

# Comparison of CNN and GAN-Based Super-Resolution Methods for 3D Porous Microstructures

Rishabh Saxena\*, Thomas Carraro

Applied Mathematics, Institute for Modeling and Computational Science  
Faculty of Mechanical and Civil Engineering  
Helmut Schmidt University – University of the Federal Armed Forces Hamburg

**InterPore2026**  
19 – 22 May 2026, Nantes, France

May 22, 2026



HELMUT SCHMIDT  
UNIVERSITÄT  
Universität der Bundeswehr Hamburg

# Outline

- 1 Introduction
- 2 Super Resolution Model (NMC Material)
- 3 Effective Transport Parameters
- 4 Results & Discussion
- 5 Conclusion
- 6 Acknowledgement

# Introduction, Motivation & Objectives

## Introduction

- Effective transport parameters such as diffusivity, tortuosity, and permeability strongly depend on the 3D microstructure of NMC materials.

## Motivation

- Low-resolution microstructures may lose important pore connectivity and transport-relevant features.
- Super-resolution can reconstruct detailed high-resolution NMC microstructures from low-resolution data.

## Objectives

- Develop 3D super-resolution models for NMC materials.
- Preserve effective transport behavior in reconstructed microstructures.

# Super Resolution for NMC-Type Materials

## NMC Materials:

- NMC (Nickel-Manganese-Cobalt) oxides are key cathode materials in lithium-ion batteries.
- Microstructural features (e.g., cracks, porosity, phase boundaries) directly affect battery performance and degradation.

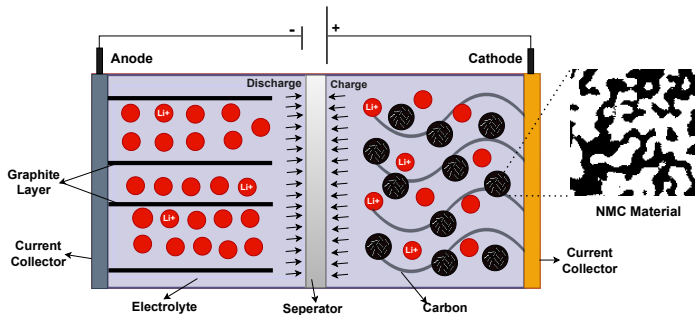
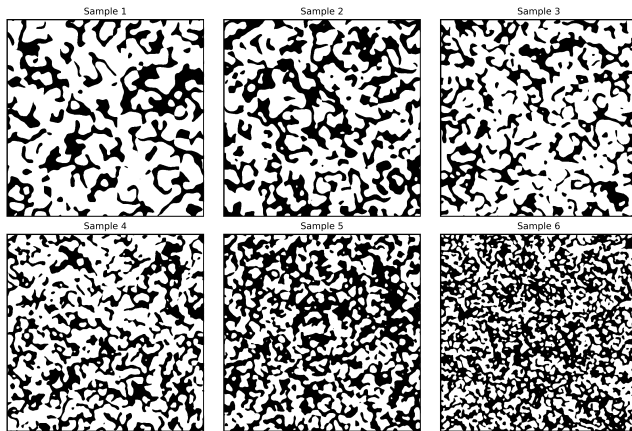


Figure: NMC-Type material visualization

# Virtual NMC Microstructure



**Figure:** Middle slices (z-direction) of six virtual 3D NMC microstructure realizations used for super-resolution analysis.

Reference: Furat, Orkun, Phillip Gräfensteiner, Rishabh Saxena, Markus Osenberg, Matthias Neumann, Ingo Manke, Thomas Carraro, and Volker Schmidt. "Super-resolving 3D nanostructures using artificially generated image data and spatial transport simulations." *Machine Learning: Science and Technology* 6, no. 4 (2025): 045006.

# Preparation of Training Data for Super-Resolution Models

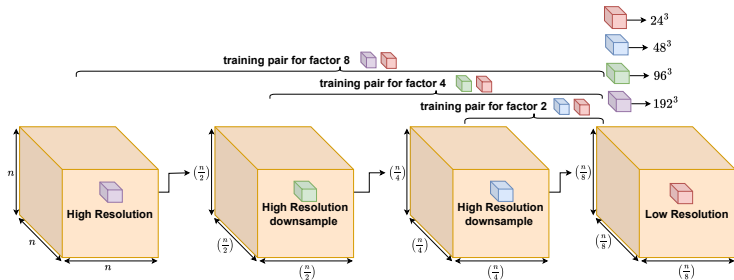


Figure: Generation of low- and high-resolution training pairs.

- Start from a high-resolution microstructure image.
- Generate low-resolution images by downsampling with factors 2, 4, and 8.
- Use the low-resolution image as input and the corresponding high-resolution image as ground truth.
- Train the model for super-resolution factors  $\alpha \in \{2, 4, 8\}$ .

# SRResNet and SRGAN Models

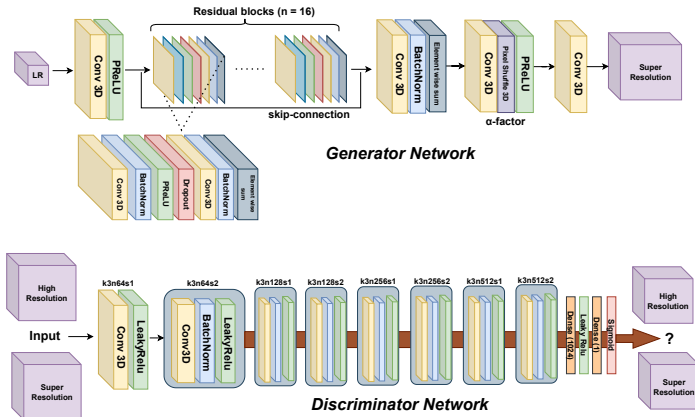


Figure: The SRGAN generator is based on the SRResNet architecture and is trained together with a discriminator.

# SRResNet and SRGAN Training Details

Model	Scale	Batch Size	Loss Function	Parameters	Per Epoch Time
SRResNet	×2	64	MSE	5.10 M	36 sec
SRResNet	×4	32	MSE	11.29 M	77 sec
SRResNet	×8	4	MSE	60.87 M	451 sec
SRGAN	×2	32	Adversarial	5.10 M + 14.57 M	110 sec
SRGAN	×4	16	Adversarial	11.29 M + 14.57 M	478 sec
SRGAN	×8	2	Adversarial	60.87 M + 14.57 M	1707 sec

**Table:** Training configuration and computational cost of SRResNet and SRGAN models.

## MSE Loss:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^N (I_i^{\text{SR}} - I_i^{\text{HR}})^2$$

## Adversarial Loss:

$$\mathcal{L}_{\text{Adv}} = -\log(D(G(I^{\text{LR}})))$$

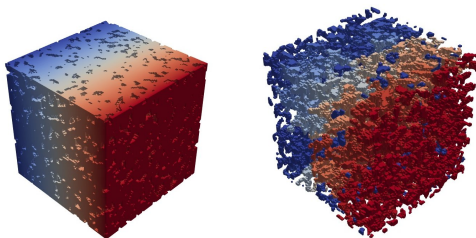
where  $I^{\text{SR}}$  is the super-resolved image,  $I^{\text{HR}}$  is the high-resolution image,  $G$  is the generator, and  $D$  is the discriminator.

# Governing Equations

- **Laplace equation** is used to model diffusion and compute **effective tortuosity** ( $\tau_{\text{eff}}$ ):

$$-\nabla \cdot (D\nabla u) = 0$$

- Laplace equation is solved on the 3D microstructure using the **finite element method (FEM)**.



# Definition of Effective Transport Parameters

$$\tau_{\text{eff}} = \varepsilon \frac{D}{D_{\text{eff}}}$$

- **Tortuosity** measures how difficult it is for diffusion to pass through the microstructure.

## Variables:

- $\tau_{\text{eff}}$  : effective tortuosity
- $\varepsilon$  : porosity (volume fraction for particular phase)
- $D$  : intrinsic diffusion coefficient
- $D_{\text{eff}}$  : effective diffusion coefficient

# Visual comparison between HR & SR for Sample 1

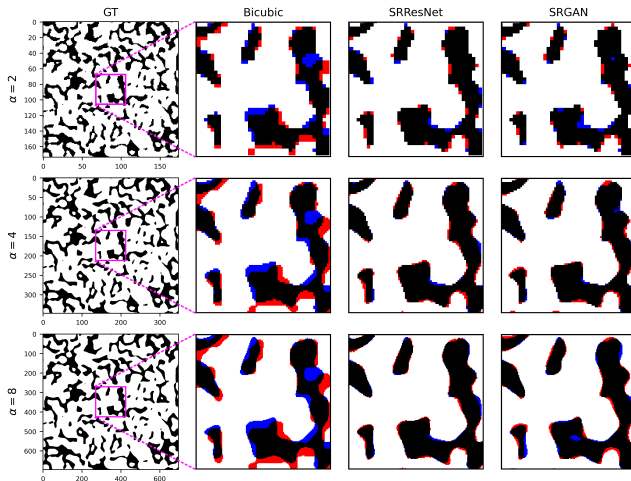


Figure: **Material misclassified as pore** ; **Pore misclassified as material**

# Visual comparison between HR & SR for Sample 4

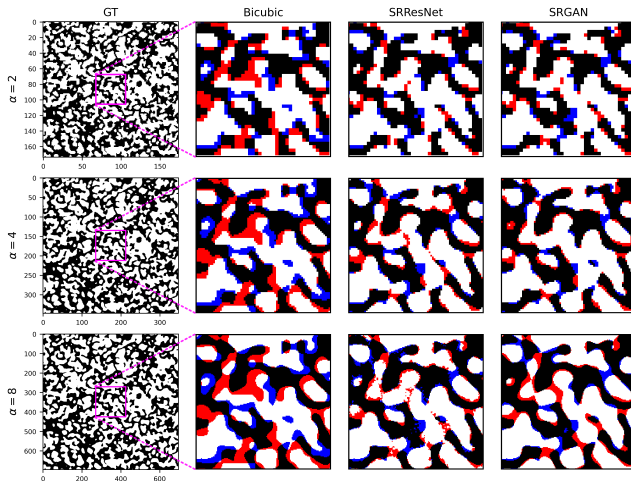


Figure: **Material misclassified as pore** ; **Pore misclassified as material**

# Visual comparison between HR & SR for Sample 6

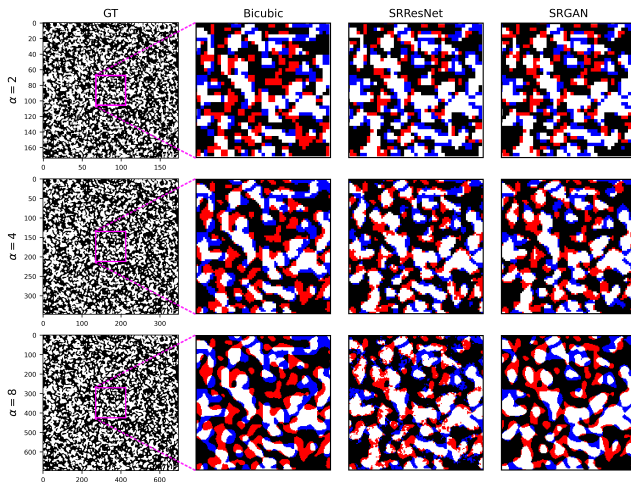


Figure: **Material misclassified as pore** ; **Pore misclassified as material**

# Geometric metric analysis

- Higher **PSNR** and **SSIM** indicate better reconstruction quality.
- Lower **LPIPS** indicates better perceptual similarity.

Sample	Model	Factor 2			Factor 4			Factor 8		
		PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
1	Bicubic	11.28	0.63	0.20	9.75	0.45	0.45	9.13	0.46	0.70
	SRGAN	15.65	0.86	0.09	15.03	0.80	0.17	14.73	0.72	0.42
	SRResNet	<b>15.98</b>	<b>0.87</b>	<b>0.09</b>	<b>15.44</b>	<b>0.81</b>	<b>0.16</b>	<b>15.37</b>	<b>0.78</b>	<b>0.29</b>
4	Bicubic	8.96	0.59	0.20	7.54	0.29	0.48	6.98	0.23	0.72
	SRGAN	12.06	0.79	0.14	11.33	0.61	0.26	11.42	<b>0.54</b>	0.43
	SRResNet	<b>12.19</b>	<b>0.80</b>	<b>0.13</b>	11.59	<b>0.62</b>	<b>0.26</b>	11.38	0.51	<b>0.40</b>
6	Bicubic	6.67	0.39	0.37	5.75	0.17	0.52	5.41	0.09	0.71
	SRGAN	8.27	0.52	0.33	7.75	0.37	0.45	7.04	<b>0.25</b>	0.45
	SRResNet	<b>8.29</b>	0.52	<b>0.33</b>	<b>7.81</b>	0.36	<b>0.37</b>	<b>7.31</b>	0.20	<b>0.41</b>

**Table:** Quantitative comparison of Bicubic, SRGAN, and SRResNet for different Samples.

- Both **SRGAN** and **SRResNet** clearly outperform **Bicubic**.

# Transport metric analysis

$$\text{RE}_{\tau_{\text{eff}}}^{(i)} = \frac{\left| \tau_{\text{eff}}^{(i)}(I^{\text{SR}}) - \tau_{\text{eff}}^{(i)}(I^{\text{HR}}) \right|}{\tau_{\text{eff}}^{(i)}(I^{\text{HR}})} \times 100. \quad (1)$$

Sample	Model	Pore Phase ( $i = 0$ )			Material Phase ( $i = 1$ )		
		Factor 2	Factor 4	Factor 8	Factor 2	Factor 4	Factor 8
1	SRGAN	1.27	1.91	0.08	0.42	0.78	0.07
	SResNet	1.52	1.12	0.50	0.17	0.43	0.16
4	SRGAN	1.28	2.53	2.61	2.35	0.51	0.05
	SResNet	1.85	2.81	0.59	1.78	1.20	2.73
6	SRGAN	2.73	1.56	1.53	5.48	1.65	13.50
	SResNet	8.68	0.96	6.01	12.05	2.30	3.00

**Table:** Relative error (%) in effective tortuosity for pore and material phases in different samples.

# Conclusion

- SRResNet and SRGAN reconstruct microstructures much better than Bicubic interpolation for all scale factors.
- Compared to SRGAN, SRResNet requires fewer training parameters and lower computational power, making it more efficient for large-scale super-resolution problems.
- Both models preserve transport properties with low tortuosity error for pore and material phases.

## Future Work

- Looking for suggestions to extend this work using Physics-Informed Neural Networks (PINNs) for direct prediction of effective transport properties such as tortuosity, permeability, and diffusivity from reconstructed microstructures.

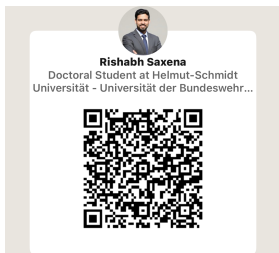
# Acknowledgement

- I would like to express my sincere gratitude to my supervisor **Prof. Thomas Carraro** for their continuous guidance and support throughout this work.
- I acknowledge the use of the **deal.II finite element library** (<https://www.dealii.org>) for implementing and solving the numerical problems presented in this study.
- Special thanks to the high performance computing **HSuper** (<https://www.hsu-hh.de/hpc/en/hsuper/>) for providing computational resources.
- I also appreciate the support from dtec.bw – the Digitalization and Technology Research Center of the Bundeswehr.



# Thank You!

Questions or Comments?



Scan for LinkedIn Profile

email:saxenar@hsu-hh.de

# Metric Definitions (Summary)

- **PSNR (dB):** Image fidelity derived from MSE (higher = better).

$$\text{PSNR} = 20 \cdot \log_{10} \left( \frac{\text{MAX}_I}{\sqrt{\text{MSE}}} \right) \quad (\text{Higher} = \text{better image fidelity})$$

- **SSIM:** Structural similarity index considering contrast, luminance, and structure (closer to 1 = better).

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (\text{Perceptual similarity})$$