Deep-Learning Based Microstructure Reconstruction
For Characterizing the Electromechanical Property of Nanomaterial Networks

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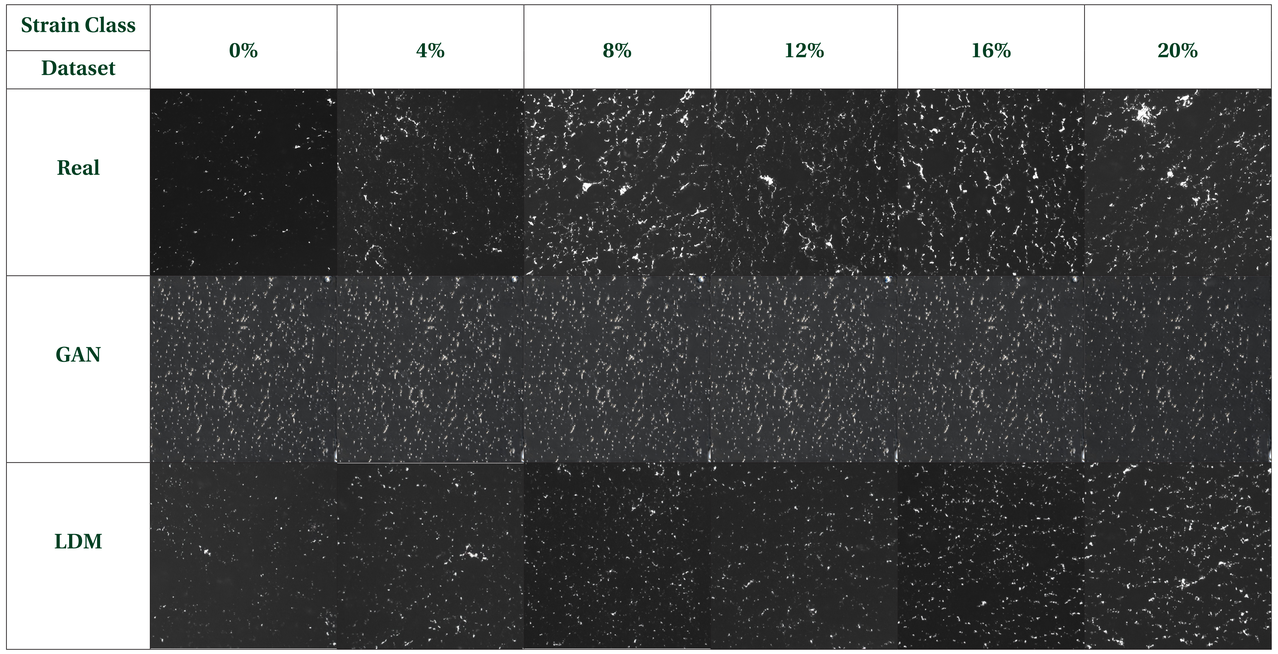


Figure 1: A comparison of GAN and LDM outputs to the training set, sorted by strain class. Notice the similarity between GAN outputs across strain classes, as opposed to the progression shown by the LDM.

Reconstructing Nanomaterials

ABSTRACT

Establishing large microstructural image libraries through **experimental imaging is expensive**, time-consuming, and inaccessible, a challenge compounded in extreme low-data regimes. While generative deep learning approaches offer a promising alternative, **small datasets introduce critical failure modes such as mode collapse**, wherein the generator produces limited, repetitive outputs that fail to capture the full diversity of the underlying distribution. In this study, we **systematically evaluate the performance of three generative architectures:** FastGAN, FastGAN with a modified loss function, and a Latent Diffusion Model (LDM) with the goal of synthesizing microstructures of strain-sensing carbon nanotube (CNT) networks fabricated via corona-enabled electrostatic printing. We introduce a data-efficient training pipeline incorporating aspect-ratio-preserving resizing and flip-based augmentation to maximize utility from approximately 40 images per strain class. Compared to previous GAN-based approaches[1], **the LDM successfully eliminates mode collapse** and produces class-conditional microstructures that more **faithfully reproduce experimentally observed structural trends** validated through the Lineal Path Function, Pore Size Distribution, Chord Length Distribution, and Two-Point Correlation. **This work establishes a generalizable blueprint for diffusion-based microstructure synthesis in low-data material systems, and provides a rigorous precedent for evaluating and comparing the performances of different machine learning models.**

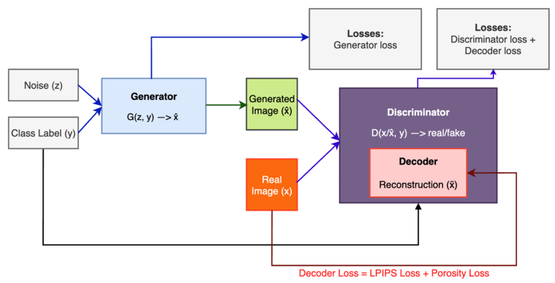


Figure 2: Modified GAN model architecture[1]

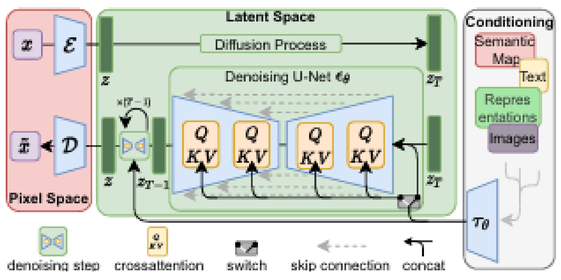


Figure 3: Standard LDM model architecture[2]

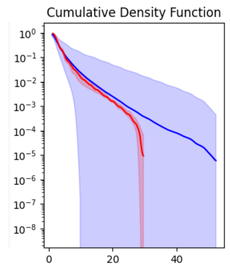
Performance Metrics

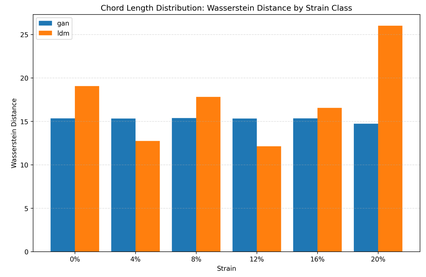
CLD **CHORD LENGTH DISTRIBUTION**

How large are the pores?

Figure 4: An example survival function generated by CLD (left). Blue represents the real distribution, red the synthetic.

Figure 5: Bar graph comparing CLD errors computed by Wasserstein Distance, by strain class, between LDM and GAN (right)



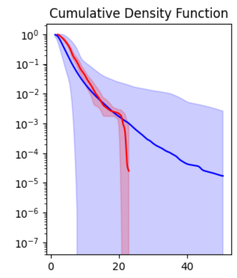


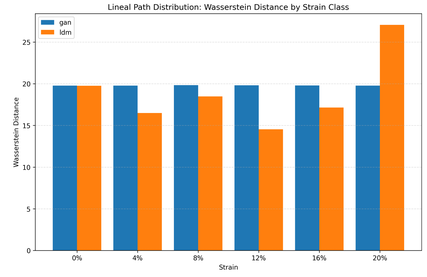
LPF **LINEAL PATH FUNCTION**

How broken-up or connected is the pore structure?

Figure 6: An example survival function generated by LPF (left). Blue represents the real distribution, red the synthetic.

Figure 7: Bar graph comparing LPF errors computed by Wasserstein Distance, by strain class, between LDM and GAN (right)



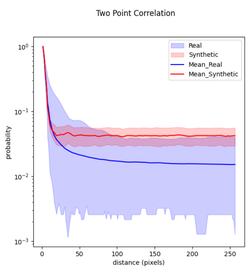


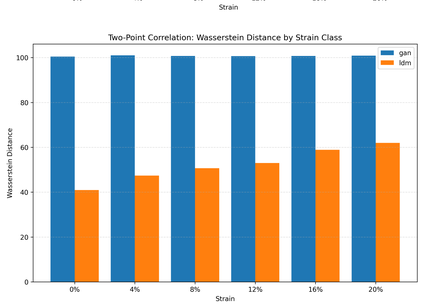
2PC **2-POINT CORRELATION**

How strong is the structural pattern across the image?

Figure 8: An example function generated by 2PC (left). Legend applies to previous survival functions, as do X-axis units.

Figure 9: Bar graph comparing 2PC errors computed by Wasserstein Distance, by strain class, between LDM and GAN (right)





WASSERSTEIN DISTANCE: Work needed to transform one probability distribution into another = (probability mass) x (distance). We can use this to compare each synthetic metric curve to the real one, quantifying the model's error (by metric). We can now quantatively compare model performances!

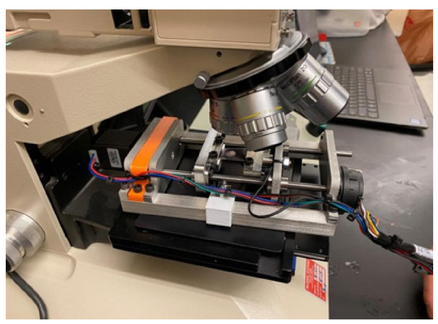
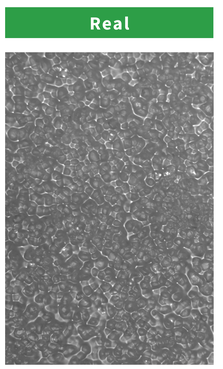
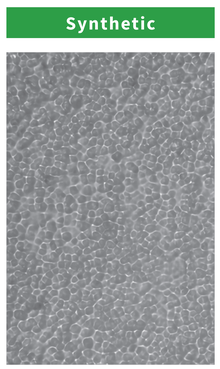


Figure 10: Experimental Imaging setup[1]

Figures 11 & 12: Real images of composite nanomaterial and LDM reconstruction ->

Bonus Images!!!!





The LDM can reconstruct composite nanomaterials too!

REFERENCES

1 C. J. Maloney, L. Taliaferro, J. D. Ventura, and L. Wang, "Deep Learning-Based Microstructure Reconstruction for Characterizing the Electromechanical Property of Nanomaterial Networks," Proc. SPIE, vol. 13433, 134330E, 2025, doi: 10.1117/12.3051137.

2 R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-Resolution Image Synthesis with Latent Diffusion Models," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 10684–10695, doi: 10.1109/CVPR52688.2022.01042.