Quantifying complex microstructures of earth materials: Reconstructing higher-order spatial correlations using deep generative adversarial networks (GAN)

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1. Background

- Many geological phenomena result from physiochemical processes occurring at different scales, from nanometres to micrometres. Hence, it is crucial to understand and determine how rock properties at small scales, i.e., **microstructures**, control the macroscopic properties. One promising way to visualize and characterise these microstructures is digital rock physics (DRP) which is all about imaging and computing!

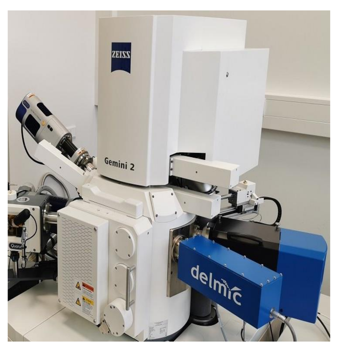
Problem statement

- Despite rapid advances in imaging techniques in the past decades, their inherent limitation is the trade-off between resolution and sample size which simply means that in order to characterise small features in the rocks (high resolution), we have to zoom into the sample, i.e., smaller field of view (FoV). But, this FoV needs to be sufficiently large to be representative of the whole system.

Granite sample with a multiscale pore network

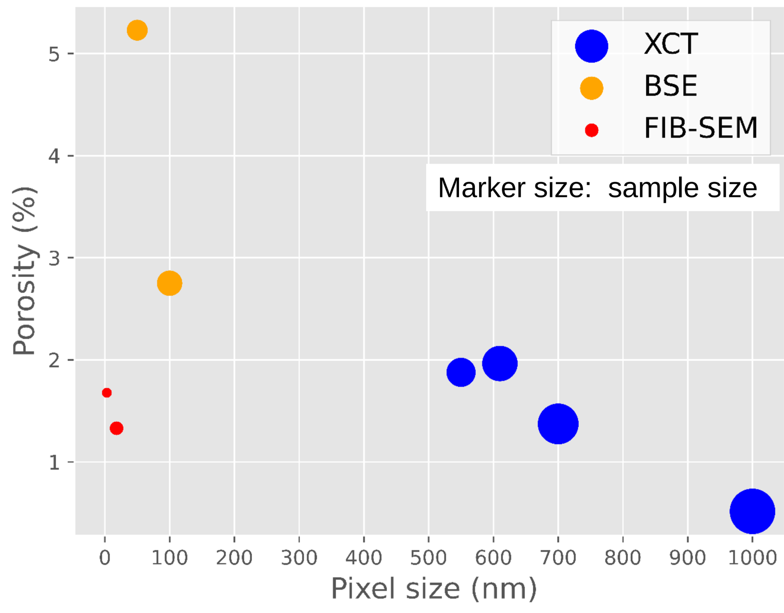
XCT (3D)

BSE (2D)



FIB-SEM (3D)

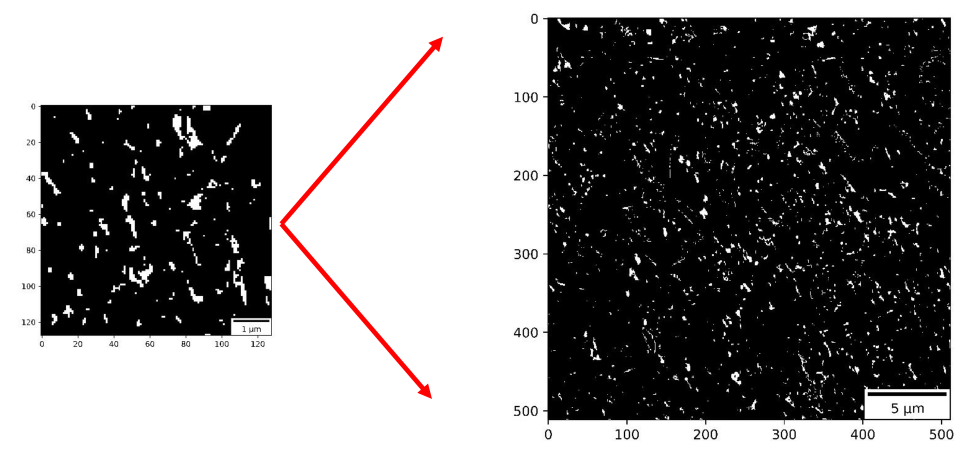
- The figure shows that:
- In X-**ray computed tomography (XCT):**
  - The sample is large. But the resolution is insufficient to capture the tiny pores, so the porosity is low.
- In **focused ion beam (FIB-SEM):**
  - The resolution is high, but FoV is too small to be representative.
- In **backscattered electron microscopy (BSE):**
  - The resolution is high, and It covers a large area. But it is 2D, and its applications are limited.



Our approach

- In this work, we make use of high-resolution 2D BSE images of rock surfaces at two orthogonal dimensions to infer 3D structural properties of the rock, which is known as *image reconstruction.*
- **Image reconstruction** is the process of generating statistically equivalent microstructures but with larger sizes and/or additional dimensions.
- To ensure that reconstructed microstructures share the same structural and topological properties as the original ones, we employ spatial correlations known as ***statistical microstructural descriptors*** (SMDs).

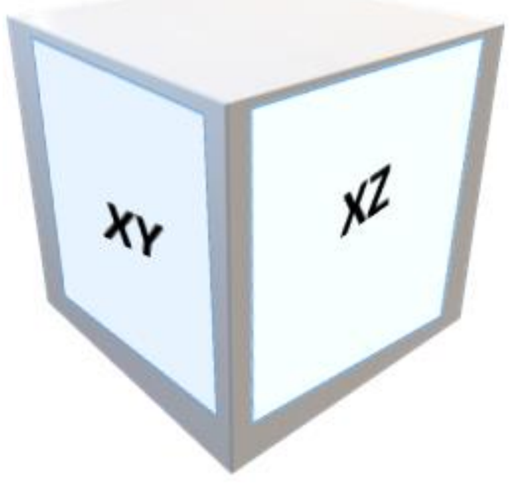
Upsampling and upscaling



- ✓ High-resolution
- ✖ Small field of view

- ✓ High-resolution
- ✓ Representative size

2D to 3D reconstruction

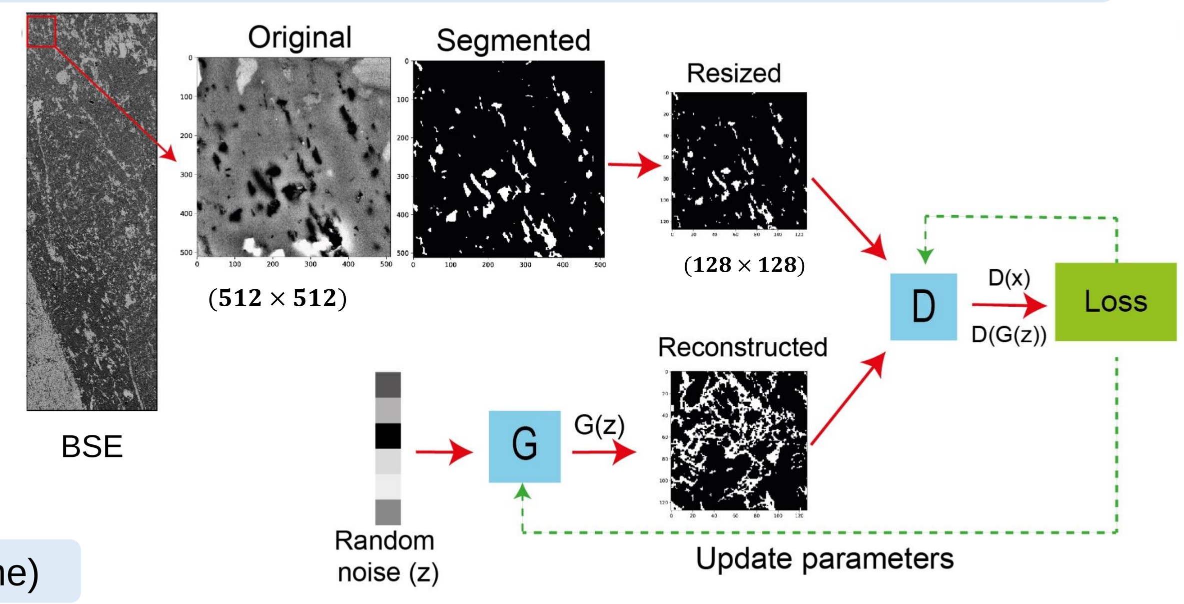


2. Methodology

1. Generative adversarial network (GAN)

- GAN is a deep learning-based generative model based on game theory which can learn complex high-dimensional probability distributions from input data.

- In GANS, we have 2 convolutional neural networks (CNNs) competing against each other:
  - Generator → G
  - Discriminator → D



Non-cooperative game (Minimax game)

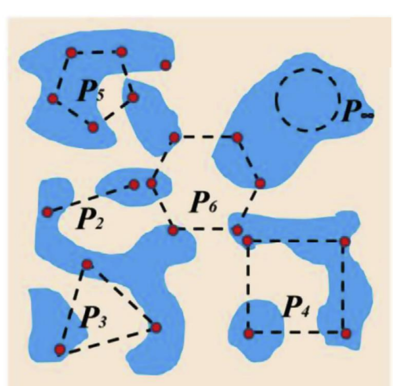
- Wasserstein loss with
- Gradient penalty (WGAN-GP):

Regularization term

(Gulrajani et al., 2017) $\min_G \max_D \; E(D(x) - E(D(g(z)) + \lambda E(\|\nabla(D(\hat{x})\|_2 - 1)^2$

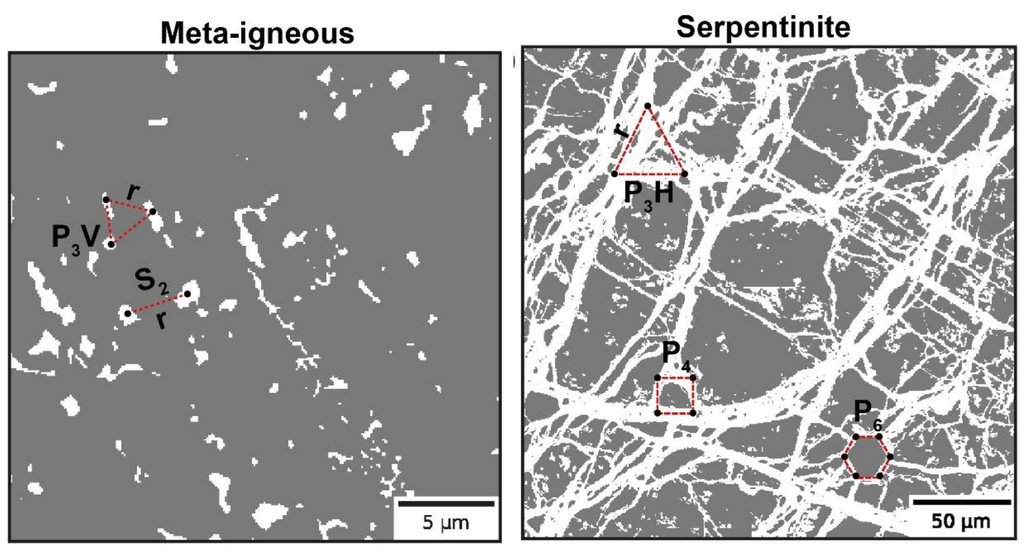
2. Statistical microstructure descriptors (SMDs)

- SMDs are spatial correlation functions showing different geometrical patterns in an image and can be used to quantify precisely the microstructures.



(Chen et al., 2019)

Probability of *n* random points of distance *r* to lie in the same phase of interest.

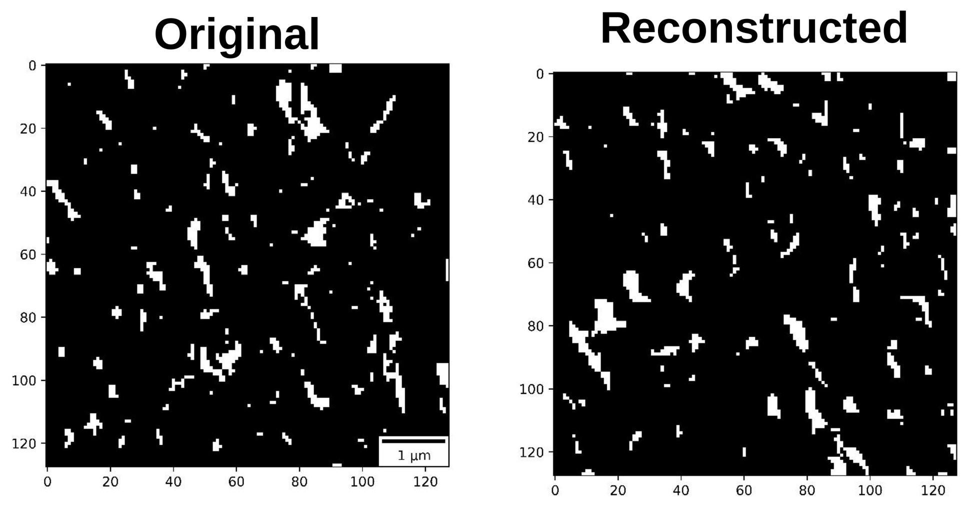


3. Results

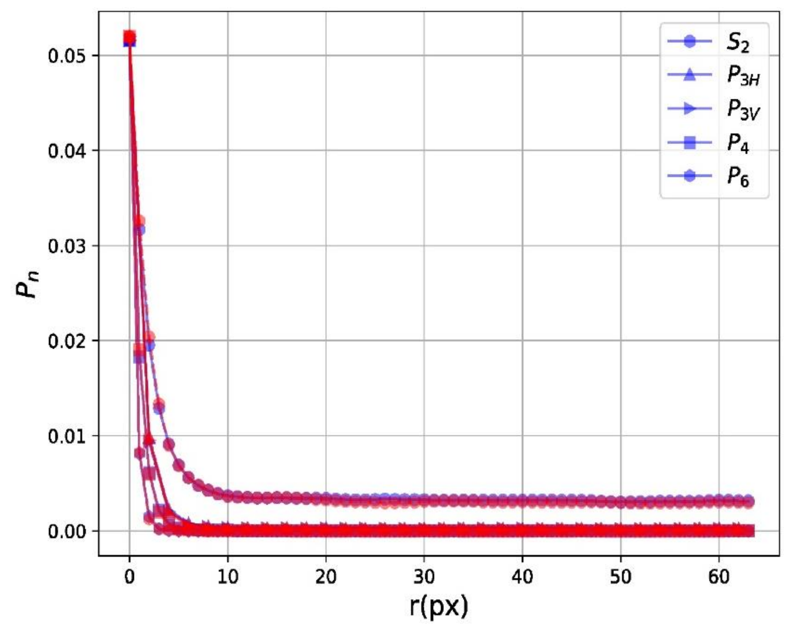
2D reconstruction

- **Meta-igneous Pore network**

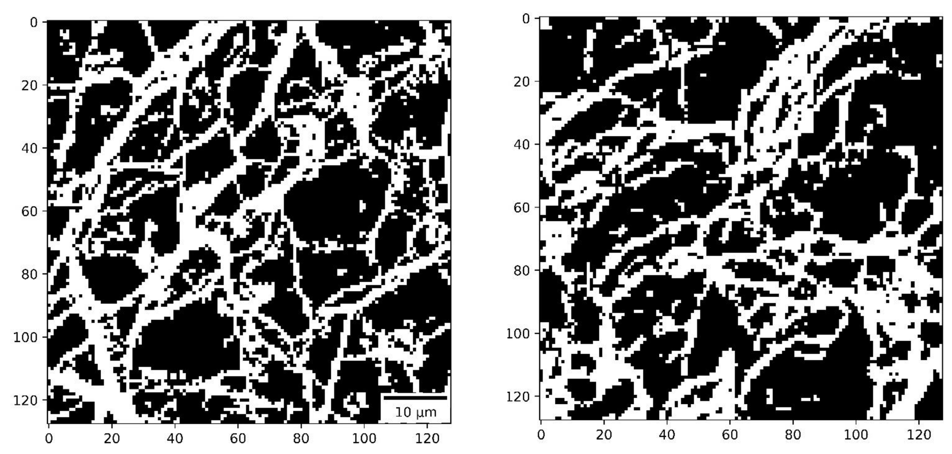
Original **Reconstructed**

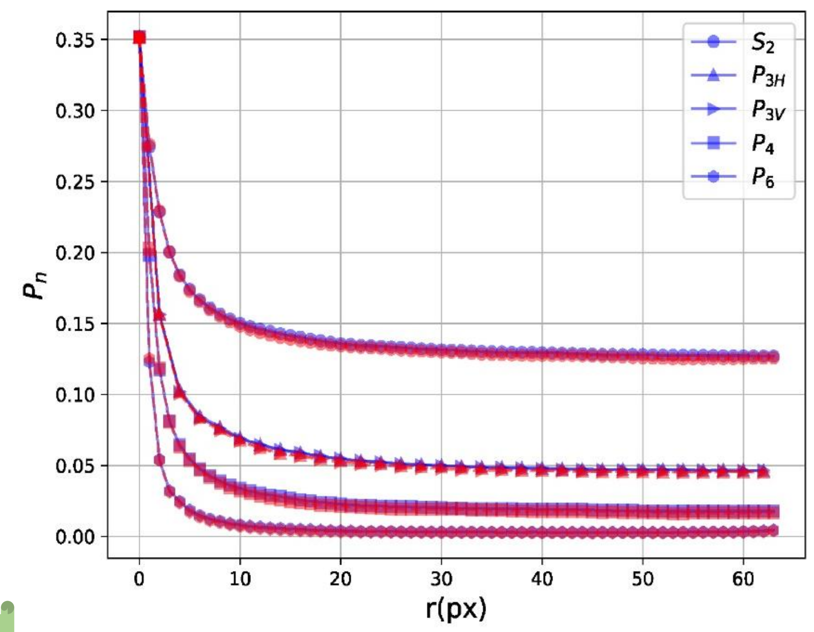


Correlation functions

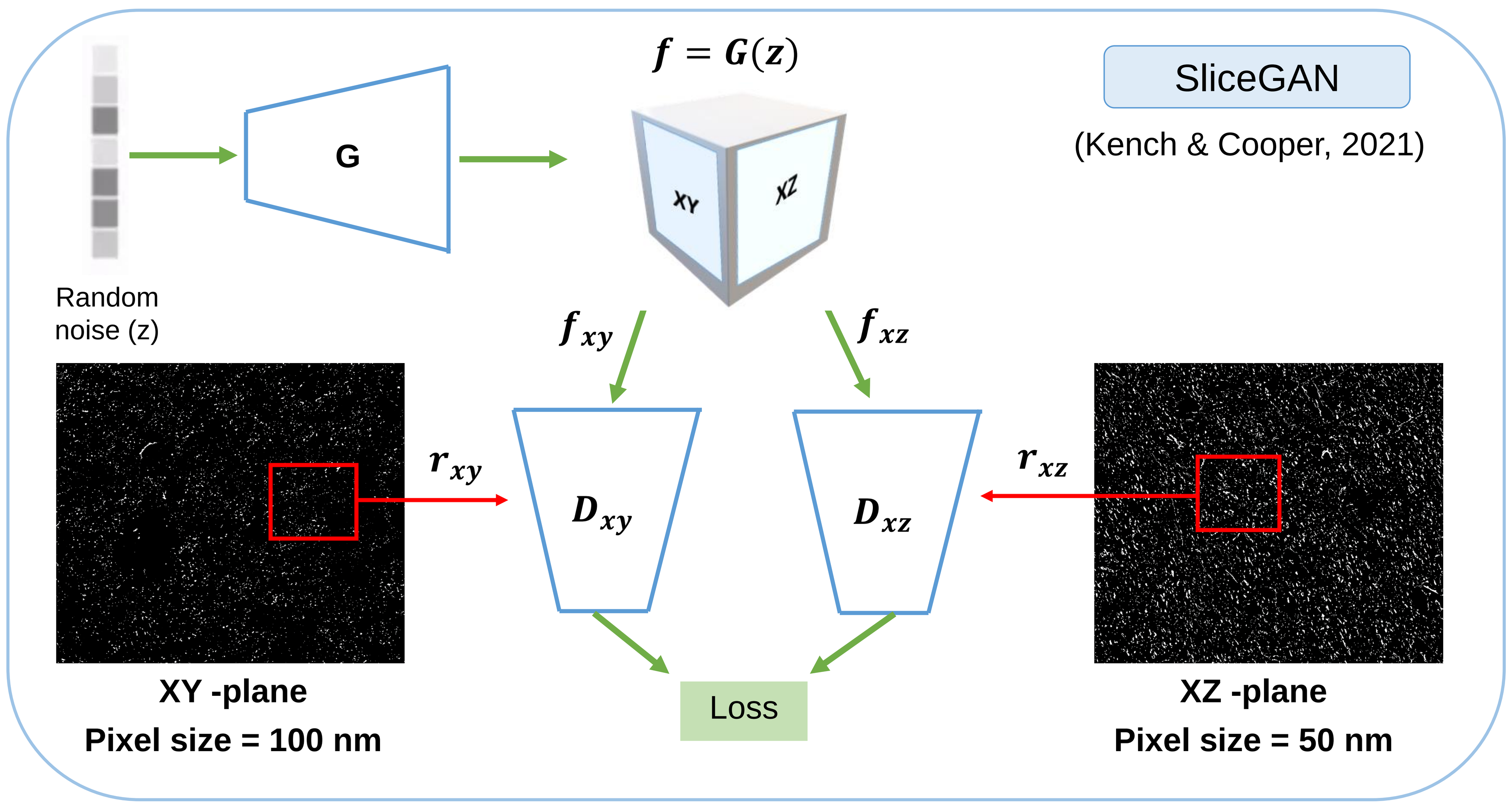


- **Serpentinite fracture network**





2D to 3D reconstruction



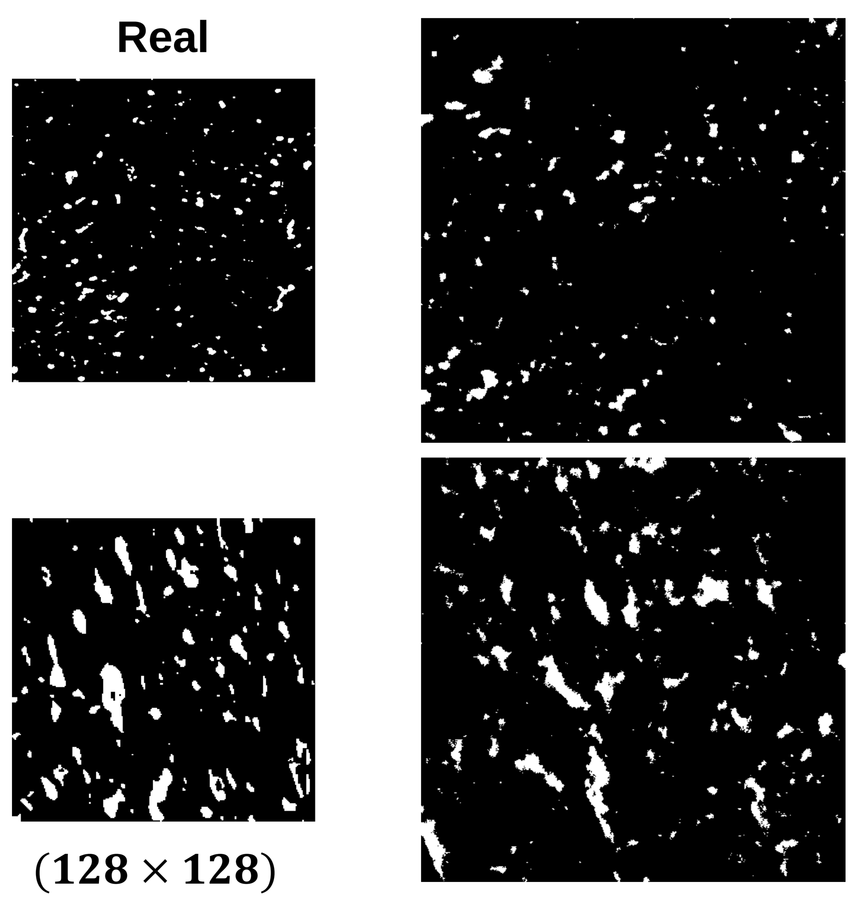
SliceGAN

(Kench & Cooper, 2021)

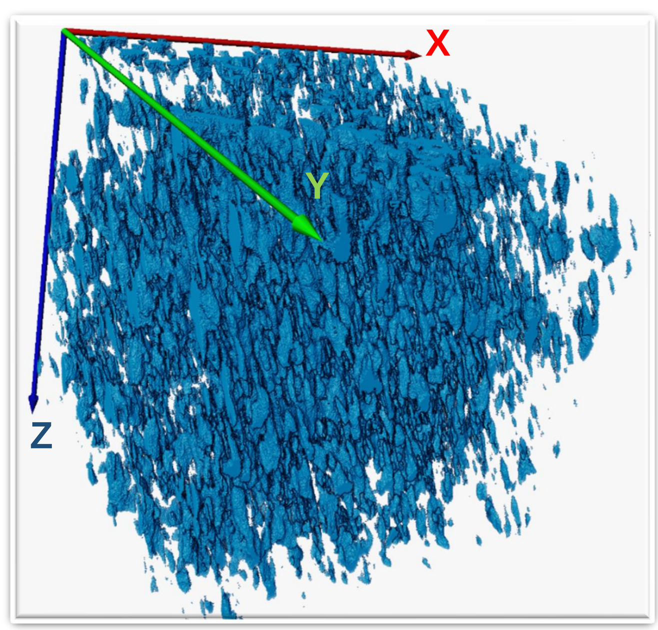
Real **Reconstructed**

XY-plane

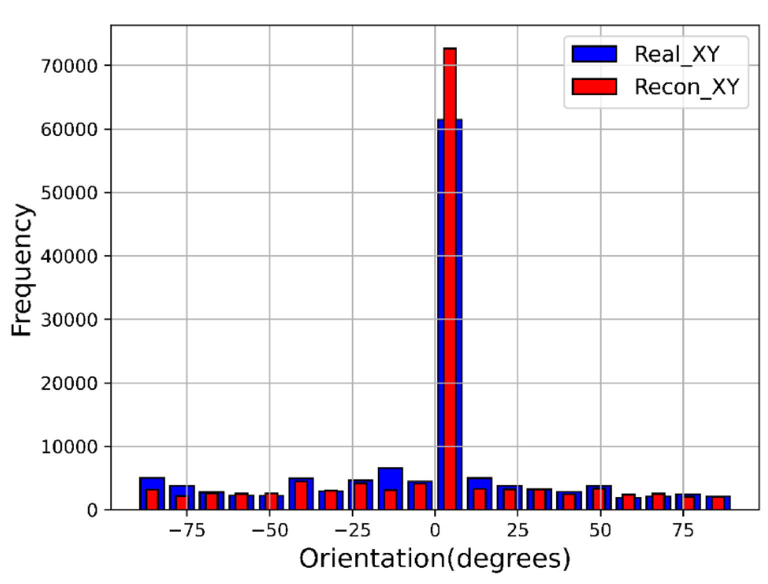
XZ-plane

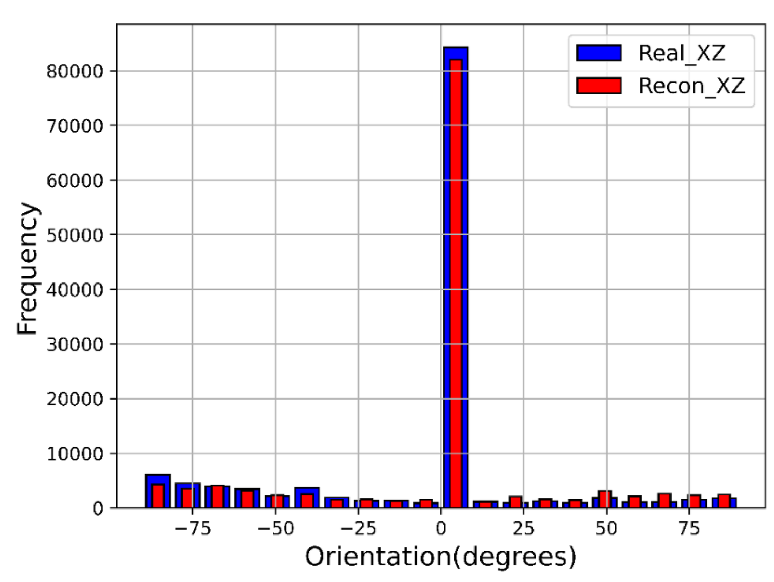


(128 × 128)



512 × 512 × 512





Conclusions

- Modern deep learning algorithms such as GANs can be used to overcome the limitations of imaging techniques.
- Once trained, these models can generate realistic microstructures with larger, representative sizes.
- 2D-to-3D reconstruction is a promising trend in image reconstruction as 2D images are of higher resolution, of less const, and available.
- Higher-order spatial correlation functions should be employed to verify that reconstructed microstructures are sharing same structural and topological properties as real ones.

References

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