Reconstructing 3D Porosity Distributions Using Generative Adversarial Networks (GANs)

1. Introduction

Reconstructing 3D porosity distributions from limited data is a challenge in various fields. Traditional methods typically rely on domain-specific knowledge and statistical modeling. Recently, machine learning (ML) approaches have been explored for solving such inverse problems.

Generative models, including Generative Adversarial Networks (GANs), have emerged as an interesting alternative in this domain.They can be useful for reconstructing microstructures with high-dimensional spatial dependencies, making them a possible choice for reconstructing 3D porosity grids from limited input data. This work explores the application of GANs for the task of reconstructing 3D porous media and presents a methodology that combines these.

2. Background

Recently, the application of deep learning techniques, particularly generative models such as GANs, has shown promise in reconstructing complex structures. GANs are designed to generate realistic data by learning the distribution of real data through an adversarial training process, where a generator network creates fake data, and a discriminator network distinguishes between real and generated data. GANs have been used to reconstruct porous structures in materials science and geophysics, showing impressive results in capturing realistic pore structures from training data.

Given that, deep learning models can account for the stochastic nature of pore structures and can quickly generate multiple realizations once trained. Therefore, we investigated the use of GANs for reconstructing 3D porosity distribution..

3. Methodology

The curse of dimensionality and the stochastic nature of the porosity reconstruction problem make it difficult for conventional machine learning methods to capture the complex dependencies between voxels. GANs, due to their ability to learn complex distributions, offer an effective solution to this problem. Unlike traditional models, GANs generate new data points by learning the underlying data distribution through the adversarial process.

For this study, we propose using a conditional GAN (cGAN), which extends the standard GAN framework by conditioning the generator on the density factor. This allows the model to generate porosity grids that respect the specified global porosity while capturing the inherent stochasticity and spatial dependencies of pore structures.

In the GAN framework:

- Generator: The generator network takes the density factor as an input, alongside a random latent vector sampled from a prior distribution, and generates a 3D binary grid representing the porosity structure. The generator is tasked with producing realistic pore distributions that conform to the input density factor.
- Discriminato*: The discriminator network evaluates the authenticity of the generated grid, distinguishing between real and fake porosity grids. It is also conditioned on the density factor, ensuring that the discriminator enforces both the structural realism and the density constraint in the generated grids.

The goal of the GAN is to optimize both networks in an adversarial fashion, such that the generator learns to produce realistic 3D porosity grids that are indistinguishable from real data according to the discriminator.

3.3 Architecture

The architecture of the GAN consists of 3D Convolutional Neural Networks (CNNs) for both the generator and the discriminator.

Both the generator and discriminator use several layers of 3D convolution, with batch normalization applied between layers to stabilize training. ReLU activation functions are used throughout the networks to introduce non-linearity, and the output of the generator is passed through a sigmoid activation function to ensure the generated values are within the valid range [0, 1].

The generator network takes as input both the density factor and a latent vector and outputs a 3D grid, while the discriminator network takes a 3D grid and the density factor as input and outputs a probability score representing the likelihood that the grid is real or fake.

3.4 Loss Function

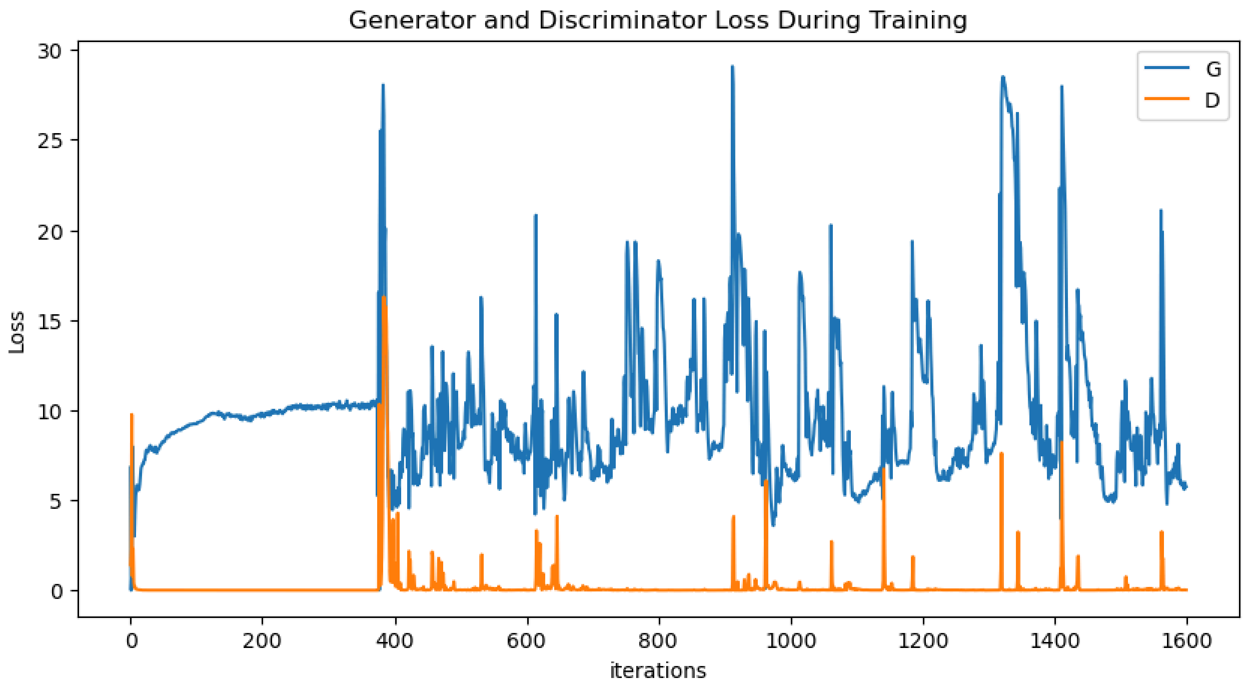
The traditional adversarial loss, which measures the discrepancy between real and generated data, is employed as the primary loss.

3.5 Reconstruction

Once the GAN is trained, porosity grids can be generated by sampling a latent vector and providing a desired density factor. The generator produces a new grid.

4. Results

Evaluation is conducted using qualitative metrics and some quantitative metrics like minkowski functionals.


Generator and Discriminator Loss During Training
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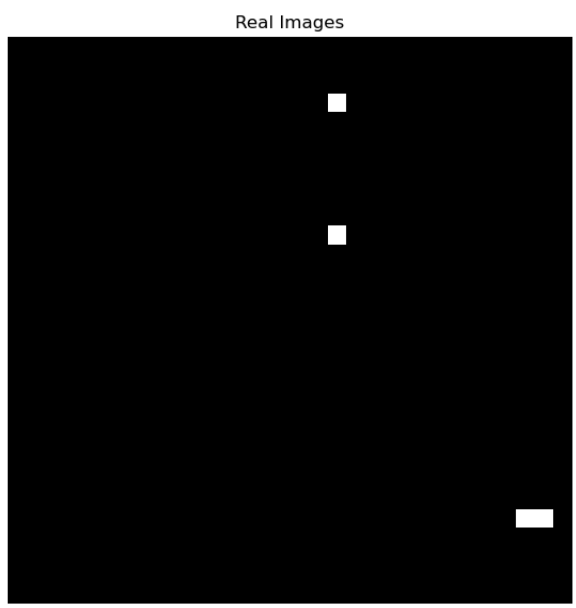
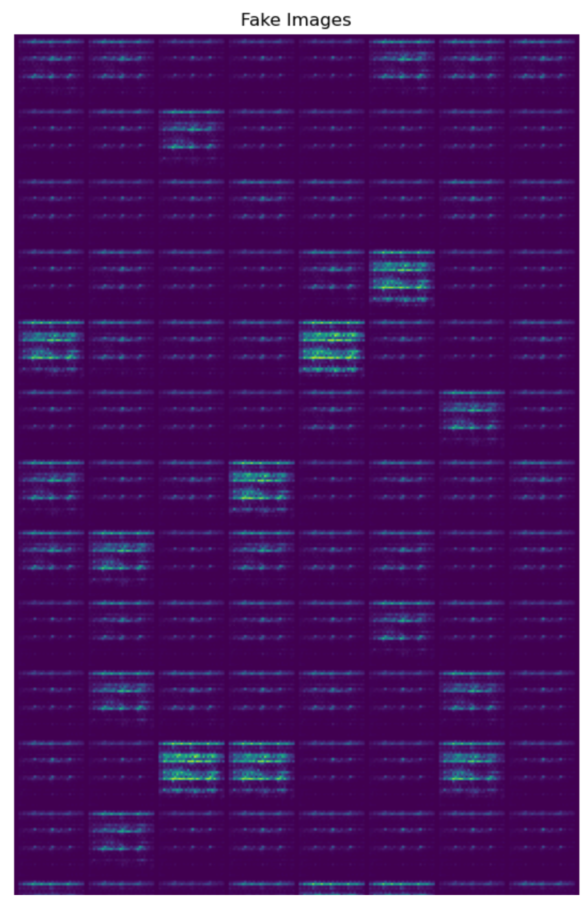
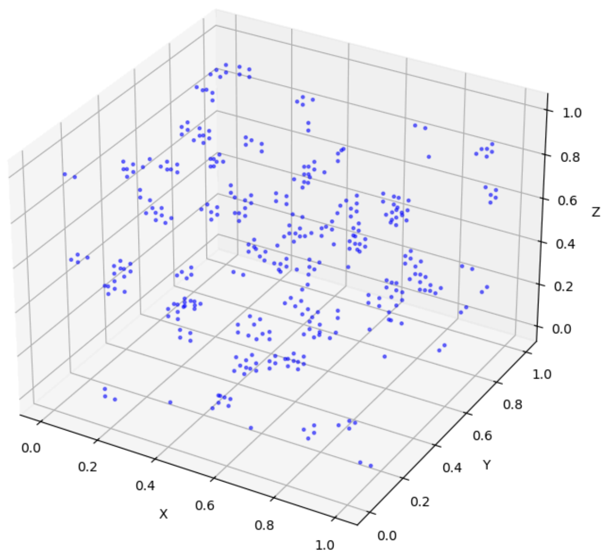

Real Images


Fake Images

Density Factor: 0.41499999165534973

Simulation: 10



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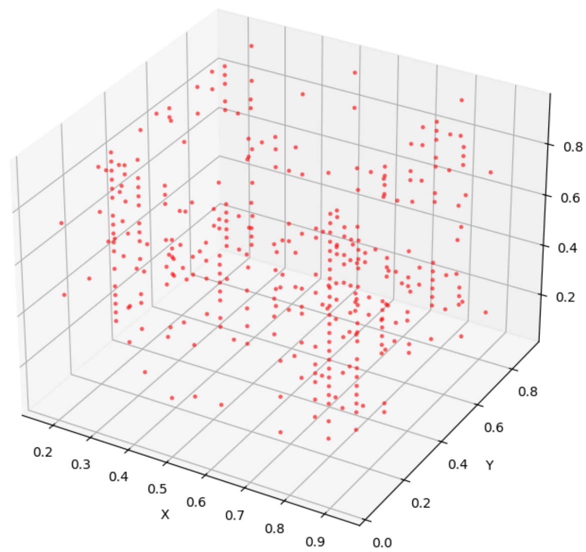
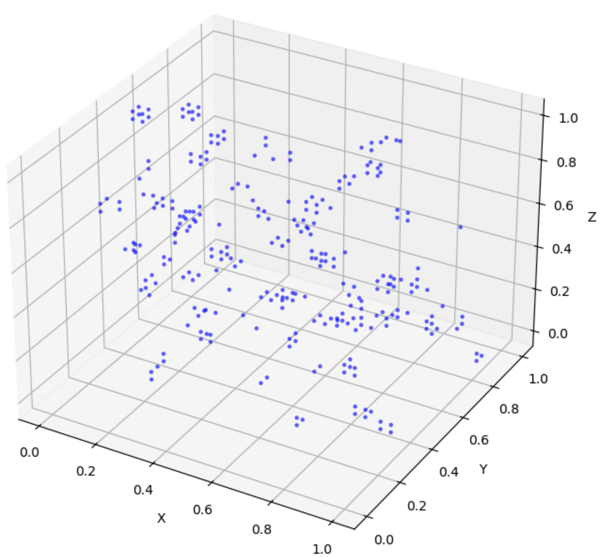
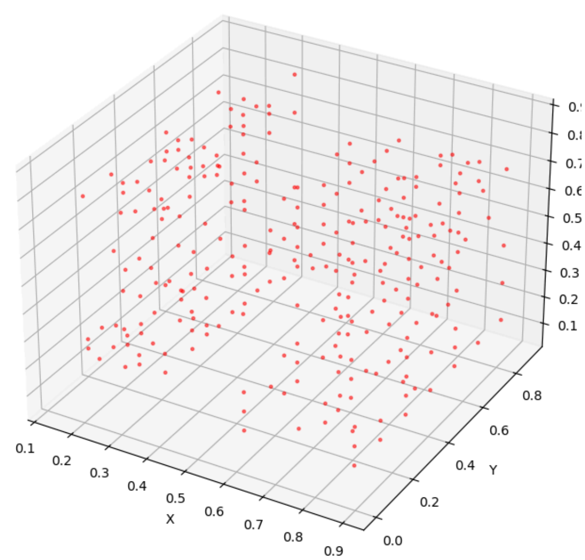


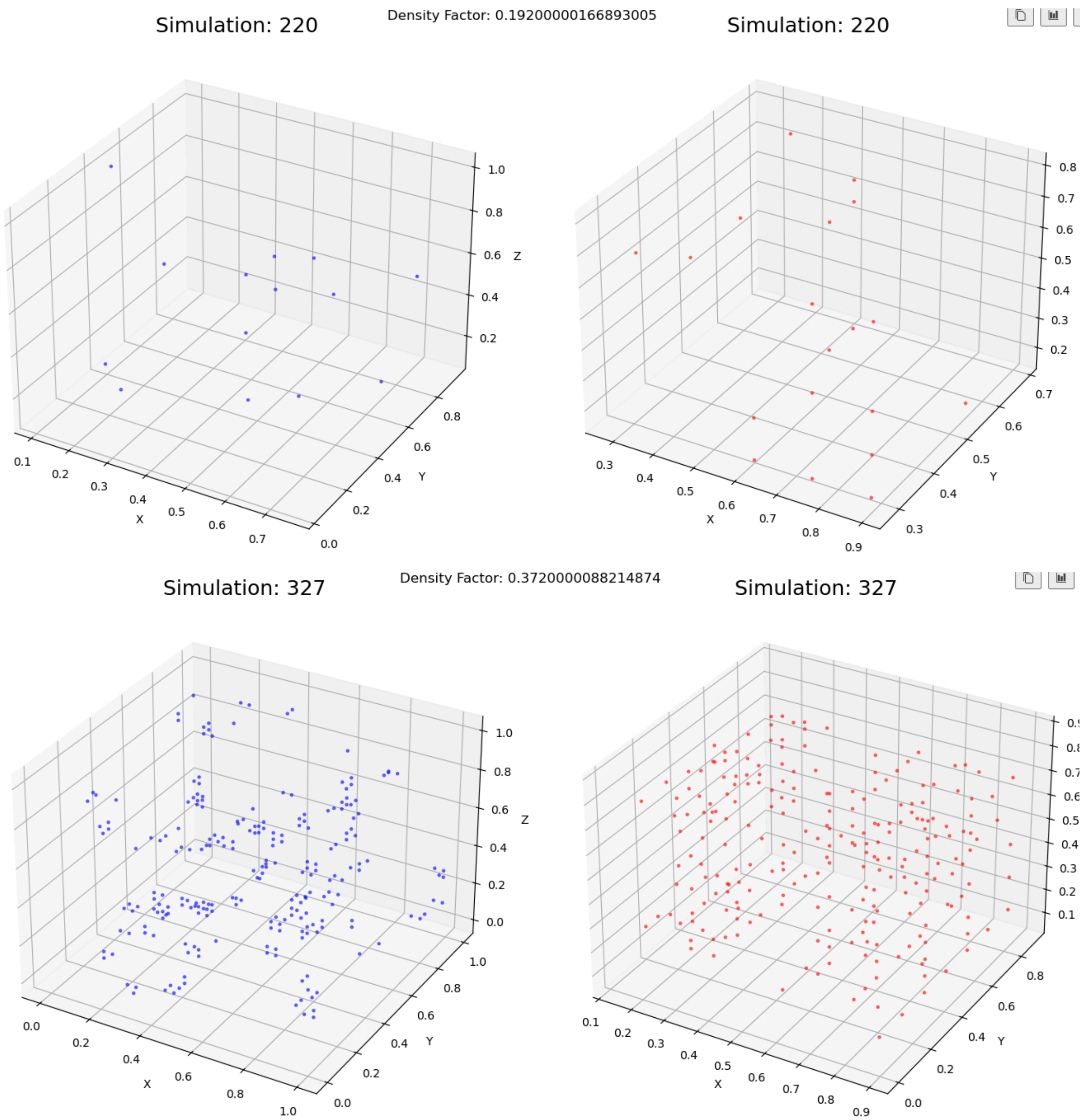
Density Factor: 0.3869999945163727

Simulation: 110



Simulation: 110





5. Conclusion

This approach shows how GANs can be used for reconstructing 3D porosity distributions conditioned on density factors. While the results are promising, further work is needed to explore additional and more established approaches. GANs offer an interesting framework for generating porosity grids, and would be interesting to understand the intrinsic complexities adhered to the original nature of the problem.