Automated XCT Simulation, SOM Clustering, and CNN Refinement

Demo for CHIPS Program – Nondestructive Defect Detection Metrology

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End-to-End XCT Defect Detection Pipeline

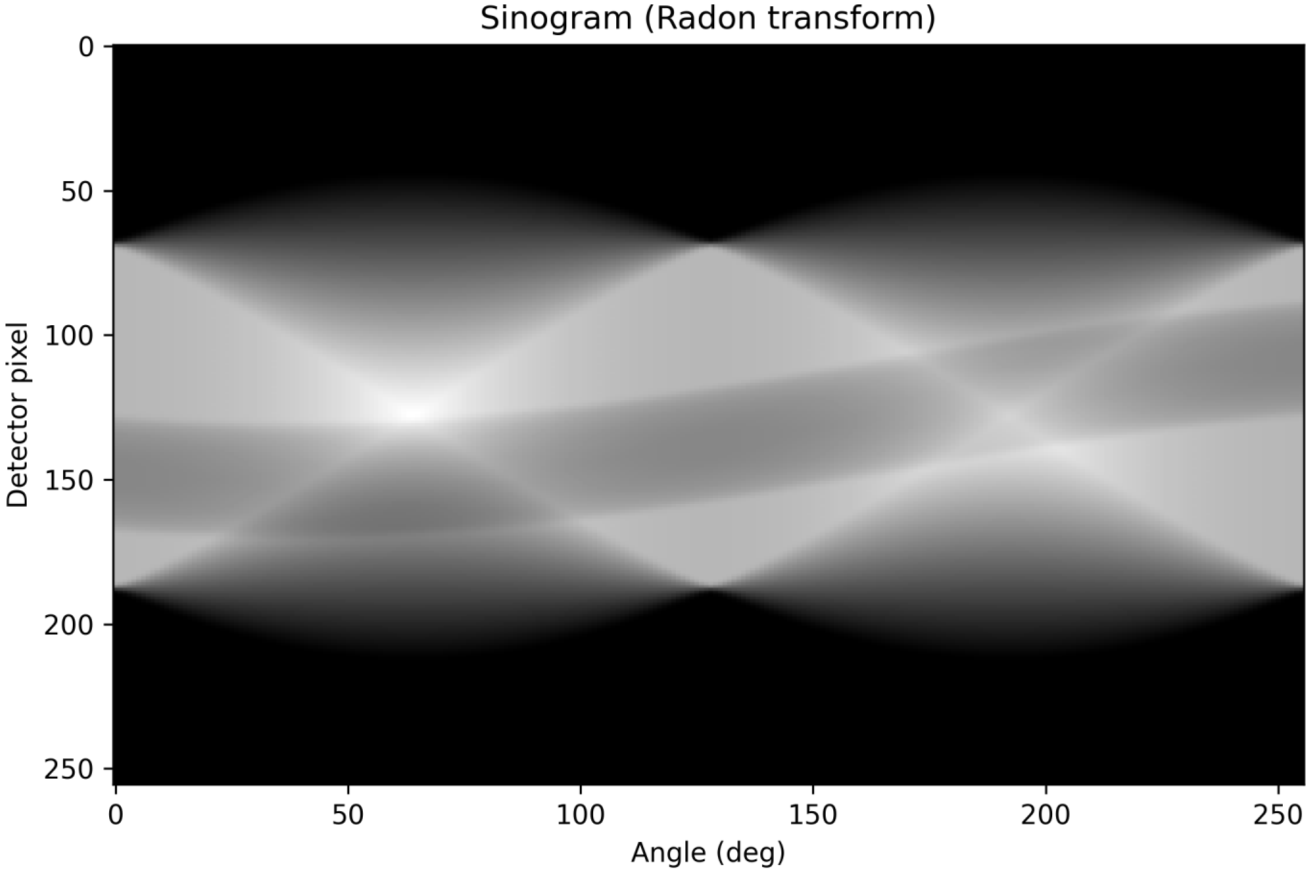
- Phantom → Sinogram → FBP Reconstruction → SOM Clustering → Class Extraction → CNN Refinement
  - • Physics-based XCT simulation
  - • 9D feature extraction + PCA + SOM unsupervised clustering
  - • CNN (Mini-UNet) refinement via teacher–student learning

Phantom with Seeded Defect

- Synthetic 256×256 reference artifact
- Square package + circular void defect

Simulated Sinogram (Radon Transform)

- Generated over 0–250 degrees
- Captures projection of structural and defect geometry



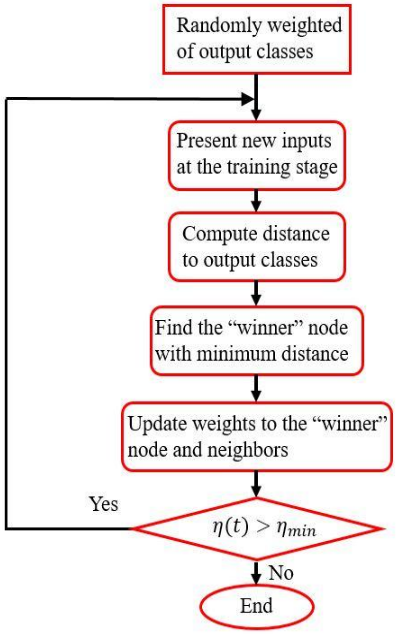
FBP Reconstruction

- Typical XCT reconstruction with mild streaking
- Used as input for SOM-based segmentation

Method Overview

Self-Organizing Map (SOM) for Label-Free, Physics-Informed Segmentation (X-ray CT Reconstruction)

Feature	Physical / Statistical Meaning in XCT
Grayscale intensity	Local X-ray attenuation; material density contrast
Edge magnitude	Boundary and interface sharpness; reveals defect edges
Local contrast	Heterogeneity of reconstructed materials; streak-robust
Thinness / filament metric	Captures circular voids and thin structures
Local mean (3×3 / 5×5)	Neighborhood background estimator; denoising
Anisotropy (ρ, γ)	Sensitivity to directional artifacts or coherence
Hue surrogate	Pseudo-channel to improve feature diversity and visualization



Workflow Summary

1.Extract 9-dimensional pixel features from the 256×256 FBP reconstruction.

2.PCA reduction (9→6 dimensions) preserving >95% variance.

3.Unsupervised SOM forms physically interpretable clusters:

1. Background
2. Material body
3. Defect region
4. Boundary / edge

4.Automatic selection of cluster count via Elbow method.

5.Produce class-label map + radar plot to quantify physical differences.

Key Advantages

- **Label-free** — No manual annotation required.
- **Physics-informed** — Features reflect attenuation, structure, and reconstruction artifacts.
- **Interpretable** — Each cluster corresponds to a statistically distinct material regime.
- **Noise-tolerant** — Stable under streaking and low-dose reconstructions.
- **Repeatable & transferable** — Centroids can be reused on new XCT datasets.
- **Efficient** — Runs in seconds on CPU for 256×256 images.

METHOD OVERVIEW (SOM → CNN Refinement)

From Unsupervised SOM Labels to CNN Refinement
A Teacher-Student Framework for Robust XCT Segmentation

Core Idea

- SOM provides **interpretable, noise-robust pseudo-labels** without any ground truth.
- CNN (U-Net) **learns from SOM pseudo-labels**—a teacher→student process.
- The hybrid model leverages physics-driven initialization (SOM) and deep learning refinement (CNN).
- A **self-consistency loop (ΔIoU → 0)** ensures a stable, converged segmentation model.

Workflow

SOM labeling (Teacher)

Produces initial cluster masks: background / material / defect / boundary.

CNN training (Student)

Input: reconstructed image
Label: SOM output
CNN learns a smooth, high-fidelity version of SOM segmentation.

Pseudo-labeling (extension)

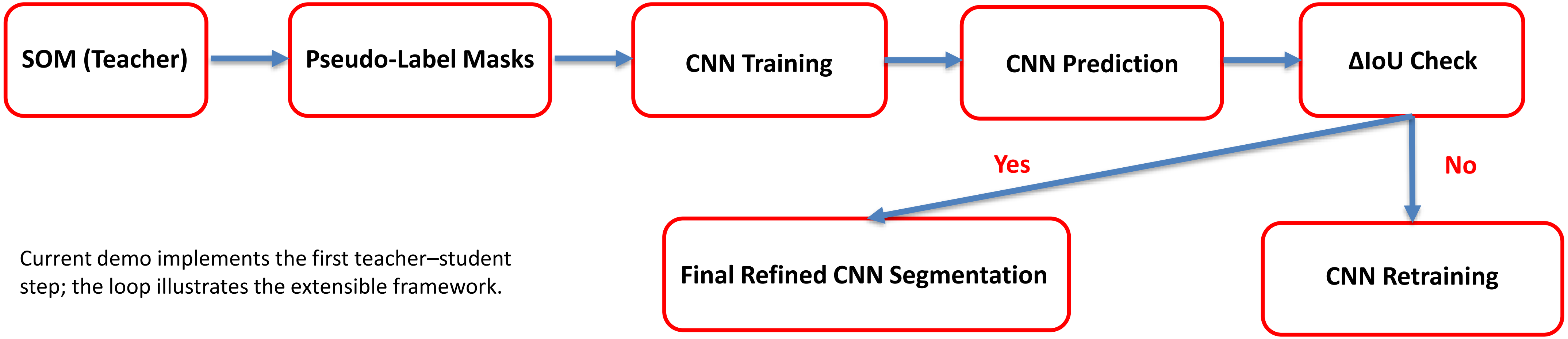
CNN can be applied to new or unlabeled XCT frames to generate pseudo-labels.

Self-consistency loop (extension)

Retrain CNN on its own predictions until improvement in IoU falls below a threshold ($\Delta IoU < 0.005$), ensuring stable and physically consistent masks.

Key Advantages

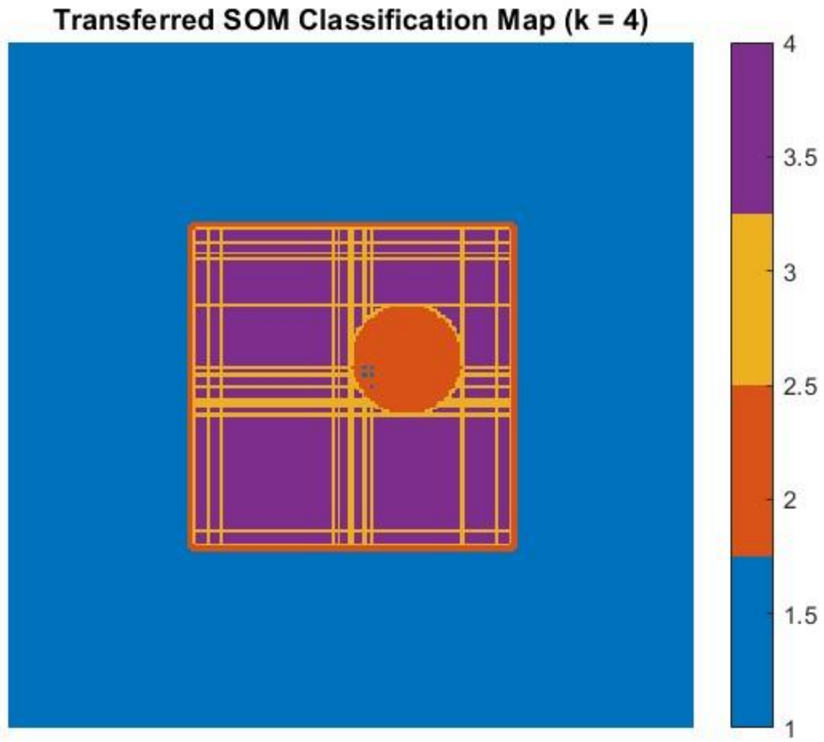
Label-free segmentation pipeline (no ground truth required).
Noise-robust — CNN trained on SOM's stable clusters is resistant to artifacts.
Explainable — SOM provides physics interpretation; CNN provides geometric refinement.
Transferable — Same pipeline applicable to XCT, ghost imaging, quantum imaging, etc.
Efficient — Patch-based U-Net converges quickly on 256×256 XCT images.

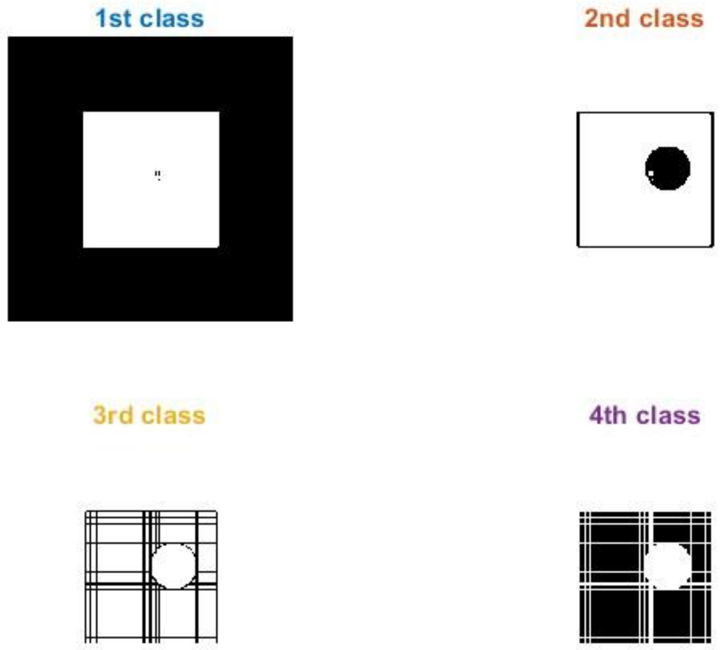


Current demo implements the first teacher–student step; the loop illustrates the extensible framework.

SOM Clustering (k = 4)

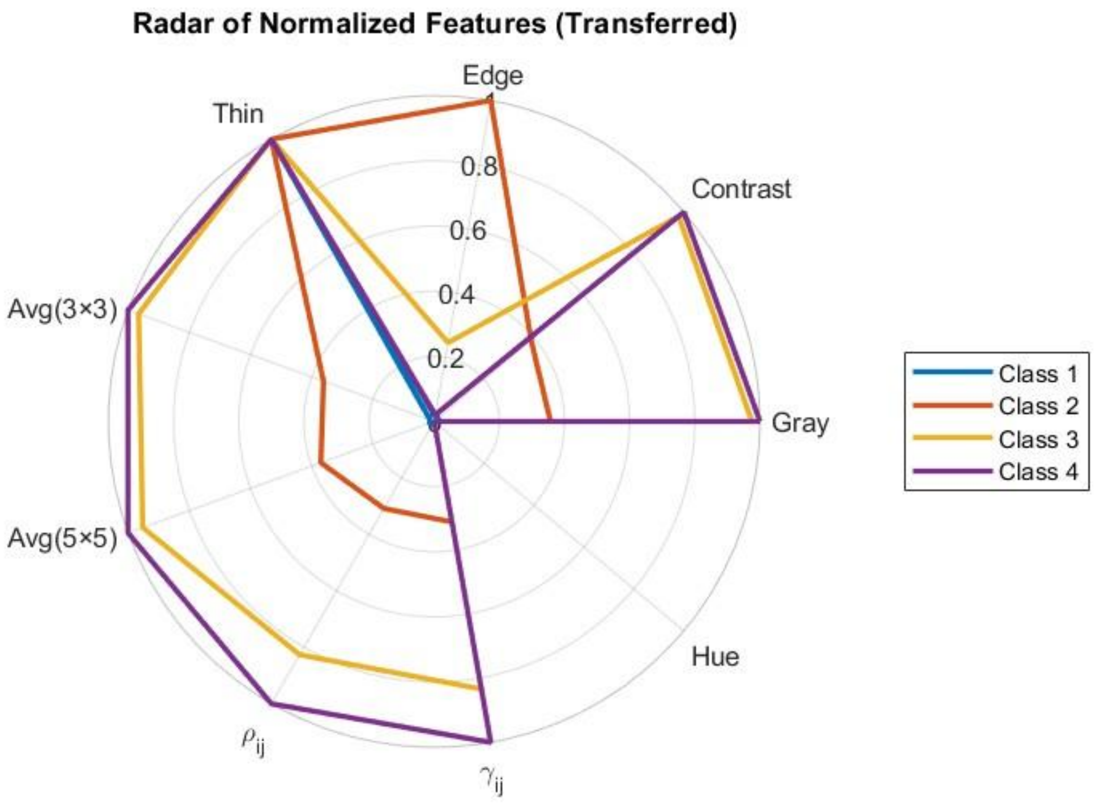
- 9D pixel-level physics features + PCA dimensionality reduction
- Automatically determines optimal cluster number via the Elbow criterion
- Class 2 consistently corresponds to the circular defect region





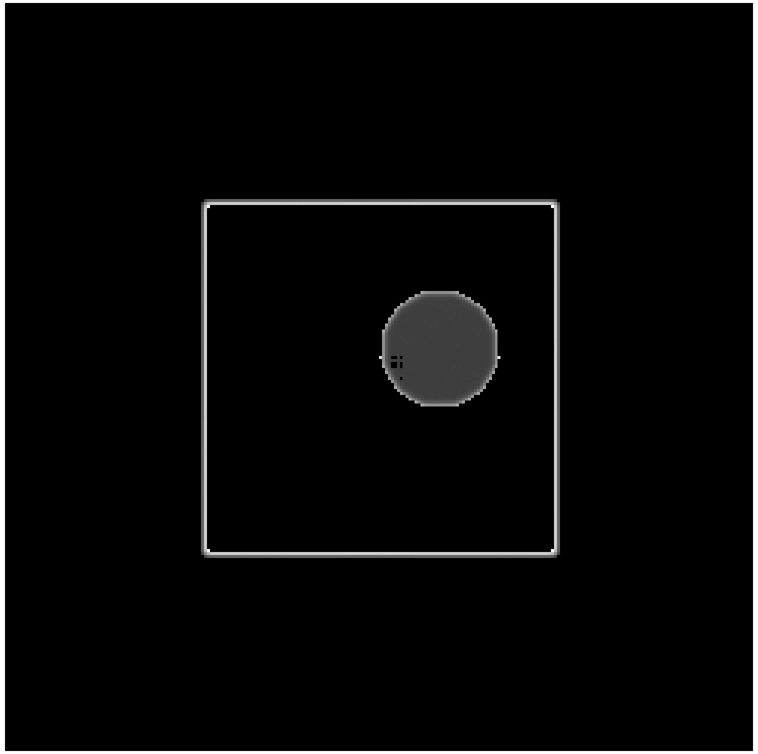
Radar Plot of Normalized 9D Feature Statistics (Transferred SOM Classes)

- Colors consistent with SOM map
- Confirms feature distribution per class



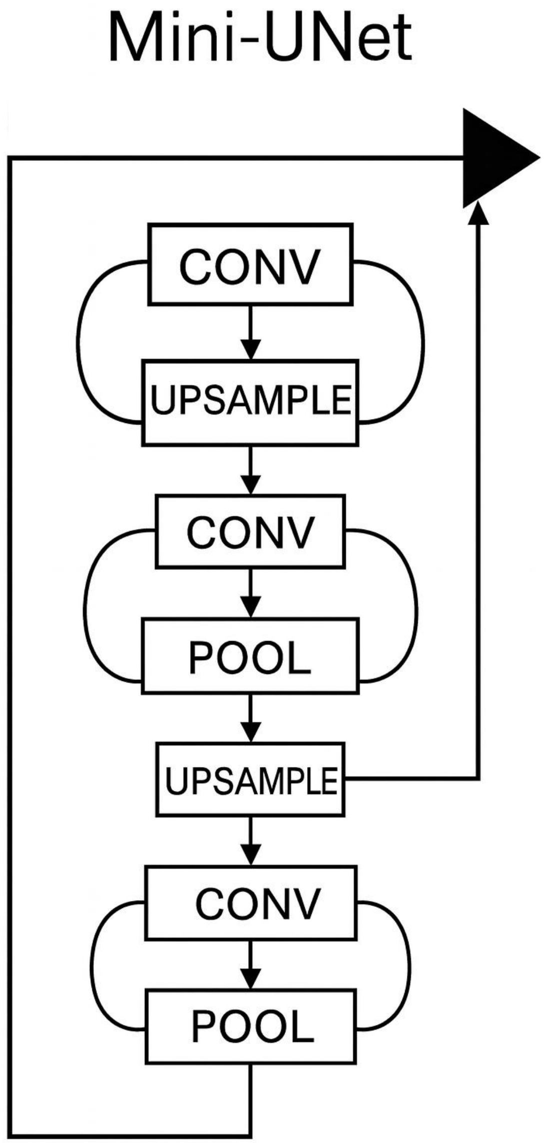
Extracted Class 2 Region

- SOM isolates defect region in grayscale
- Serves as the pseudo-ground-truth (teacher signal) for CNN refinement



Mini-UNet CNN Student Model

- Learns from SOM teacher labels
- 64×64 patch-based training
- BCE loss + ΔIoU convergence



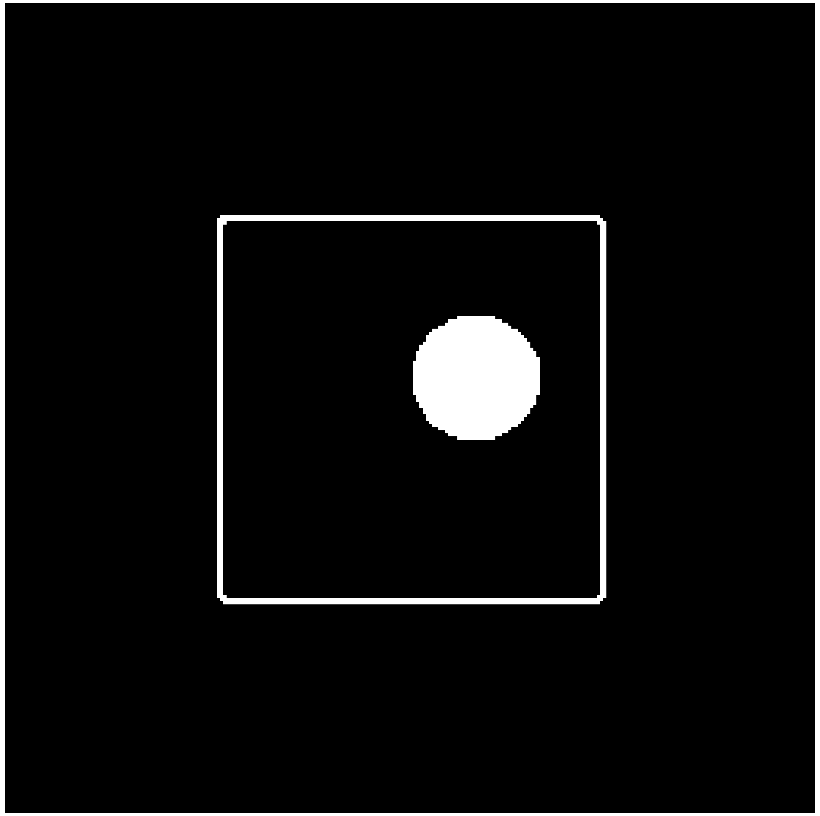
CNN Training Convergence

- IoU ≈ 0.96 from first epoch
- ΔIoU < 0.003 → Early stopping
- Model saved as cnn_from_som.pth

```
Epoch 0: loss=0.0068, IoU=0.9685
Epoch 1: loss=0.0048, IoU=0.9658
Converged at Epoch 1, ΔIoU=0.0026
Model saved.
```

CNN-Refined Segmentation Mask

- Smoother, more geometric defect boundaries
- Higher-quality benchmark mask than raw SOM



Summary and Relevance to CHIPS Program

- Automated XCT simulation + clustering + DL refinement
  - Generates clean benchmark defect datasets
  - Aligns with CHIPS goals in metrology, automation, and AI evaluation