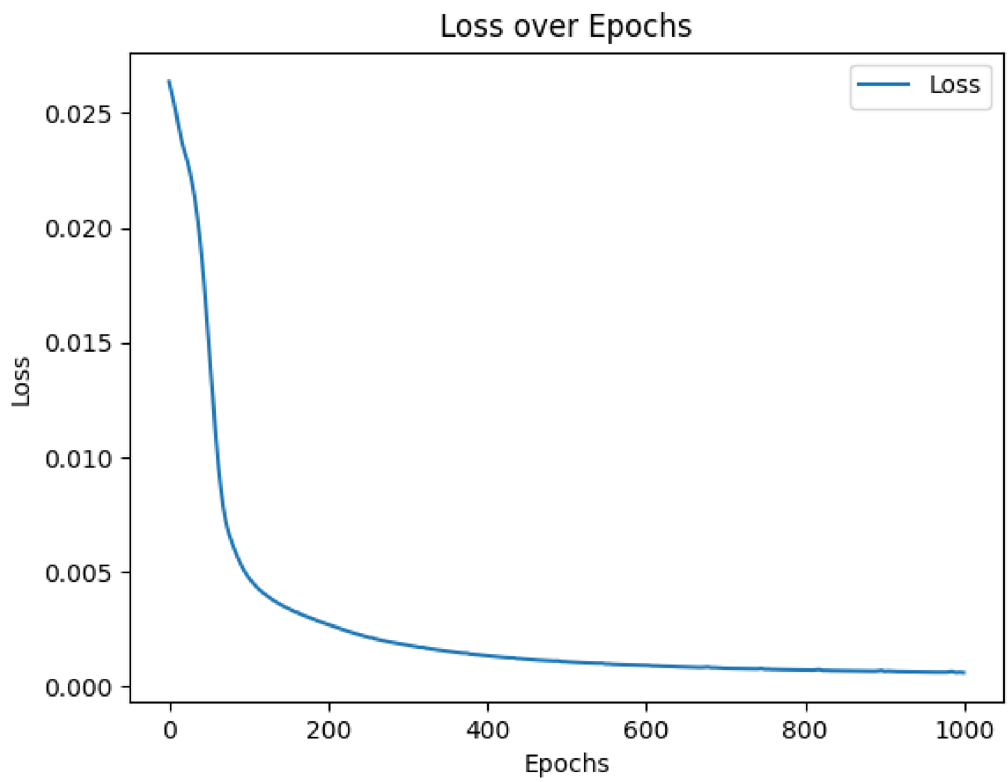
1. **DDPM Only**: Traditional DDPM training with progressively increasing noise.
2. **DIP Only**: DIP used to fit directly to the noisy image version, without training on a dataset.
3. **Combined DDPM and DIP**: Starts with a DIP phase for initial prior, followed by DDPM training.

Each model underwent training for 1000 epochs, with evaluations every 50 epochs using PSNR as the metric.

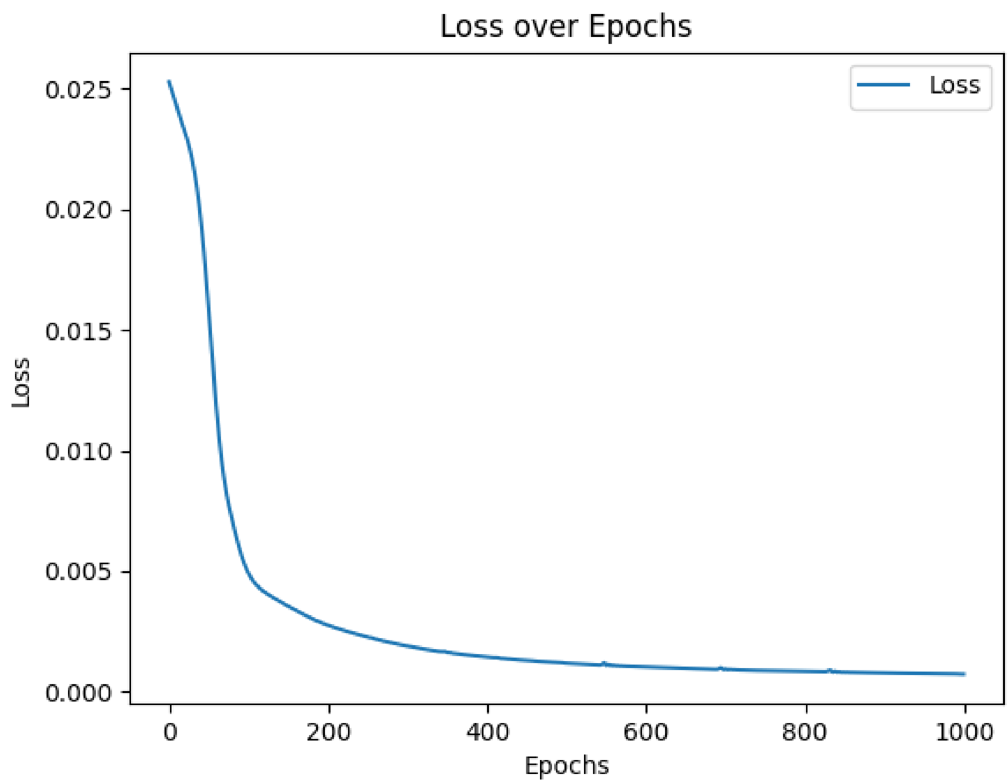
Results and Analysis

Quantitative Results

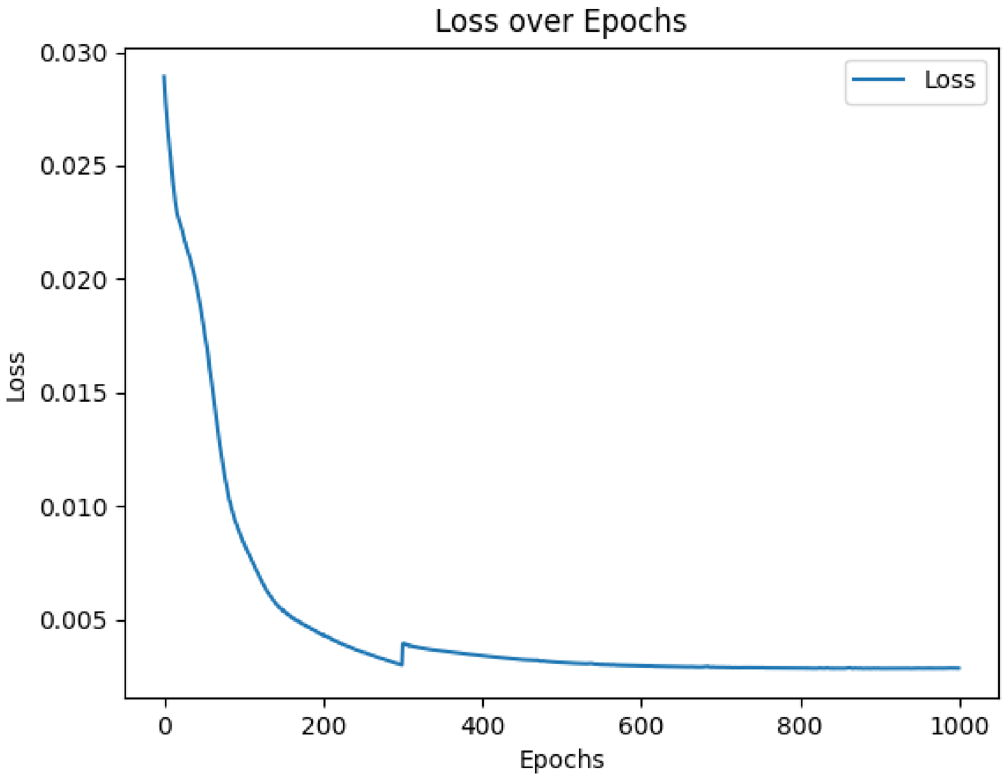
- **DDPM Only**: PSNR started at 16.17 and improved to 29.75 by the end of 1000 epochs.



- **DIP Only**: Began at a lower PSNR of 15.56, indicating early robust feature capture, and improved significantly over time.



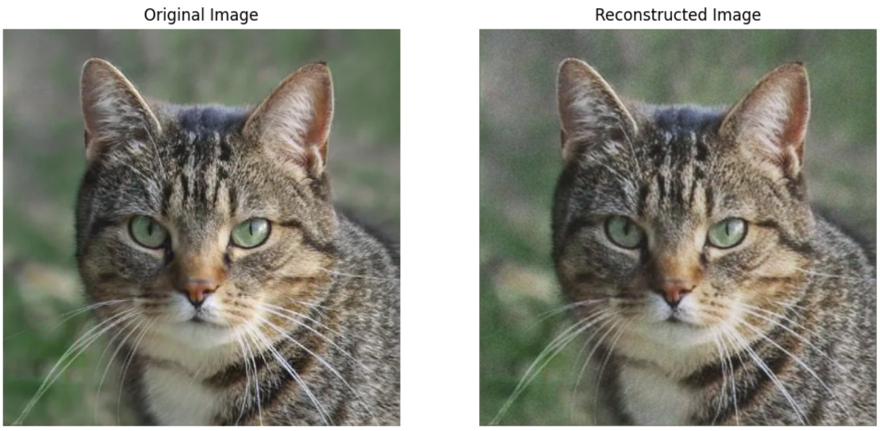
- **Combined Model**: Utilized early DIP advantages for a better starting point in DDPM, showing faster early PSNR improvements and stabilizing at high values sooner than other methods.



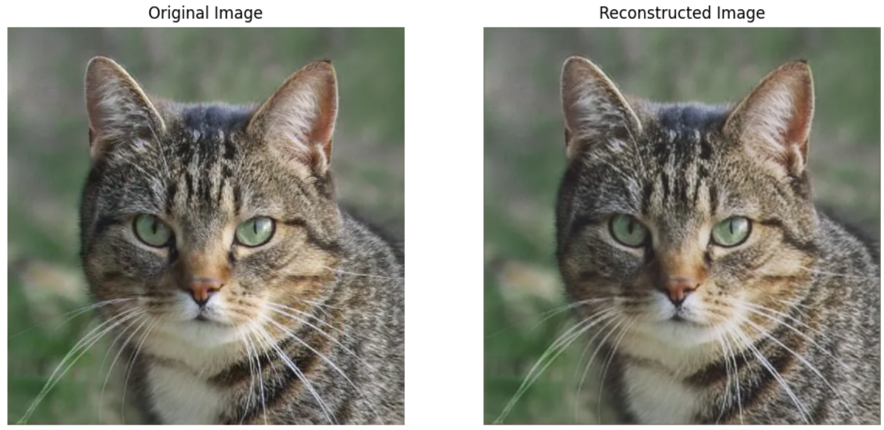
Visual Results

Comparative analysis of reconstructed images:

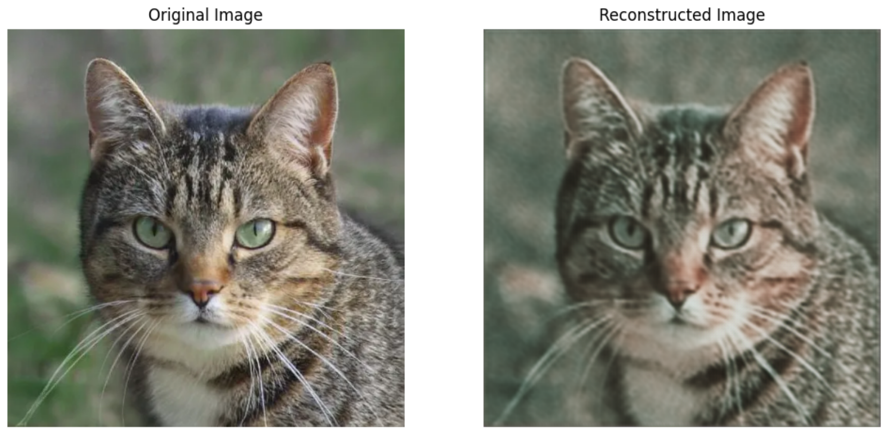
- **DDPM Only** reconstructed major features early but lacked detail.



- **DIP Only** gradually developed finer details, achieving high fidelity by the later stages.



- **Combined Approach** demonstrated quicker convergence towards high-quality reconstructions, observable as early as mid-training.



Conclusion

The experiments confirmed that integrating DIP with DDPM can enhance the diffusion process, making it both faster and potentially more effective for high-quality image reconstruction. This synergy utilizes DIP's capability for rapid feature approximation and DDPM's strength in detail refinement, presenting a promising avenue for efficient image synthesis and restoration.