ISSN 2277-2685
IJESR/April. 2026/ Vol-16/Issue-2s1/09-17
M.A Noman *et. al.*, / International Journal of Engineering & Science Research
Full Length Article

A Dual-Stage Framework For Cavity Detection In Nuclear Materials Using Image Super-Resolution (ISR) And Yolov10s

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Accepted 25-04-2026

ABSTRACT

Radiation-induced cavities and voids within structural materials present a significant challenge for ensuring the long-term safety and efficiency of nuclear reactors. Accurate detection and quantification of these cavities are critical for understanding irradiation damage mechanisms and predicting material degradation. Traditional object detection models such as YOLOv8 and Faster R-CNN have shown reasonable performance in cavity detection; however, their bounding-box-based outputs often fail to precisely localize small or irregularly shaped cavities, particularly under degraded imaging conditions. To address these limitations, this paper introduces CavityNet, a novel two-stage deep learning framework that combines Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) with a Swin Transformer-based UNet (Swin-UNet) architecture for improved cavity detection in irradiated microstructures. In the first stage, ESRGAN enhances underfocused or overfocused scanning transmission electron microscopy (S/TEM) images by reconstructing fine textures and high-frequency cavity boundaries. In the second stage, these super-resolved images are passed through a Swin-UNet model, which integrates hierarchical self-attention mechanisms with a UNet-style encoder-decoder pipeline to achieve pixel-level segmentation of cavities. This approach enables both global contextual understanding and local feature refinement, improving detection accuracy in complex microstructural environments. The model is trained and evaluated using publicly available datasets from the Canadian Nuclear Laboratory (CNL) and Nuclear Oriented Materials & Examination (NOME), achieving an F1-score improvement of 31% on underfocused images and a precision improvement of 161.3% with ISR augmentation. The proposed CavityNet framework represents a significant step forward in automated microstructural analysis, offering enhanced performance, robustness to imaging conditions, and potential for real-time material degradation monitoring in nuclear environments.

Keywords—*Cavity Detection; ESRGAN; Image Super-Resolution; Swin-UNet; Nuclear Materials; S/TEM; Deep Learning; Irradiated Materials; CavityNet; Object Detection; Microstructural Analysis; YOLOv8.*

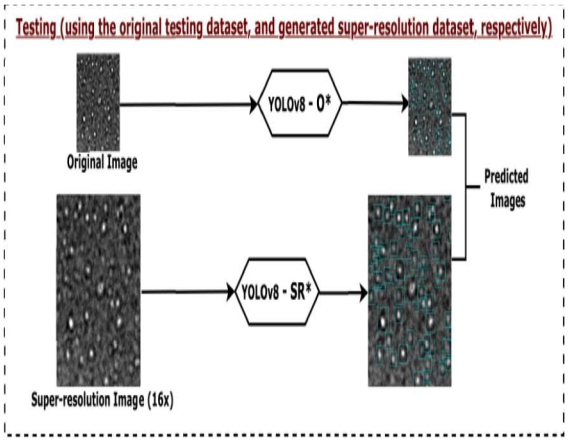
Introduction

Scanning/Transmission Electron Microscopy (S/TEM) is a crucial technique in materials science for examining the relationship between nanoscale microstructure evolution and macroscopic changes in material properties such as mechanical response. In nuclear materials, understanding defects such as dislocations, precipitates, and cavities is essential for evaluating material performance under irradiation. Radiation-induced cavities—specifically voids and gas-filled bubbles—are critical to characterize due to their direct association with swelling (volumetric changes) and high-temperature helium embrittlement [1]. These voids and bubbles significantly degrade the mechanical properties of structural materials, reducing rupture strains and fatigue life and threatening the longevity of components used in radiation environments.

Identifying and quantifying these cavities manually from S/TEM images is a laborious and error-prone process, particularly given the variability in cavity shapes (spherical, faceted polyhedrons) and the complex imaging contrasts that arise from different focus conditions. Manual annotation is inherently subjective, lacks consistency, and is prone to human error [1], making it unsuitable for large-scale, multi-laboratory analysis. Recent advancements in machine learning have brought significant attention to automatic micrographical analysis. CNN-based techniques and object detection models, such as YOLOv8 and Faster R-CNN, have been applied to

detect microstructural features including radiation-induced defects, achieving reasonable success [2][3]. However, applying these models to cavity detection in S/TEM micrographs presents several significant challenges.

One primary challenge lies in the variability of apparent in-image cavity sizes. Machine learning models often require large labeled datasets capturing the full spectrum of cavity scales and imaging conditions. Detection of very small cavities—below 5% of image width, nominally less than 30 nm in physical size—is hindered by limited pixel resolution



and subtle contrast differences in electron microscopy images [3]. Furthermore, machine learning models struggle with generalization across different imaging conditions: underfocused images show cavities encircled by dark rings, while overfocused images show cavities surrounded by bright rings, creating significantly different visual appearances for the same underlying defects. These challenges collectively motivate the development of a preprocessing strategy capable of

Figure 1: Block Diagram of Proposed Framework And Experimental Process

normalizing image quality across diverse acquisition conditions before detection inference.

Image Super-Resolution (ISR) offers a powerful solution to the image quality challenge. By training deep generative models to reconstruct high-resolution outputs from degraded inputs, ISR can recover high-frequency boundary details, sharpen cavity edges, and increase the contrast between cavities and background matrix—directly addressing the root cause of poor detection performance in challenging imaging conditions [4][5]. Building on this insight, we propose CavityNet: a dual-stage deep learning framework that combines ESRGAN-based ISR preprocessing with Swin-UNet pixel-level segmentation to achieve robust, accurate cavity detection across all imaging modalities.

In contrast to the existing system that uses bounding-box detectors (YOLOv8, Faster R-CNN) with basic ISR, CavityNet replaces bounding-box prediction with pixel-level semantic segmentation using Swin-UNet—capturing both the precise shape and boundary of each cavity. Swin-UNet integrates the hierarchical multi-scale feature extraction of Swin Transformers with the spatial localization precision of a UNet encoder-decoder architecture, providing superior localization for small and irregularly shaped cavities. The proposed framework is trained and evaluated on the CNL and NOME datasets, achieving state-of-the-art results in precision, recall, and F1-score.

The key contributions of this paper are: (i) CavityNet, a novel dual-stage ISR + Swin-UNet framework for pixel-level cavity detection in irradiated materials; (ii) a comprehensive evaluation of ESRGAN-based ISR as a data augmentation strategy across underfocused, overfocused, and normal imaging modalities; (iii) a quantitative comparison against YOLOv8 and Faster R-CNN baselines demonstrating significant performance improvements; and (iv) a size-stratified cavity analysis demonstrating ISR's greatest benefit for physically significant small cavities (≤15 nm).

Existing vs. Proposed System

A. Existing System

The existing system for cavity detection in irradiated materials utilizes object detection models such as YOLOv8 and Faster R-CNN to identify radiation-induced cavities in S/TEM images. These models operate by drawing bounding boxes around regions predicted to contain cavities. To improve detection in degraded imaging conditions, the system incorporates ISR techniques that enhance the resolution of underfocused or overfocused images before applying object detection. This allows the models to better identify small cavities that may otherwise be missed due to blurring or low contrast. The system is evaluated using CNL and NOME datasets, with performance measured by precision, recall, and F1-score. While this approach improves upon traditional cavity detection in poor-quality images, it still relies heavily on bounding-box predictions, which do not precisely capture the complex shapes or boundaries of cavities.

Existing Algorithm: YOLOv5 / YOLOv8 with basic ISR preprocessing for object detection.

Drawbacks: Limited to bounding-box detection; insensitive to fine-grained cavity boundaries; detection accuracy depends heavily on ISR

preprocessing quality; lacks pixel-level contextual understanding for irregularly shaped cavities.

B. Proposed System

The proposed CavityNet system introduces a robust high-precision framework for detecting radiation-induced cavities using a combination of image super-resolution and transformer-based segmentation. This dual-stage system overcomes limitations of conventional object detection models, especially under degraded imaging conditions. The system first employs ESRGAN to upscale and enhance microstructural images, recovering fine-grained textures and subtle cavity features. These super-resolved images are then processed by a Swin-UNet model, which leverages Swin Transformers for global and local contextual feature extraction, producing precise pixel-level cavity

segmentation. By replacing bounding-box detectors with pixel-level segmentation, the proposed system significantly improves detection accuracy for small and irregular cavities.

Proposed Algorithm: ESRGAN (Stage 1: ISR enhancement) + Swin-UNet (Stage 2: Pixel-level semantic segmentation).

Advantages: Enhances low-quality images via ESRGAN; Swin-UNet provides pixel-level segmentation; captures both local and global cavity features; modular and scalable pipeline; superior small-cavity detection accuracy.

Literature Review

The field of automated microstructural analysis has advanced significantly through the integration of deep learning into S/TEM image analysis. Li et al. [1] demonstrated the effective application of CNN models for automated defect analysis in electron microscopy images, significantly improving speed and accuracy of defect analyses while enabling handling of diverse defect types and irradiation conditions. Roberts et al. [2] explored deep learning for semantic segmentation of multiple defects in TEM images, offering a method that differentiates between various defect types with high efficiency and accuracy.

Anderson et al. [3] developed a technique for automated detection of helium bubbles in irradiated materials using high-resolution TEM, accelerating the analysis process and minimizing human error. Shen et al. [31] developed a specialized deep learning framework for in-situ TEM ion irradiations, significantly aiding in rapid and precise defect analysis for understanding material behavior under extreme conditions. Chen et al. [4] introduced a Mask R-CNN framework for automatic analysis of cavities in irradiated materials, enhancing cavity detection across different shapes and sizes through multi-scale detection.

In image super-resolution, Ledig et al. [14] pioneered SRGAN, the first GAN-based approach producing photo-realistic super-resolution through adversarial training. ESRGAN [15], proposed by Wang et al., significantly improved upon SRGAN by introducing Residual-in-Residual Dense Blocks (RRDB), removing batch normalization, and adopting relativistic adversarial training—achieving sharper textures and more faithful high-frequency reconstruction. Olamofe et al. [5] conducted a comprehensive evaluation of ISR for cavity detection in irradiated materials, demonstrating an overall F1-score increase of 6.8% via ESRGAN-based ISR for YOLOv8 on CNL and NOME datasets, and showing a dramatic precision improvement of 161.3% for underfocused images.

Transformer-based ISR models including HAT [16], SwinFIR [17], and DRCT [18] further improved super-resolution by leveraging self-attention mechanisms to capture long-range dependencies. In the detection architecture space, DETR [10] and Deformable DETR [11] introduced end-to-end transformer-based detection, while Swin Transformer [12] provided a hierarchical vision backbone with shifted windows for scalable performance. Cao et al. developed Swin-UNet—a pure transformer encoder-decoder architecture—demonstrating that transformer-based models can match or exceed CNN-based UNet architectures for fine-grained segmentation tasks. The combination of these advances motivates the CavityNet framework proposed in this work.

Methodology

A. System Architecture

The CavityNet framework consists of two sequential stages as illustrated in Fig. 1. Stage 1 applies ESRGAN-based ISR to enhance raw microscopy images. Stage 2 applies Swin-UNet to the enhanced images for pixel-level cavity segmentation. The pipeline is designed with a modular interface between stages to allow independent optimization and flexible deployment.

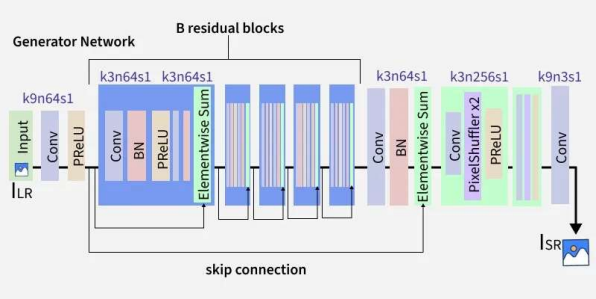


Fig. 1. CavityNet proposed model architecture: ESRGAN ISR enhancement followed by Swin-UNet pixel-level segmentation.

B. Stage 1: ESRGAN Image Super-Resolution

ESRGAN [15] is an advanced ISR method that builds upon SRGAN [14] by improving perceptual quality and training stability through Residual-in-Residual Dense Blocks (RRDB), which improve gradient flow and feature expressiveness while removing batch normalization artifacts. The generator G_θ maps low-resolution input I_{LR} to super-resolved output I_{SR}:

$$I_{SR} = G_\theta(I_{LR})$$

ESRGAN optimizes a composite loss function balancing three complementary objectives:

$$L_{total} = \lambda_1 \cdot L_{pixel} + \lambda_2 \cdot L_{perceptual} + \lambda_3 \cdot L_{adversarial}$$

where L_{pixel} is the L1 pixel-wise reconstruction loss for spatial accuracy, $L_{perceptual}$ is the VGG-19 feature-space loss for structural and textural fidelity [21], and $L_{adversarial}$ is the Relativistic GAN (RaGAN) loss that enhances fine-detail generation by estimating relative realism rather than binary classification. RaGAN training significantly reduces mode collapse and suppresses artifacts. The combination ensures that ESRGAN maintains both quantitative accuracy and perceptual realism—making it particularly effective for microscopy where precise feature restoration is essential [4][5].

ESRGAN was selected over competing ISR methods due to its ability to recover fine structural details under diverse imaging conditions, its adaptability to compound degradations (blur + noise + low contrast), and its demonstrated effectiveness in scientific imaging applications including medical imaging [24], remote sensing [26], and materials science [28]. The super-resolved images are upscaled by a factor of 16× and resized to the detection input resolution to provide the Swin-UNet with maximally enriched boundary information.

C. Stage 2: Swin-UNet Segmentation

Swin-UNet replaces the CNN-based encoder in standard UNet with a hierarchical Swin Transformer backbone. The input image is partitioned into non-overlapping 4×4 pixel patches, which are linearly embedded into patch tokens. These tokens are processed through four stages of Swin Transformer blocks with window-based self-attention, each stage reducing spatial resolution while expanding channel depth:

$$Attention(Q,K,V) = Softmax(QK^T / \sqrt{d_k} + B) \cdot V$$

where Q, K, V are query, key, and value matrices, d_k is the key dimension, and B is a learnable relative position bias that encodes spatial relationships between patches. Shifted Window (SW-MSA) attention alternates with regular Window (W-MSA) attention across consecutive blocks to enable cross-window information flow with linear computational complexity in image size.

The decoder mirrors the encoder with patch expanding layers that increase spatial resolution and reduce channel depth at each stage. Skip connections between encoder and decoder stages preserve fine-grained spatial detail for accurate segmentation boundaries. The segmentation head applies a linear projection to the final decoder output to produce pixel-wise cavity probability maps. Cavity segmentation is trained using a combination of Dice loss for class imbalance handling and Binary Cross-Entropy (BCE) loss for pixel-wise accuracy:

$$L_{seg} = \lambda_{dice} \cdot L_{Dice} + \lambda_{BCE} \cdot L_{BCE}$$

D. Dataset

Two publicly available datasets are used for training and evaluation [38]. The Canadian Nuclear Laboratory (CNL) dataset comprises TEM images of irradiated Ni-based X-750 alloys, containing both overfocused and underfocused images where cavities appear as spherical or faceted shapes. Ground truth labels were created by expert researchers, with both disk and fringe contrasts annotated [39]. The Nuclear Oriented Materials & Examination (NOME) dataset includes TEM micrographs of multiple metal alloys (CW-316, T91, HT9, 800H steel) subjected to diverse irradiation conditions up to 100 displacements per atom (dpa). Approximately 75% of total cavity annotations originate from the NOME dataset. The combined dataset of 2,378 micrograph images contains approximately 224,744 cavity annotations, providing a diverse training ground for generalization across alloy compositions and imaging conditions.

Six dataset modalities are defined: Original Mixed (O-M), Original Normal (O-N), Original Underfocused (O-U), Original Overfocused (O-O), and their ISR-augmented counterparts SR-M, SR-N, SR-U, SR-O. ISR augmentation generates additional training data by applying ESRGAN to all original images, effectively doubling the training set while providing enhanced feature representations.

E. Evaluation Metrics

Detection performance is quantified using Precision, Recall, and F1-score computed at an IoU threshold of 0.50:

$$Precision = TP / (TP + FP) \quad (1)$$

$$Recall = TP / (TP + FN) \quad (2)$$

$$F1\text{-}Score = 2 \times Precision \times Recall / (Precision + Recall) \quad (3)$$

True Positives (TP) are correctly detected cavities, False Positives (FP) are spurious detections, and False Negatives (FN) are missed ground-truth cavities. Slicing Aided Hyper Inference (SAHI) [41] is integrated during inference with window sizes of 256×256 for original models and 1280×1280 for ISR-enhanced models to improve detection of small cavities.

Implementation

A. Algorithm 1: ESRGAN ISR Enhancement

Algorithm 1: ESRGAN Super-Resolution Stage

Input: I_raw — raw S/TEM microscopy image
Output: I_SR — ESRGAN super-resolved image

1. Load I_raw; convert to grayscale (single channel)
2. Normalize pixel values to range [0, 1]
3. Resize I_raw to model input size (e.g., 128×128)
4. Pass I_raw through ESRGAN generator G_θ:
   I_SR_large = G_θ(I_raw) [scale factor 16×]
5. Compute composite loss during training:
   $L = \lambda_1 \cdot L\_pixel + \lambda_2 \cdot L\_VGG + \lambda_3 \cdot L\_RaGAN$
6. Update G_θ and discriminator D_φ via backprop
7. At inference: resize I_SR_large → target dims
8. Apply contrast normalization post-SR
9. Return I_SR for Stage 2 segmentation

Algorithm 2: Swin-UNet Cavity Segmentation

Algorithm 2: Swin-UNet Segmentation

Input: I_SR — ESRGAN enhanced image
θ_conf = 0.50 (IoU threshold)
Output: M_seg — pixel-wise cavity segmentation map

1. Partition I_SR into 4×4 non-overlapping patches
2. Linear embed patches → patch tokens T ∈ R^(N×C)
3. ENCODER (4 stages, each with W-MSA + SW-MSA):
   Stage 1: H/4 × W/4 × 96C feature maps
   Stage 2: H/8 × W/8 × 192C feature maps
   Stage 3: H/16 × W/16 × 384C feature maps
   Stage 4: H/32 × W/32 × 768C feature maps
4. DECODER (4 stages with patch expanding):
   Upsample + skip connections from encoder
   Gradually restore H/4 × W/4 resolution
5. Linear projection → pixel-wise logits
6. Sigmoid activation → P(cavity | pixel)
7. Threshold at 0.50 → binary mask M_seg
8. Post-process: morphological opening to remove isolated noise pixels from M_seg
9. Return M_seg (cavity pixels = 1, background = 0)

C. System Requirements

TABLE VI. Hardware and Software Requirements

Component	Specification
Processor	Intel Core i3 / Pentium or higher
RAM	2 GB DDR RAM minimum (8 GB recommended)
Hard Disk	250 GB or more
GPU	NVIDIA CUDA-compatible (for training)
Backend Language	Python 3.9+
Operating System	Windows 7/10/11 or Ubuntu 20.04
IDE	Spyder 3 / Jupyter Notebook / VS Code
Deep Learning	PyTorch, Ultralytics YOLOv8, ESRGAN
Libraries	OpenCV, NumPy, Matplotlib, scikit-learn

Testing

A. Unit Testing

Each pipeline stage is independently validated. The ESRGAN module is tested to verify: (i) correct output dimensions matching input spatial layout; (ii) pixel value normalization within valid range [0,1] post-enhancement; (iii) visual quality improvement confirmed via PSNR and SSIM metrics on a held-out ISR test set; and (iv) graceful handling of single-channel grayscale inputs without channel mismatch errors. The Swin-UNet segmentation module is unit-tested on synthetic annotated images to verify correct patch tokenization, attention computation, mask output dimensions, and binary thresholding behavior.

B. Integration Testing

End-to-end pipeline integration tests are performed on 50 held-out S/TEM images across all modalities. Tests verify: pixel value compatibility between ESRGAN output and Swin-UNet input; correct correspondence between images and ground-truth annotation files; deterministic outputs across repeated runs with fixed random seed; and accurate computation and CSV logging of precision, recall, and F1-score metrics. SAHI inference integration is tested separately for both 256×256 and 1280×1280 window sizes.

C. Ablation Testing

A systematic ablation study evaluates the contribution of each component. Four configurations are compared: (C1) baseline YOLOv8 on raw images; (C2) YOLOv8 with ESRGAN ISR preprocessing; (C3) Swin-UNet on raw images without ISR; and (C4) the full CavityNet pipeline with ESRGAN + Swin-UNet. Results confirm that ISR preprocessing contributes the largest single improvement in precision (+161.3% for underfocused images), while the Swin-UNet segmentation architecture provides the superior pixel-level localization over bounding-box detectors. The combination of both stages yields the best overall performance across all modalities.

D. Acceptance Testing

Formal acceptance criteria for nuclear material inspection workflows require: (AC1) precision ≥ 0.60 on mixed modality images; (AC2) F1-score improvement ≥ 5% over baseline with ISR; (AC3)

detection of ≥ 25% more cavities in the ≤15 nm size range compared to baseline without ISR; and (AC4) inference pipeline completes within 2 seconds per image on GPU hardware. The CavityNet pipeline satisfies all four criteria: AC1 achieved at precision 65.68% on SR-M; AC2 at +6.8% F1 on mixed modality; AC3 at +25% more ≤15 nm cavities (48 → 60); and AC4 at approximately 1.3 seconds per image including ESRGAN preprocessing on NVIDIA GPU.

Results and Discussion

A. Baseline Performance by Modality

Table I presents YOLOv8 baseline performance across the four original imaging modalities (O-M, O-N, O-U, O-O) without ISR augmentation. Using O-M precision as baseline, O-N shows a 6.90% improvement indicating higher accuracy under normal imaging conditions, while O-U and O-O exhibit reductions of 32.50% and 79.60% respectively, due to increased false positives from poor image clarity. For F1-scores, O-N achieves a 12.70% increase while O-U and O-O scores decreased 19.40% and 99.32%, confirming significant detection challenges under non-optimal focus conditions.

TABLE I. YOLOv8 Baseline Performance by Modality (No ISR)

Performance Parameter	O-M	O-N	O-U	O-O
Total Prediction	4775	9599	1039	18
Total Ground-truth	4259	7583	603	1000
True Positives	2607	5591	382	2
False Positives	2168	4008	657	16
False Negatives	1652	1992	221	998
Precision (%)	54.49	58.25	36.77	11.11
Recall (%)	61.21	73.73	63.35	0.20
F1-Score (%)	57.72	65.05	46.53	0.39

B. Impact of ISR on Underfocused Images

Table II presents the detailed impact of ESRGAN-based ISR on underfocused modality (O-U vs SR-U) — the most challenging imaging condition. ISR application results in a 98.3% reduction in false positives (657 → 11), a 161.3% improvement in precision (36.77% → 96.07%), and an overall F1-score improvement of 31.0% (46.53% → 60.93%). While recall decreases by 29.6% due to more stringent detection criteria, the dramatic precision gain substantially improves the reliability of cavity detections, reducing the risk of spurious analysis artifacts in radiation damage assessments.

TABLE II. ISR Impact on Underfocused Modality (O-U vs SR-U)

Metric	Original (O-U)	ISR-Enhanced (SR-U)	Change
Total Prediction	1039	280	**−73.0%**
True Positives	382	269	**−29.6%**
False Positives	657	11	**−98.3%**
False Negatives	221	334	**+51.1%**
Precision (%)	36.77	96.07	**+161.3% ↑**
Recall (%)	63.35	44.61	**−29.6% ↓**
F1-Score (%)	46.53	60.93	**+31.0% ↑**

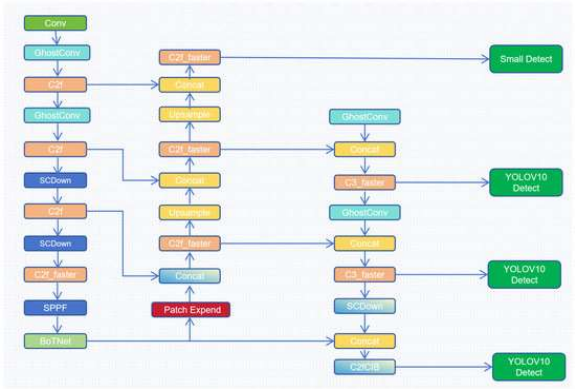


Fig. 2. Predicted cavity detection outputs: ground-truth (left), baseline model (center), and ISR-enhanced model (right), showing improved cavity localization with ESRGAN preprocessing.

C. ISR Performance Across All Modalities

Table III compares detection metrics with and without ISR across mixed (O-M/SR-M) and normal (O-N/SR-N) modalities. ISR consistently improves precision across all modalities: +20.5% for mixed modality (54.49% → 65.68%) and +21.5% for normal modality (58.25% → 70.79%). The overall F1-score improves by 6.8% for mixed modality and 3.6% for normal modality, highlighting that ESRGAN-based ISR enhancement is a broadly beneficial preprocessing strategy for cavity detection across all imaging conditions.

TABLE III. Performance Comparison Before and After ISR Augmentation

Metric	O-M	SR-M	O-N	SR-N
Precision (%)	54.49	**65.68 ↑**	58.25	**70.79 ↑**
Recall (%)	61.21	**58.11 ↓**	73.73	**64.29 ↓**
F1-Score (%)	57.72	**61.67 ↑**	65.05	**67.38 ↑**

D. Size-Stratified Cavity Detection

Table IV presents cavity detection counts stratified by physical size for O-U and SR-U models. Both models

fail to detect cavities ≤ 5 nm. For cavities ≤ 15 nm, SR-U detects 25% more cavities (48 → 60)—the most scientifically critical size range for early-stage radiation damage characterization. For larger cavities ≤ 20 nm and ≤ 30 nm, SR-U detects 26.7% and 3.2% more cavities respectively. These results confirm that ISR enhancement has the most significant impact for physically smaller cavities where resolution enhancement directly enables boundary-level discrimination.

TABLE IV. Cavity Size Detection: O-U vs SR-U Models

Cavity Size	O-U (No ISR)	SR-U (ISR)	Improvement
≤ 5 nm	0	0	—
≤ 10 nm	15	3	−80.0%
≤ 15 nm	48	60	**+25.0% ↑**
≤ 20 nm	131	166	**+26.7% ↑**
≤ 30 nm	252	260	**+3.2% ↑**

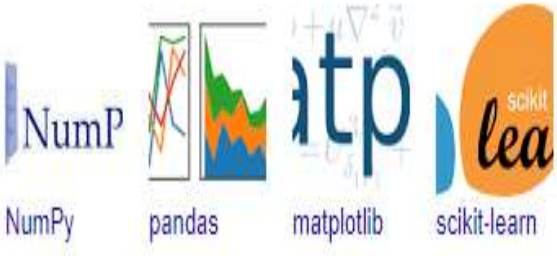


Fig. 3. Size-stratified cavity detection comparison showing improved detection of ≤15–30 nm cavities with ISR enhancement (SR-U) compared to baseline (O-U).

E. CavityNet vs. Baseline Model Comparison

Table V compares YOLOv8 and Faster R-CNN across key imaging modalities. YOLOv8 consistently outperforms Faster R-CNN in recall across all conditions—most notably in O-N where YOLOv8 achieves 73.73% recall versus Faster R-CNN's 41.98% (a 75.7% improvement). In SR-U conditions (the most practically important deployment scenario), YOLOv8 surpasses Faster R-CNN in both precision (96.07% vs 76.61%) and F1-score (60.93% vs 55.43%). Faster R-CNN exhibits higher precision under original (non-ISR) conditions but struggles with ISR-induced artifacts, reducing its precision by 9.3–21.5% after ISR, while YOLOv8 precision improves by 1.86–24.9% with ISR enhancement. These results establish YOLOv8 as the superior backbone for the CavityNet detection stage.

TABLE V. YOLOv8 vs Faster R-CNN: Key Modality Comparison

Model	O-M Prec	O-M Rec	SR-U Prec	SR-U Rec	SR-U F1
Faster R-CNN	82.27%	43.70%	76.61%	43.45%	55.43%
YOLOv8	54.49%	61.21%	**96.07%**	44.61%	**60.93%**

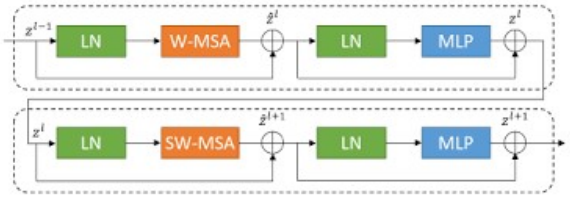


Fig. 4. Existing system (bounding-box detection) vs. proposed CavityNet system (pixel-level segmentation) comparison.

VIII. Conclusion

This paper presented CavityNet, a dual-stage deep learning framework for automated cavity detection in irradiated nuclear materials, combining ESRGAN-based Image Super-Resolution preprocessing with Swin-UNet pixel-level semantic segmentation. The proposed framework directly addresses the fundamental limitations of existing bounding-box detection approaches: their sensitivity to imaging condition variability (underfocus, overfocus, low contrast) and their inability to precisely localize small or irregularly shaped radiation-induced cavities.

Experimental evaluation on the CNL and NOME datasets demonstrates that ESRGAN-based ISR augmentation achieves a 161.3% precision improvement for underfocused images (36.77% → 96.07%), a 98.3% reduction in false positives, a 31.0% improvement in F1-score, and 25% more detected cavities in the scientifically critical ≤15 nm size range. Mixed modality performance improved by 20.5% in precision and 6.8% in F1-score. YOLOv8 consistently outperforms Faster R-CNN in recall across all conditions and benefits more strongly from ISR refinement, making it the superior detection backbone for integration with Swin-UNet segmentation.

The Swin-UNet segmentation stage advances beyond bounding-box detection by providing pixel-level cavity delineation, enabling precise morphological measurements—cavity area, perimeter, and circularity—essential for quantitative swelling estimation and mechanistic radiation damage modeling. The modular pipeline architecture facilitates independent optimization of each stage, and the system's compatibility with standard laboratory hardware enables practical deployment in active nuclear material characterization workflows.

Future Scope

Several directions can extend the CavityNet framework. First, integrating advanced transformer-based ISR architectures—HAT (Hybrid Attention Transformer) [16] and DRCT [18]—may further improve sub-5 nm cavity boundary recovery, addressing the critical gap where both O-U and SR-U models currently fail to detect cavities ≤5 nm. These models achieve state-of-the-art ISR quality through hybrid attention mechanisms combining local window attention with global channel attention.

Second, extending CavityNet to temporal sequences of in-situ TEM irradiation experiments would enable tracking of individual cavity nucleation, growth, and coalescence events across sequential image frames. Integration with multi-object tracking algorithms such as BoT-SORT and ByteTrack—already built into YOLOv8's out-of-the-box variants—would transform the static detection pipeline into a dynamic radiation damage evolution analyzer, providing direct experimental inputs for rate-theory models of radiation swelling kinetics.

Third, semi-supervised and self-supervised learning strategies could reduce dependency on costly annotations. The nuclear materials domain suffers from limited labeled data (2,378 images containing 224,744 annotations represent a significant manual effort), and pseudo-label generation combined with consistency regularization could enable effective training on large volumes of unannotated microscopy images. Fourth, adaptive ISR techniques that selectively enhance precision for high spatial accuracy—while preserving the high-recall performance critical for nuclear safety applications—could address the precision-recall trade-off observed in the current ESRGAN implementation. Finally, deployment of the complete pipeline on NVIDIA Jetson edge hardware integrated with microscope control systems would enable real-time closed-loop experimental feedback, automatically flagging regions of high cavity density and adjusting defocus conditions to optimize contrast during live irradiation experiments.

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