PHYSICS-INFORMED UNSUPERVISED-TO-SUPERVISED PIPELINE FOR QUANTUM AND GHOST IMAGING

(Integrating SOM Centroid Migration with CNN Refinement)

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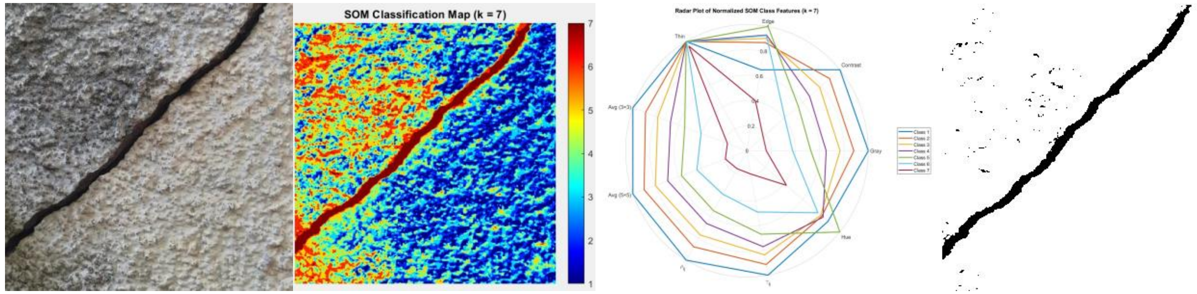
Bridging Self-Organizing Maps and Deep Learning for interpretable, data-efficient image reconstruction.

Background & Motivation

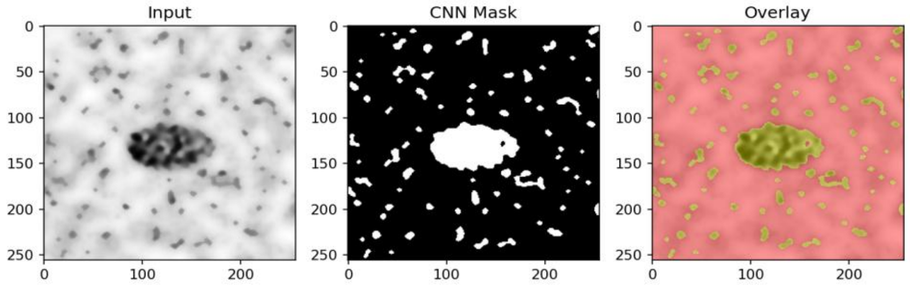
From Structural Health Monitoring to Correlation-Based Imaging

Unsupervised-to-Supervised Pipeline Generalized from Crack Segmentation to Ghost & Quantum Imaging

- Developed a **physics-guided SOM→CNN** pipeline for **pixel-level feature segmentation** and temporal evolution tracking in SHM.
- **SOM centroid migration** provides **label-free pseudo-annotation** and consistent mapping within the same imaging modality.
- The **CNN refinement stage** stabilizes reconstruction under noise and sparse photon counts.
- The same **unsupervised-to-supervised framework** extends from **crack diagnostics (SHM)** to **ghost and quantum correlation imaging**, ensuring interpretability and physical consistency.



SHM: Physics-informed segmentation (SOM features)

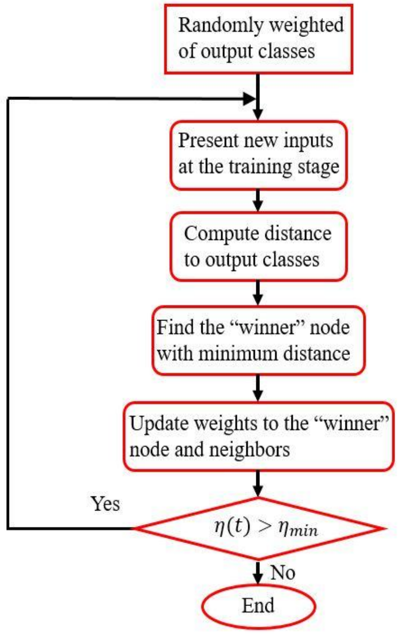


Ghost imaging: Physics-guided SOM→CNN refinement (elliptic phantom under low-photon condition)

Method Overview

Self-Organizing Map (SOM) for Label-Free, Physics-Informed Segmentation

Feature	Physical / Statistical Meaning
Grayscale intensity	Local photon density or transmission; relevant to low-fluence X-ray or quantum illumination conditions.
Edge magnitude	Gradient strength highlighting correlation or phase boundaries in reconstructed speckle patterns.
Local contrast	Measures signal heterogeneity and speckle statistics in correlation-based imaging.
Thinness / Filamentness	Captures elongated or filamentary interference features linked to coherent phase fronts.
Local mean (3×3 / 5×5)	Neighborhood average intensity; reflects coarse illumination or scattering background.
Anisotropy (A_1, A_2)	Encodes reciprocal-space anisotropy and alignment of scattering or coherence directions.
(Optional) Hue / phase surrogate	Represents pseudo-phase or color-encoded contrast for enhanced visualization.



Workflow Summary

1. **Extract 9-D pixel features** (Gray, Contrast, Edge, Thinness, Avg3, Avg5, p_{ij}, q_{ij}, Hue).
2. **Apply PCA (Principal Component Analysis)** → reduce to 6-D, preserving dominant variance.
3. **Fit SOM / K-means (unsupervised)** → cluster pixels into interpretable classes.
4. **Auto-select number of clusters (Elbow method)** → find optimal *K*.
5. **Assign each pixel to its nearest centroid** → generate class-label map and radar visualization.

Key Advantages

- **Fully unsupervised** – no manual annotation.
- **Repeatable** – fixed centroids ensure identical clustering under same conditions.
- **Explainable** – each class has clear statistical and physical meaning.
- **Reusable –** centroids can be reapplied to new datasets under similar imaging physics.
- **Efficient** – CPU-friendly, real-time capable for 256×256 images.
- **Cost-free** – no labeling, no GPU training required.

Each centroid represents a statistically and physically distinct phase-space cluster.

Method Overview

From SOM-Centroid Segmentation to CNN Refinement

A unified Framework for Ghost and Quantum Imaging

1. Core Idea

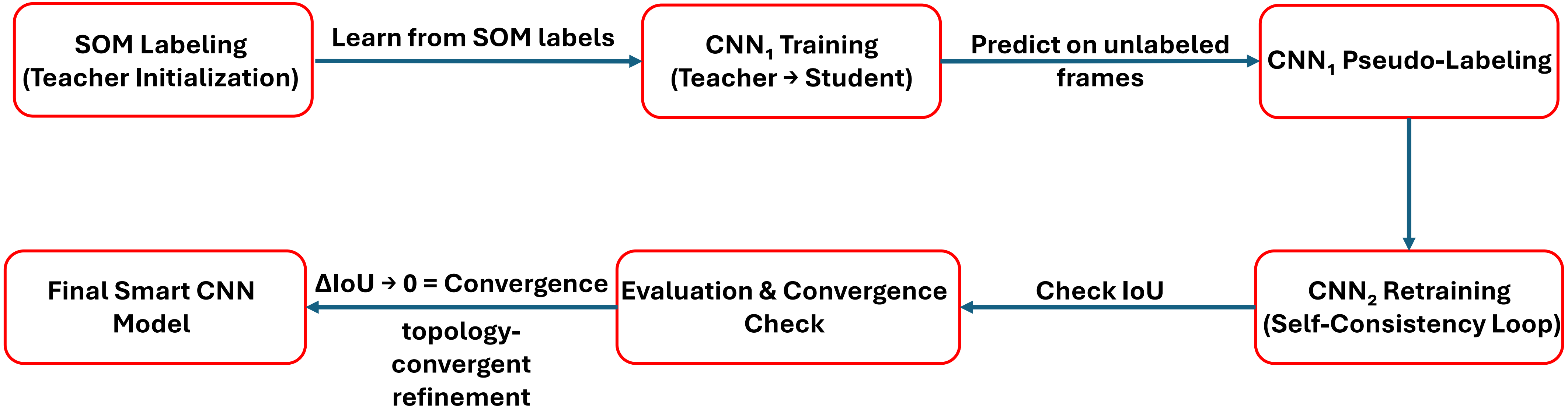
- SOM gives an interpretable, unsupervised, and noise-robust feature basis.
- CNN learns from SOM pseudo-labels (teacher→student), grounding deep learning in physical priors.
- This hybrid reduces data demand and opens the black box of CNNs.

2. Workflow

1. SOM labeling → cluster masks (no manual labels)
2. CNN training (U-Net) → reproduce & smooth SOM outputs
3. Pseudo-labeling → CNN predicts new frames
4. Self-consistency loop → retrain CNN until ΔIoU ≈ 0

3. Key Advantages

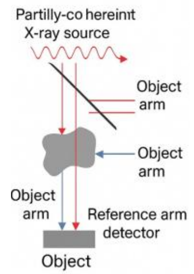
- **Label-free:** no ground truth needed
- **Noise-tolerant:** stable under low photon counts
- **Transferable:** same pipeline for ghost & quantum
- **Interpretable:** SOM explains, CNN generalizes

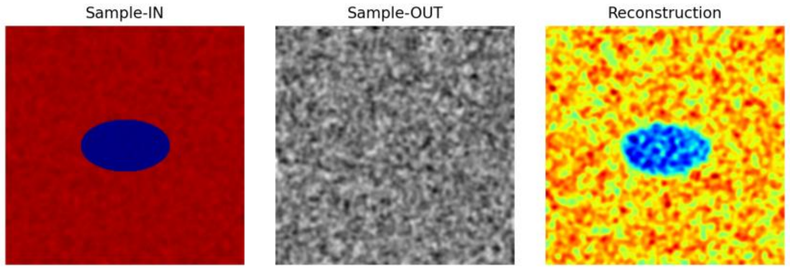


AI-Enhanced Ghost Radiography under Low-Photon Speckle Illumination

Bridging Correlation Reconstruction and Physics-Guided Learning (SOM→CNN)

Physical Baseline: Correlation-Based Ghost Imaging (GI/DGI)



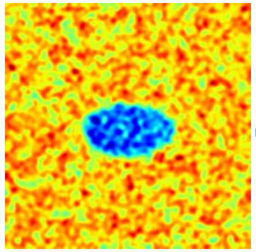


$$I_{GI}(x) = \langle (B - \langle B \rangle)(I_r(x) - \langle I_r(x) \rangle) \rangle$$

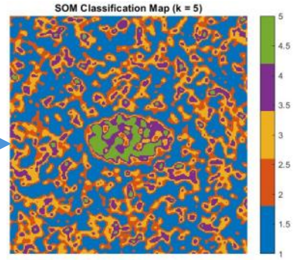
Baseline correlation-based ghost imaging (GI/DGI) reconstructs the object by correlating total transmitted intensity B with reference speckle patterns $I_r(x)$.

The reconstruction emerges statistically, without spatially resolving the object arm — achieving image recovery under low-dose, partially coherent X-ray illumination.

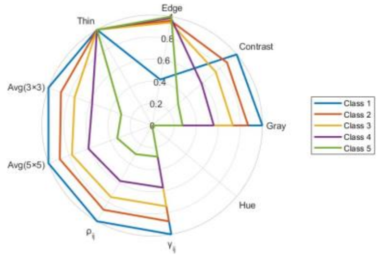
AI-Guided Enhancement I: SOM-Based Feature Segmentation



Input



SOM



SOM Radar Plot

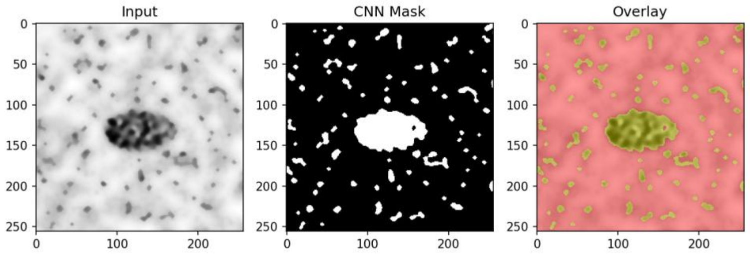
SOM clustering converts correlation-based reconstructions into interpretable feature domains, separating object-correlated and background speckle components.

AI-Guided Enhancement II: CNN Refinement via Self-Consistency (Teacher → Student Loop)

SOM-derived mask → **CNN training (teacher-student)** → **CNN output** → **Self-consistency loop ΔIoU → 0^+**

A light-weight U-Net learns from SOM pseudo-labels (teacher phase) and generates refined masks on unlabeled correlation reconstructions (student phase).

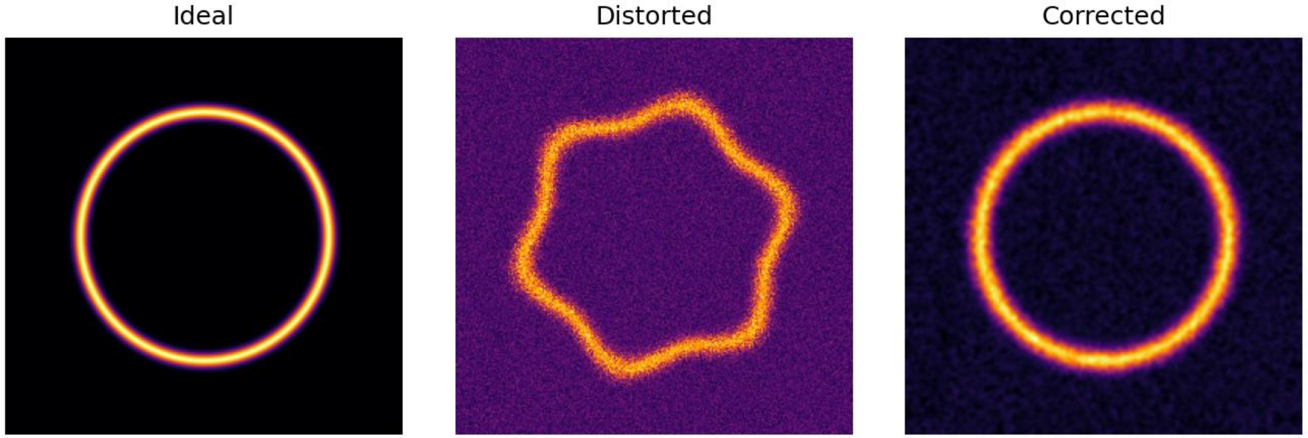
The self-consistency loop retrains the CNN until convergence (ΔIoU → 0), achieving denoised, class-aware segmentation under low-photon speckle conditions.



The combined SOM→CNN pipeline bridges physics-based correlation reconstruction and data-efficient learning, achieving interpretable, correlation-driven ghost radiography under low-photon illumination.

All Ghost results shown are simulation-based reconstructions.

SPDC Quantum Imaging under Distortion and Correction



Simulated SPDC photon-pair correlation patterns (ring-shaped phase map) under ideal, distorted, and corrected optical conditions — representing the 9.6 keV quantum beamline regime.

Correction achieved via inverse distortion mapping emulating adaptive optics calibration.

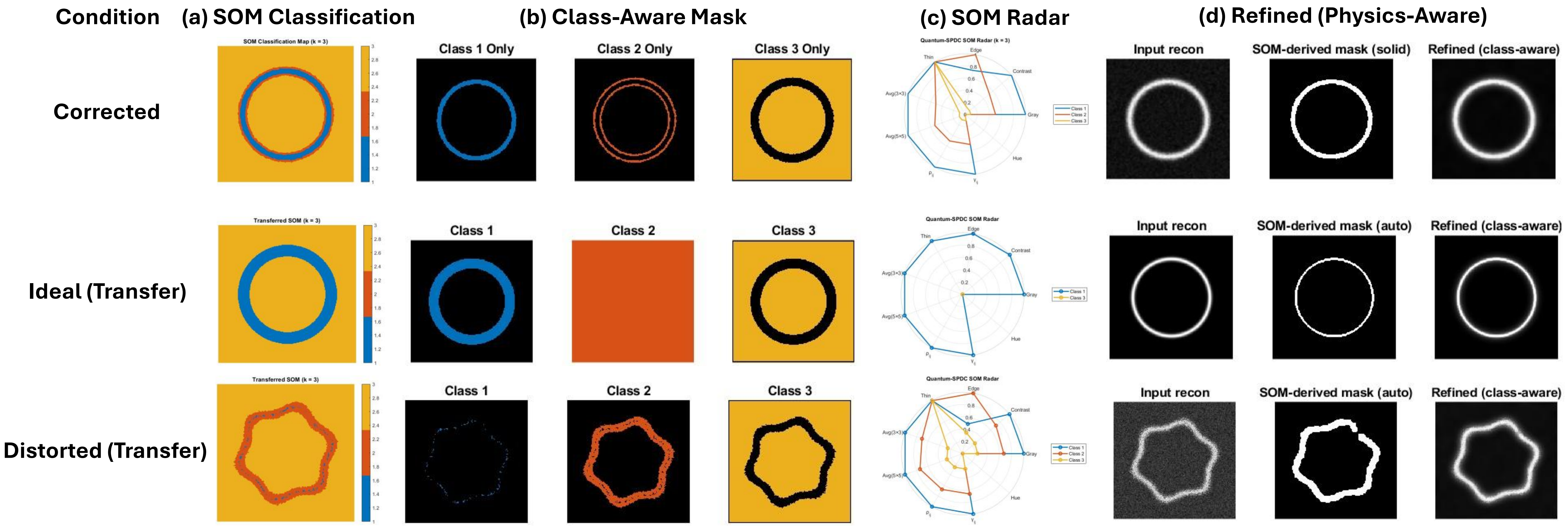
Motivation

- **Low-photon-count noise** and **partial coherence** degrade fringe and phase fidelity.
- **Traditional phase retrieval** is unstable and highly prior-dependent.
- **Supervised CNNs** require large labeled datasets unavailable in beamline settings.
- **Goal:** Develop a **physics-guided, data-efficient** pipeline that reconstructs interpretable quantum structures under distortion.

The following slides demonstrate how the **SOM + CNN** framework restores structure, explains correlations, and generalizes across optical conditions.

All SPDC results shown are simulation-based reconstructions.

Physics-Guided SOM Segmentation and Cross-Condition Transfer



The SOM–PCA feature manifold learned from the corrected quantum speckle condition is directly transferred to the ideal and distorted inputs without any retraining or external supervision.

Each input pattern is automatically partitioned into physically consistent regions—bright correlated rings versus diffuse background—within the same unsupervised topology.

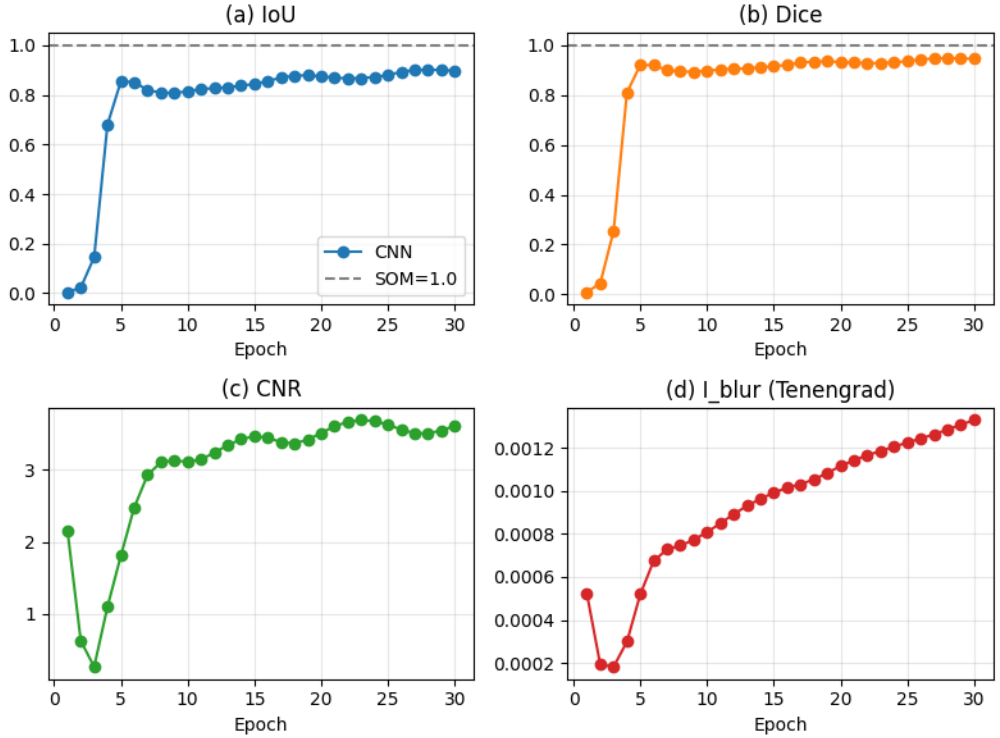
In the ideal case, higher contrast separates the ring into two adjacent energy levels (inner bright core and outer transition band), whereas in the distorted case, geometric deformation reduces the active area but maintains its mapping on the same learned manifold.

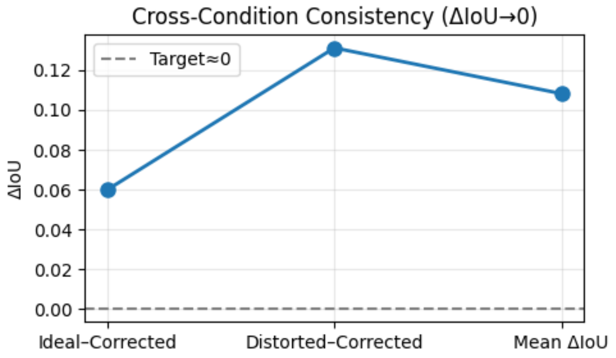
The consistent clustering patterns and radar-feature signatures across all conditions confirm that the learned feature space captures intrinsic quantum-optical correlations rather than condition-specific artifacts, demonstrating robust cross-condition transferability.

Physics-Guided SOM→CNN for Quantum Imaging

Teacher–student transfer with physically grounded priors

Quantitative Convergence





Metric Definitions

IoU (Intersection over Union)

$$\mathrm{IoU} = \frac{|\,P \cap G\,|}{|\,P \cup G\,|}$$

Dice Coefficient

$$\mathrm{Dice} = \frac{2\,|\,P \cap G\,|}{|\,P\,|+|\,G\,|}$$

CNR (Contrast-to-Noise Ratio)

$$\mathrm{CNR} = \frac{|\,\mu_f - \mu_b\,|}{\sigma_f + \sigma_b}$$

I_blur (Tenengrad focus measure)

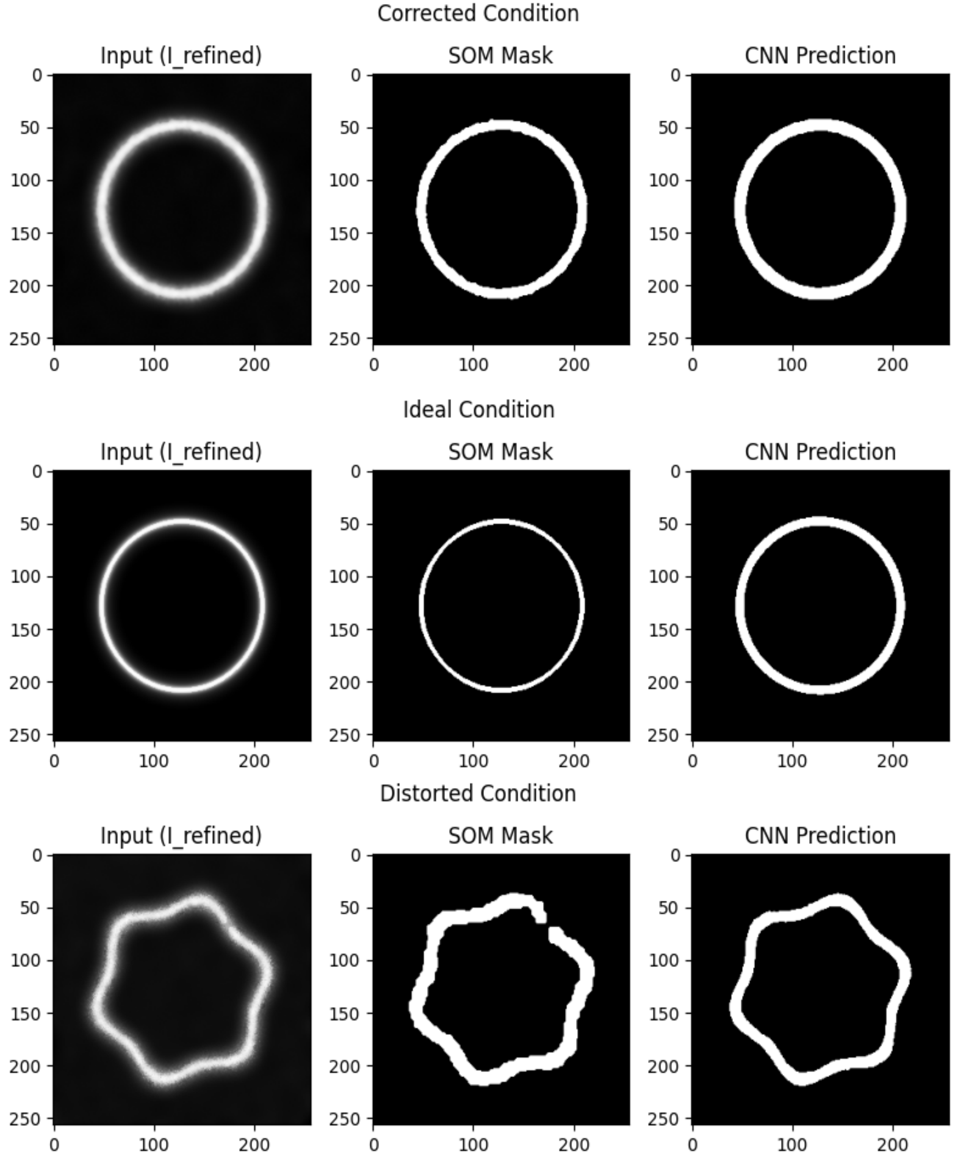
$$I_{blur} = \frac{1}{N}\sum(G_x^2 + G_y^2)$$

P: CNN prediction
G: SOM mask
μ_f, μ_b :mean intensities of foreground/background
σ_f, σ_b :corresponding standard deviations
N: number of pixels in the image
Gx,Gy: spatial gradients of G (edge strength)

ΔIoU consistency. ΔIoU → 0 (typically ≈ 0.1 within 3 teacher–student iterations) indicates the CNN preserves the SOM-defined topology across corrected/ideal/distorted inputs.

Takeaway. SOM supplies interpretable physics priors; the CNN reproduces and smooths them without manual labels.

Cross-Condition Generalization



All SPDC results shown are simulation-based reconstructions.

Backup – Simulation Design for Ghost and Quantum Imaging

Ghost Imaging

Concept
- Reconstructs an object *without directly imaging it*.
- Uses random speckle illumination and a single-pixel (bucket) detector.

Simulation Procedure
- Generate random speckle patterns $I_t(x)$.
- Compute bucket signals $B_t = \sum_x I_t(x) T(x)$.
- Recover object by correlation
  $G(x) = \langle (B_t - \bar{B}) I_t(x) \rangle_t$
- Tests algorithm robustness to noise and limited sampling conditions.

Quantum (SPDC) Correlation Imaging

Concept
- Uses *entangled photon pairs* obeying momentum conservation
  $\mathbf{k}_p = \mathbf{k}_s + \mathbf{k}_i$.
- Far-field correlations form the **photon-pair ring**.

Simulation Procedure
- Sample photon momenta on ring radius $k_\perp$.
- Add optical distortion (aberration / misalignment).
- Generate ideal, distorted, and corrected cases.

Purpose
- Validate that the SOM–CNN pipeline preserves the intrinsic correlation topology under distortion and correction.

These two simulated regimes bridge classical and quantum limits of correlation-based imaging, forming the testbed for SOM–CNN learning. Both simulations provide physics-consistent data for validating unsupervised reconstruction methods before integration with CHX photon-event data.

Backup – ΔIoU Computation and Convergence Criteria

A. Teacher Initialization (SOM Stage)

- Start from *Corrected* condition images.
- Extract 9D features → reduce to 6D via PCA → cluster using SOM.
- Obtain pseudo-labels G_{corr} without manual annotation.
- Transfer the same SOM weights to *Ideal* and *Distorted* conditions → G_{ideal}, G_{dist}.

B. Student Learning (CNN Stage)

- Use (I_{corr}, G_{corr}) to train the CNN.
- CNN predicts segmentation masks for all three conditions: $P_{corr}, P_{ideal}, P_{dist}$.
- The CNN aims to reproduce and smooth the SOM's topology.

Both ΔIoU metrics confirm that the CNN internalizes the SOM-defined topology and maintains cross-condition consistency across *ideal*, *distorted*, and *corrected* photon-pair datasets.

C. ΔIoU Metrics

1.Self-Consistency (within iteration):

$$\Delta IoU_{iter} = | IoU^{(t)} - IoU^{(t-1)} |$$

CNN retraining continues until
$\Delta IoU_{iter} < 0.01$,
indicating convergence between teacher (SOM) and student (CNN).

2.Cross-Condition Consistency:

$$\Delta IoU_{cond} = \frac{1}{2}(| IoU_{ideal} - IoU_{corr} | + | IoU_{dist} - IoU_{corr} |)$$

When $\Delta IoU_{cond} \rightarrow 0$,CNN predictions remain consistent under distortion and correction.

D. Practical Implementation

- Use *Corrected* SOM masks as teacher labels; merge *Ideal* and *Distorted* predictions with high CNN confidence (p > 0.9) into retraining data.
- Apply slightly lower segmentation thresholds (e.g., 0.45) on *Distorted* cases to maintain connected topology.
- Typically, 2–3 teacher–student iterations reduce $\Delta IoU_{iter} \approx 0$ and $\Delta IoU_{cond} \lesssim 0.1$.

Backup – Cross-Domain Applicability and Generalization

A. Generalizable Principle

- The SOM → CNN framework is physics-agnostic yet structure-preserving.
- It learns topological relationships from data without requiring manual labels.
- Applicable to any modality where signals exhibit correlated spatial or frequency patterns.

B. Representative Extensions

- **Bragg Coherent Diffraction Imaging (CDI):** Phase retrieval from coherent diffraction patterns with sparse data.
- **Structural Health Monitoring (SHM):** Tracking crack growth and damage topology from field images or videos.
- **Optical / Speckle Imaging:** Low-dose biomedical or materials imaging under random illumination.

C. Key Advantages

- Unifies unsupervised learning and physics constraints across domains.
- Reduces label and data requirements by ≈ order of magnitude.
- Provides interpretable latent representations linked to physical features (e.g., strain fields, wavefront phase).

D. Takeaway

A single physics-guided framework that extends from quantum and X-ray imaging to real-world experimental diagnostics, bridging materials, mechanics, and photon science.