Adapting Segment Anything Model (SAM) to Experimental Datasets via Fine-Tuning on GAN-based Simulation: A Case Study in Additive Manufacturing

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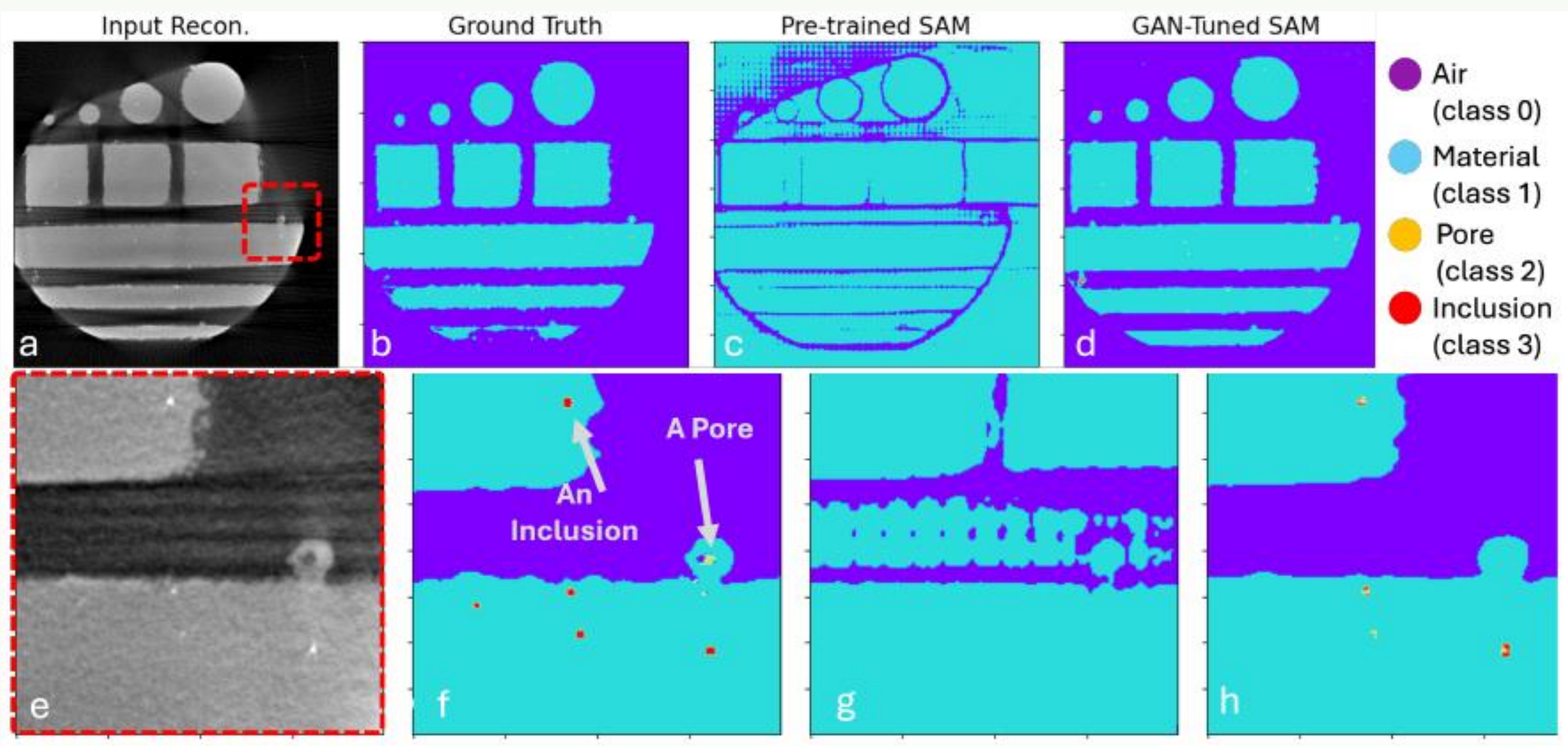
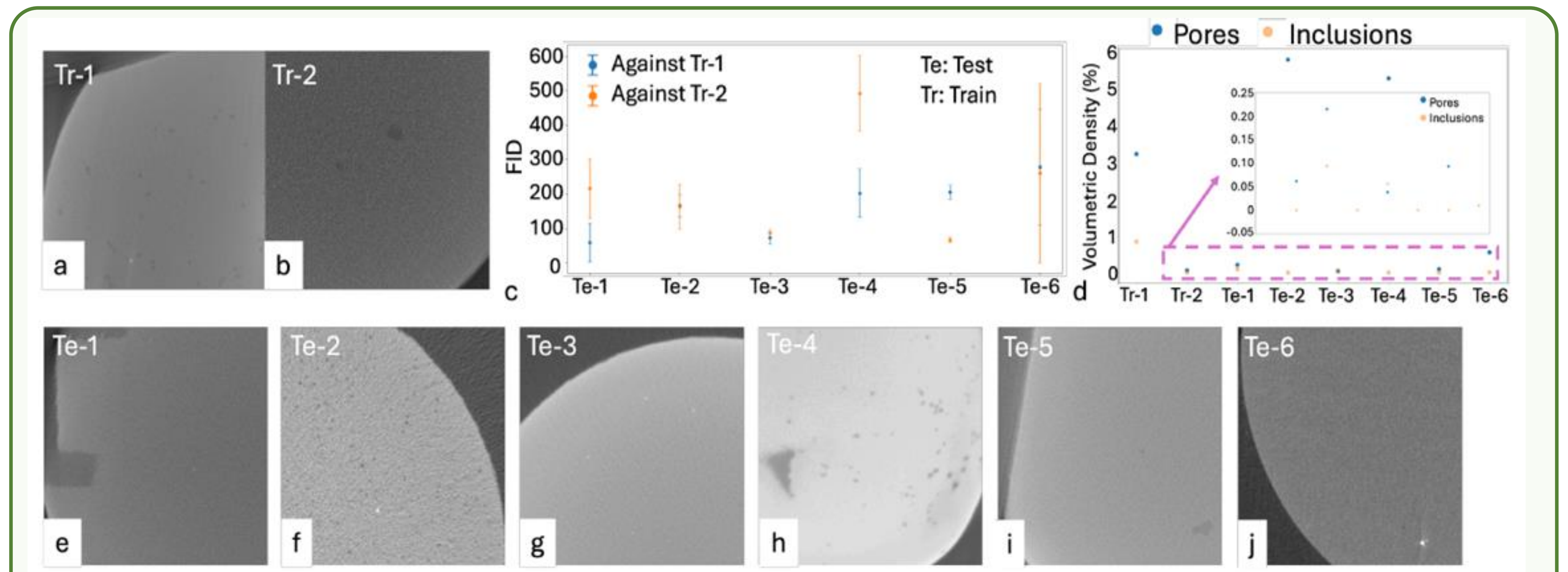
Overview

Foundational Segment Anything Model (SAM) lacks to distinguish multi-class, zero-shot segmentation for scientific images like X-ray Computed Tomography (XCT)

- ❑ Address limitations to SAM Fine-tuning for scientific image segmentation
- ❑ Showcase promise for leveraging GAN-generated synthetic data
- ❑ Demonstrate improved performance in out-of-distribution experimental data

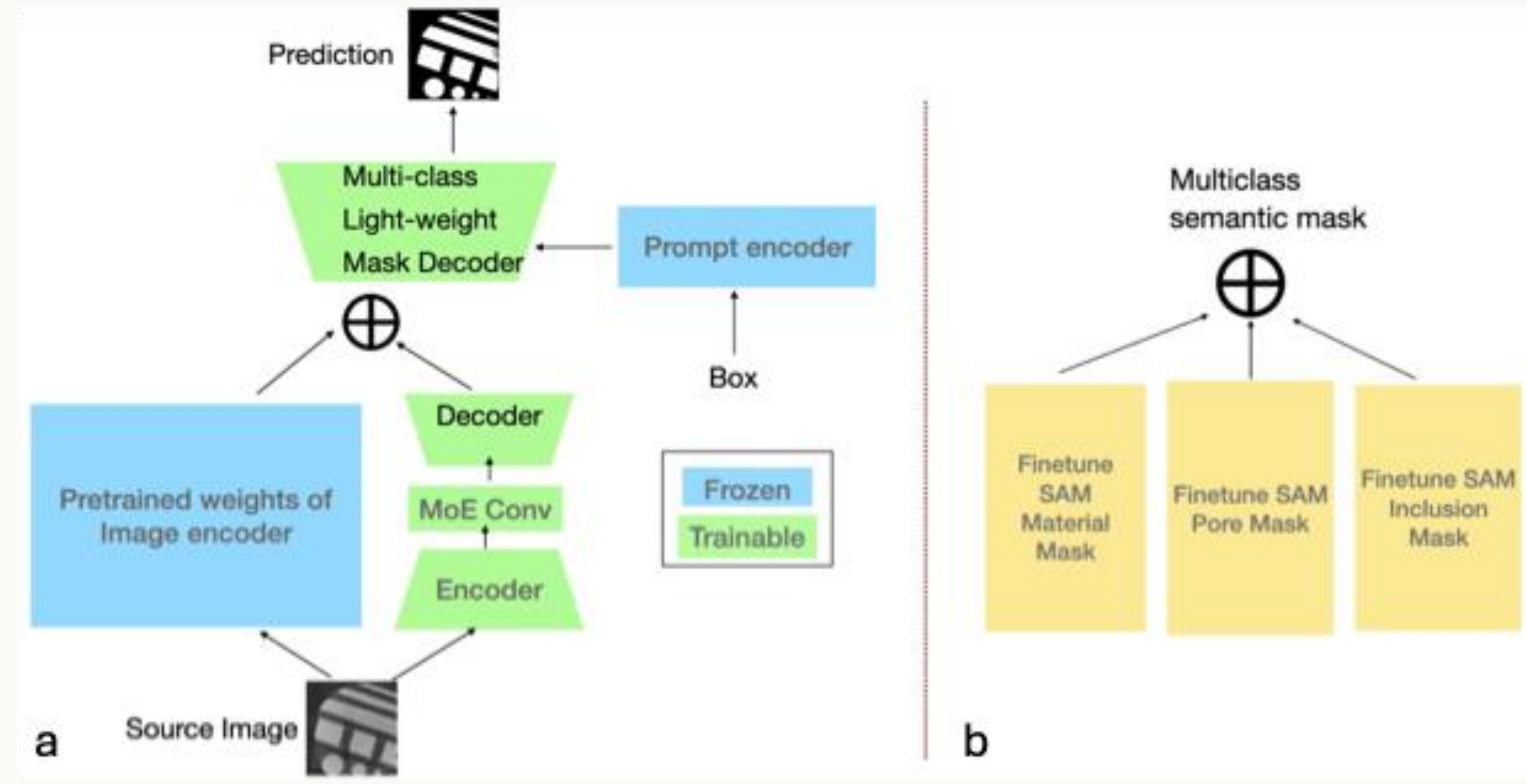


Training Data Generation



- ❑ Synthetic data generation: Cycle-GAN (Training data: Tr-*, Test data: Te-*)
- ❑ Data type: 2 metallic materials, different scan settings (e.g., beam hardening)
- ❑ Degree of Out-of-Distribution of Te-1–Te-6 compares in terms of Frechet inception distance (FID)
- ❑ Test Data description (compared to training):
  - Te-1: Real (OoD), more inclusion, few pore
  - Te-2: Real (OoD), More pore, few inclusion
  - Te-3: In-distribution (same noise as training)
  - Te-4: Real (OoD), more pore, no inclusion
  - Te-5: Synthetic (OOD), more pore, no inclusion (different training noise)
  - Te-6: Real ***(strong OoD)***, more pore, more inclusion, striking noise from training

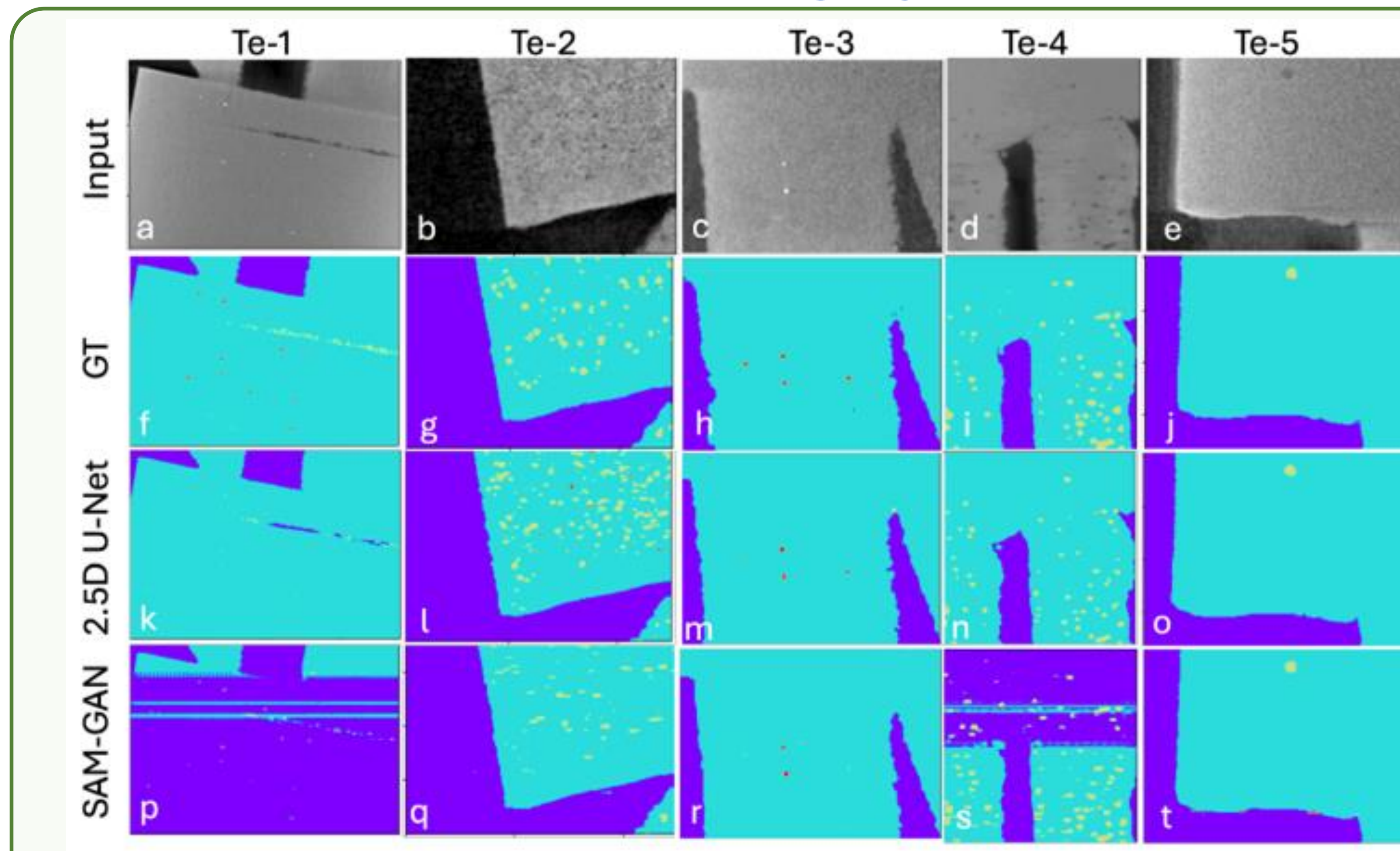
Parameter Efficient SAM (PEFT-SAM)



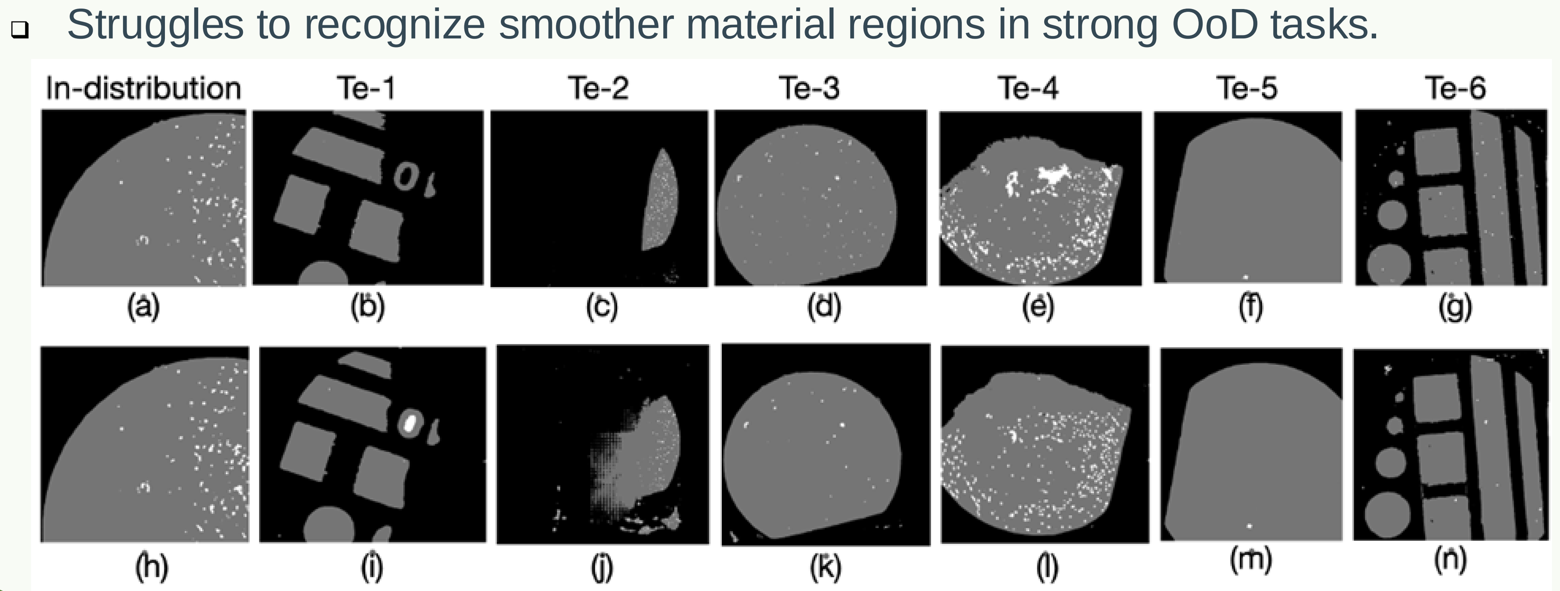
$$H = \mathbf{W}_0 x + \mathbf{W}_D \sum_i^n Conv((\mathbf{W}_E x)_i N_i W_E(x)),$$

- ▪ Parameter-efficient fine-tuned SAM (PEFT-SAM) for multiclass segmentation utilizing mixture-of-expert architecture Conv LoRA for trainable parameters (green).

Performance utilizing Synthetic Data

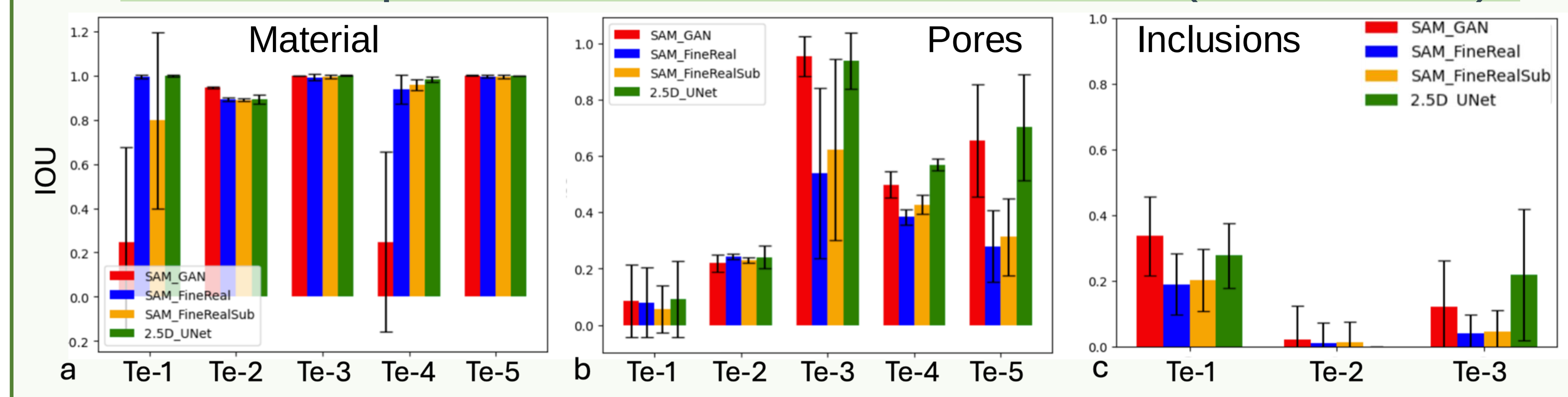


- ▪ PEFT-SAM consistent across the different InD and OoD datasets. [**Note**: **Even InD was real experiment, while training was on Synthetic data**]
- ▪ Captures materials, pores, and inclusions for InD (Real) and weak OoD cases
- ▪ Struggles to recognize smoother material regions in strong OoD tasks.

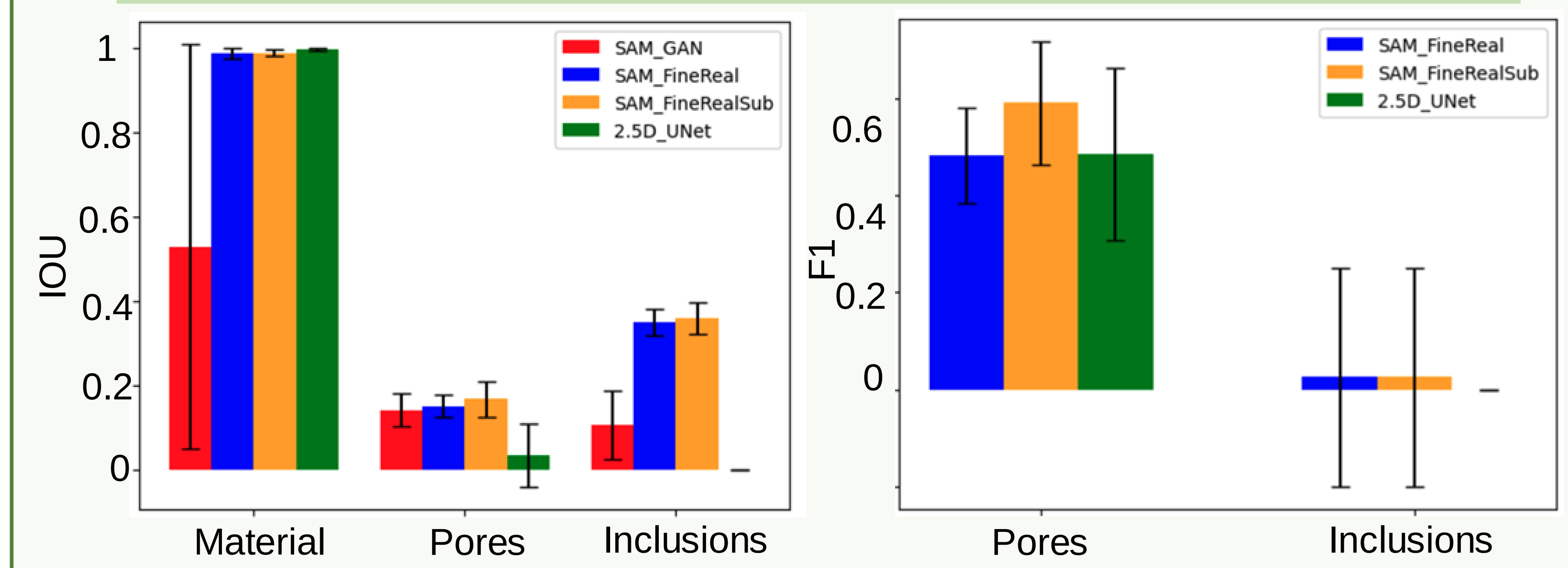


Out-of-Distribution Performance

IOU Comparison: SAM-GAN vs. Baseline (2.5D U-Net)



Robustness to Noise



Impact of Catastrophic Forgetting

Class	Model	
	SAM-FineReal-Sub	*SAM-FineReal*
Material	0.24	0.27
Pore	-0.15	-0.18
Inclusion	-0.072	-0.079

Mean change in IOU performance Performance on re-finetuning

Demonstrates forgetting in as decrease of IOU on pores and inclusions

Key Observation and Future Plan

- ❑ SAM-GAN shows good performance for zero/few-shot generalization on real XCT data
- ❑ SAM has limits to account for 3D XCT and generalization to various degrees of OOD data (defined through noise, resolution, and anomalies)
- ❑ Unexpected observation of Catastrophic forgetting during re-fine-tuning with real data
- ❑ *Future*: developing a foundational model for science-specific (e.g. 3D XCT materials) to address challenges

References

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