

# Automated Defect Detection in Aerospace Radiography Using a Domain-Generalized Transformer Machine Learning Model

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# Outline

- ❑ Introduction
- ❑ Aircraft NDI Inspection
- ❑ Digital Radiography (CR/DR)
- ❑ Machine Learning
- ❑ Proposed Method: CrackDETR
- ❑ Experimental results
- ❑ Summary and future work



# Aircraft Reliability, Quality Assurance, and Intelligent NDT

- ❑ Aircraft are engineered for long-term, failure-resistant operation under demanding conditions
- ❑ Structural integrity and durability are maintained through advanced materials, precision manufacturing
- ❑ Continuous inspection ensures sustained airworthiness throughout the aircraft's life cycle
- ❑ Aerospace industry enforces rigorous standards to guarantee flight-critical component reliability
- ❑ Nondestructive inspection processes are mandatory to verify product quality and detect defects early
- ❑ Preventive maintenance strategies ensure safety and mission readiness before defects reach critical size

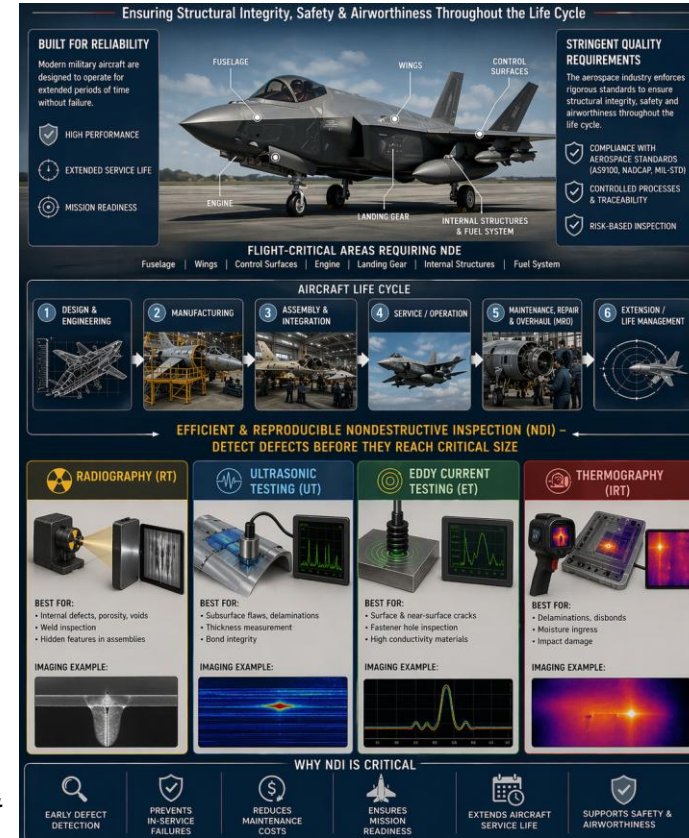
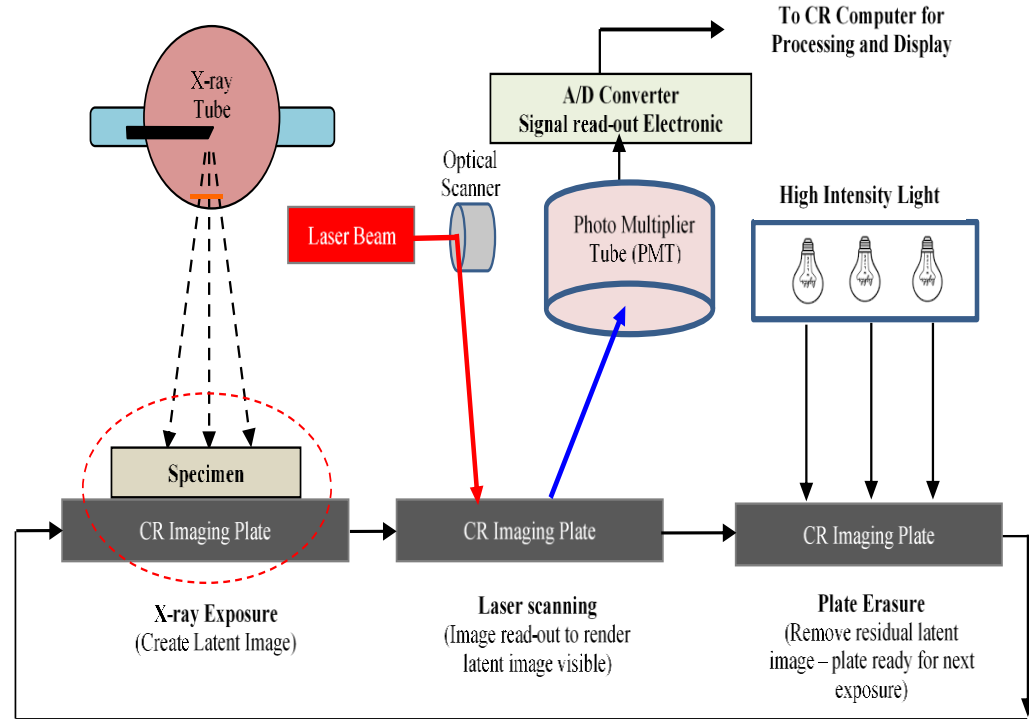


Figure: AI-assisted Aircraft NDE Concept

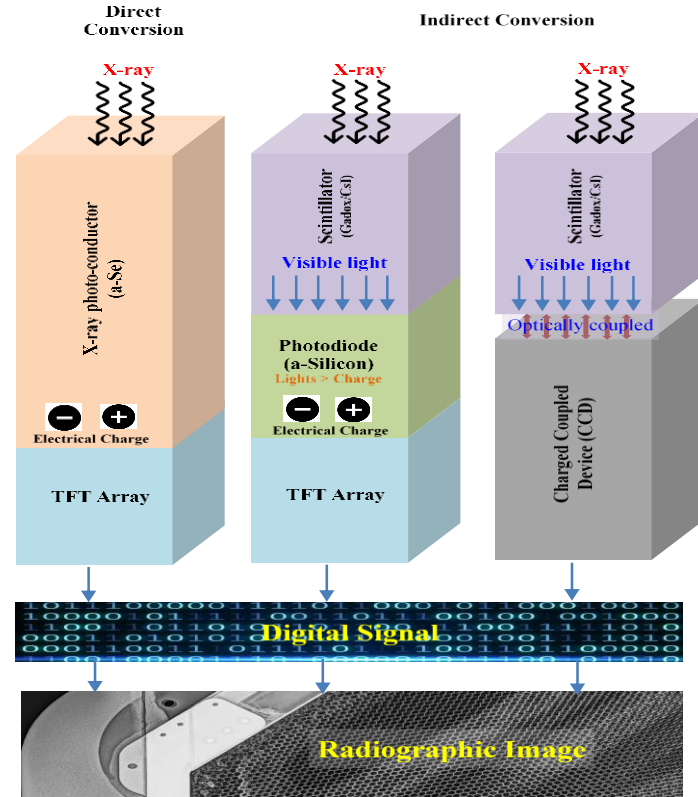
# Computed Radiography (CR) Workflow

- ❑ PSP plate in a cassette captures X-ray exposure and stores a latent image.
- ❑ CR reader scans the plate with a laser, releasing light (PSL) that is converted to a digital signal.
- ❑ ADC digitizes the signal to form the radiographic image.
- ❑ PSP plate is erased with bright light and reused; images are processed, stored, and shared digitally.



# Digital Radiography (DR, Digital Detector Array) Workflow

- ❑ Scintillator layer (CsI or GOS) converts X-rays to visible light, which is read by a photodiode/TFT pixel array.
- ❑ Electrical signals are digitized instantly, producing real-time radiographic images.
- ❑ Fully integrated detector enables fast acquisition, high resolution, and lower dose compared to CR.
- ❑ Supports immediate display, digital enhancement, and seamless archiving with no cassettes or processing.



# Radiography NDE in Aerospace Components *(in order of ease of detection)*

- ❑ Radiography NDE predominantly use in aircraft inspection
- ❑ Foreign object damage, Broken internal parts, component misalignment
- ❑ Water ingress, Damage in honeycomb, Core Damage and several damages in composite parts
- ❑ Fatigue Crack, crack growth detection

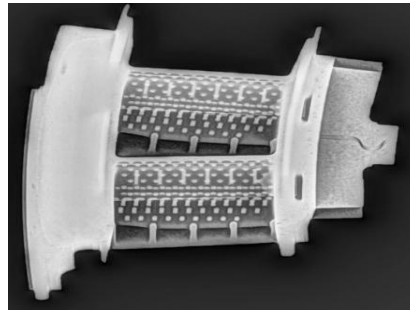
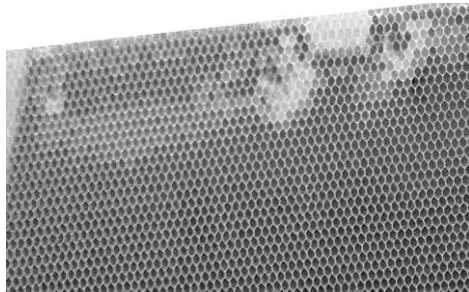
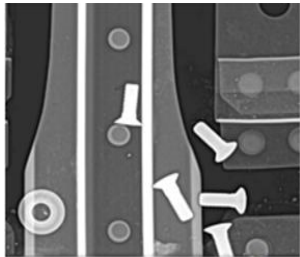
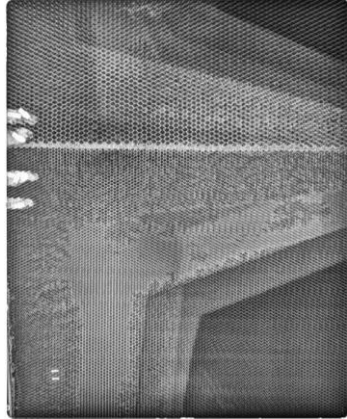


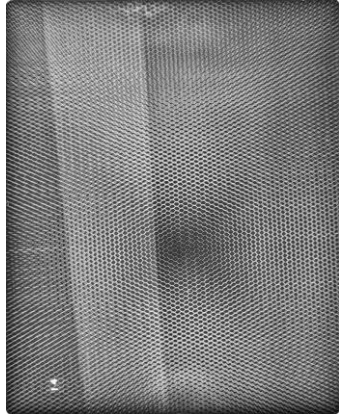
Figure: AI-assisted Radiography NDE in Aircraft

# Radiography NDE in Aerospace Components

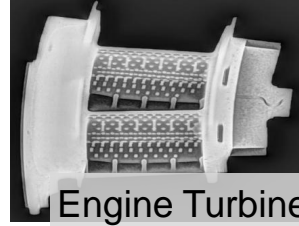
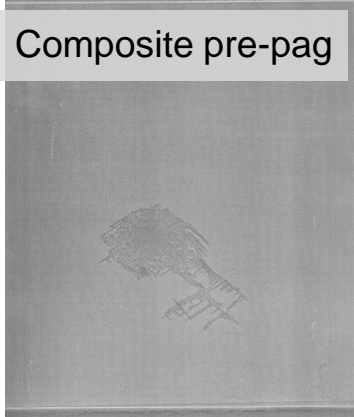
*(Case studies examples performed at NRC)*



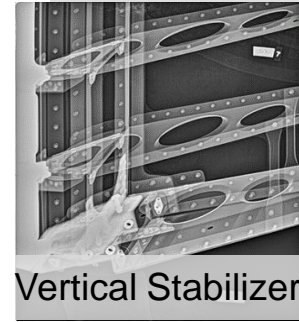
Pushed Fastener in Trailing Edge



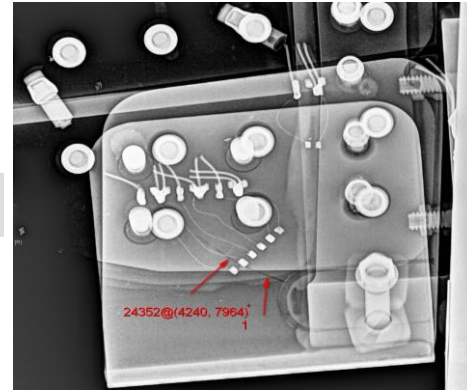
Trailing Edge Flap



Engine Turbine

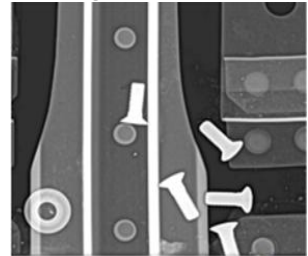


Vertical Stabilizer

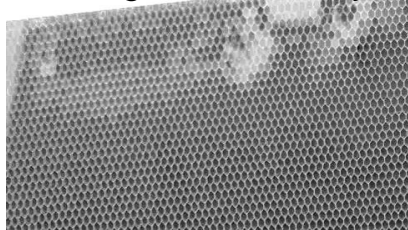


Crack at leading edge

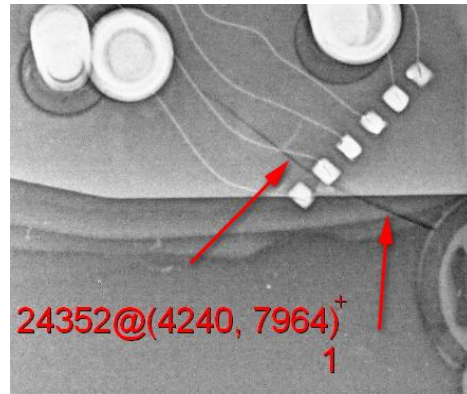
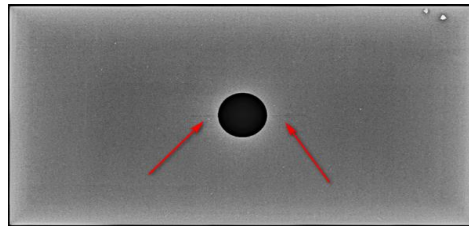
Foreign Object Damage



Water Ingress in Honeycomb



Crack from Bolt Hole



24352@(4240, 7964)<sup>+</sup>  
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# Digital Radiography NDE in Aerospace (Film, CR, DR)

## ❑ CR/DR has better “latitude” (Dynamic Range) than film

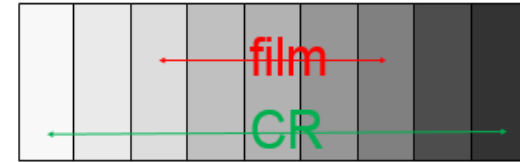
- ❖ Wider range of thicknesses/densities in a single exposure
- ❖ Single exposure can reveal both low-attenuation and high-attenuation regions without loss of diagnostic information

## ❑ Digital RT more sensitive to contrast changes

- ❖ Capability to “window/level” to visualize a contrast step
- ❖ Contrast sensitivity > film
- ❖ Subtle variations in material attenuation are more easily detected
- ❖ Improved contrast resolution enables clearer visualization of low-contrast defects

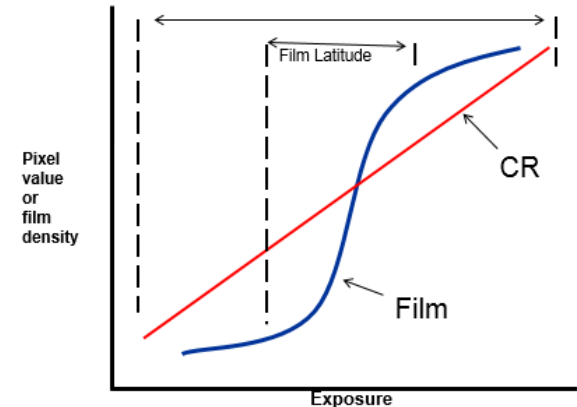
## ❑ Digital offers significant workflow and operational advantages

- ❖ Eliminate need for physical films, darkroom and chemical processing
- ❖ Faster inspection workflows, Simplified storage, sharing
- ❖ Support digital enhancement, Zoom, filtering, Window/level



1%                      2%                      3%                      4%

Digital Latitude



# Automated Defect Detection in Digital Radiography

## ❑ Digital Imaging and Intelligent Analysis

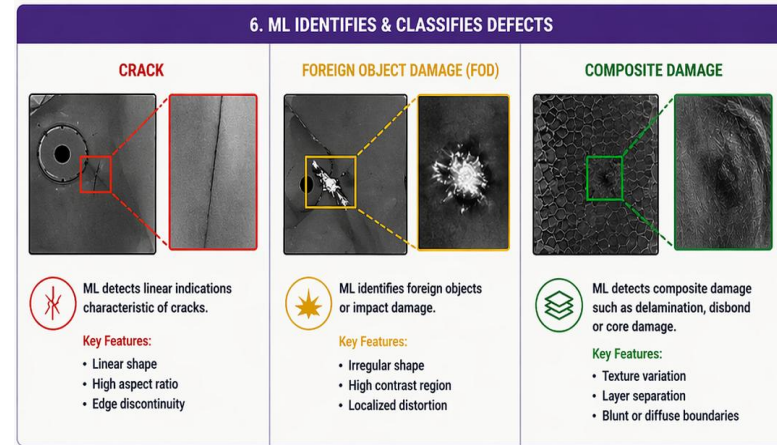
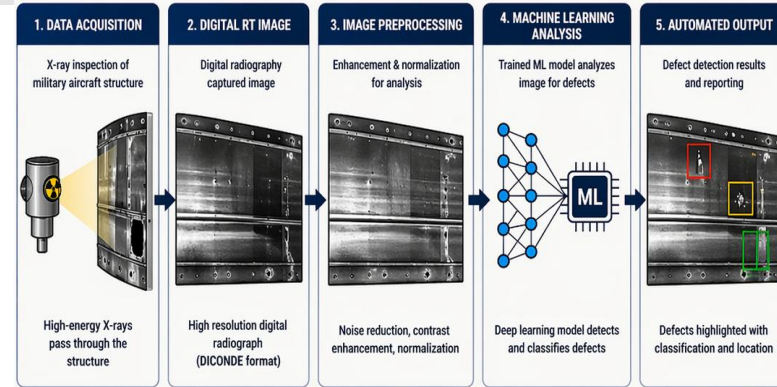
- ❖ ML and DL algorithms can analyze radiographic data directly
- ❖ Human interpretation is augmented by computational tools
- ❖ Some inspection tasks can now be fully automated for speed and consistency.

## ❑ Benefits for Aerospace NDT

- ❖ Improves defect detection accuracy and reduces false calls
- ❖ Processes large image volumes rapidly, increasing throughput
- ❖ Minimizes human variability and supports objective decision-making.

## ❑ Workflow Integration and Industry 4.0 Alignment

- ❖ Highlights regions of interest and supports inspector decisions
- ❖ Enables quantitative evaluation (POD, false-call metrics)
- ❖ Drives predictive quality control and process optimization



# Machine Learning-Based ADD: Key Challenges

## ❑ Data Limitations and Model Generalization

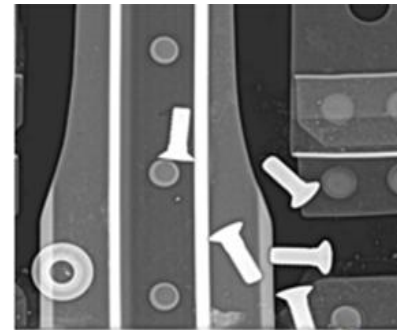
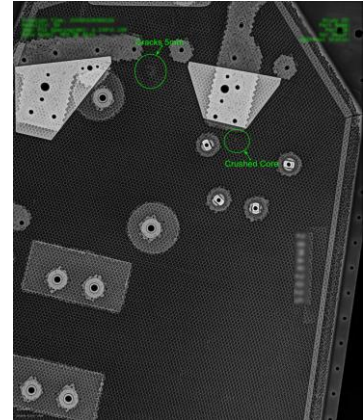
- ❖ Scarcity of high-quality, labeled radiographic training datasets
- ❖ Proprietary aerospace X-ray data and rare true defect samples
- ❖ Synthetic data often fails to replicate real radiographic complexity, limiting generalization.

## ❑ Imaging Variability and Domain Shifts

- ❖ Variations in material thickness, exposure, detector performance
- ❖ Low contrast and complex backgrounds hinder defect detection
- ❖ Fine-scale cracks and subtle defects remain difficult for general-purpose.

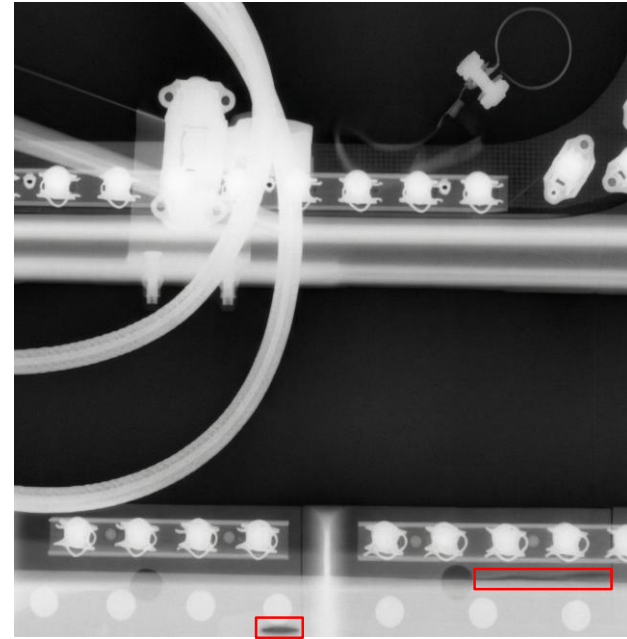
## ❑ Practical Deployment and Workflow Integration

- ❖ Real-time performance and low false calls required for deployment
- ❖ Seamless integration with existing NDT workflows, inspector trust are critical
- ❖ Regulatory validation, interpretability remain barriers to widespread adoption



# X-ray Crack Image Data Introduction

- ❑ Cracks in aerospace components appear as low-contrast, narrow features.
- ❑ X-ray radiography enables inspection of internal structures without disassembly or damage, making it ideal for in-service aerospace components.
- ❑ X-ray radiography struggles to reveal subtle cracks in complex backgrounds like composites or dense alloys.
- ❑ Manual inspection often misses cracks, especially when inspecting large volumes of parts.
- ❑ Deep learning-based models offer a promising solution, but crack detection poses unique challenges.



*Example of cracks in aerospace components revealed by X-ray imaging.*

# Challenges in M/DL for Cracks/Proposed Solution

## ❑ Lack of orientation awareness /Data Limitation

- ❖ Scarcity of high-quality, labeled radiographic training datasets
- ❖ Public datasets for real X-ray cracks are extremely limited

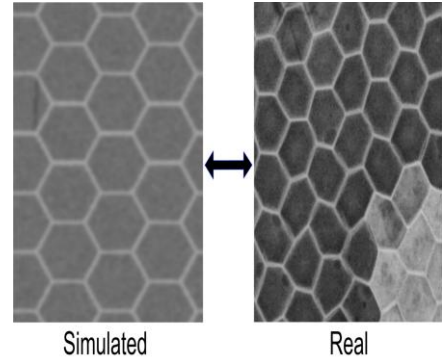
## ❑ Domain Shift

- ❖ Simulated data is often used to address the lack of real data, but synthetic images lack realistic noise, scattering, and lighting, as shown in right Figure

## ❑ CrackDETR is proposed for unified crack detection and segmentation, built on RT-DETR<sup>[1]</sup>. It has two key components:

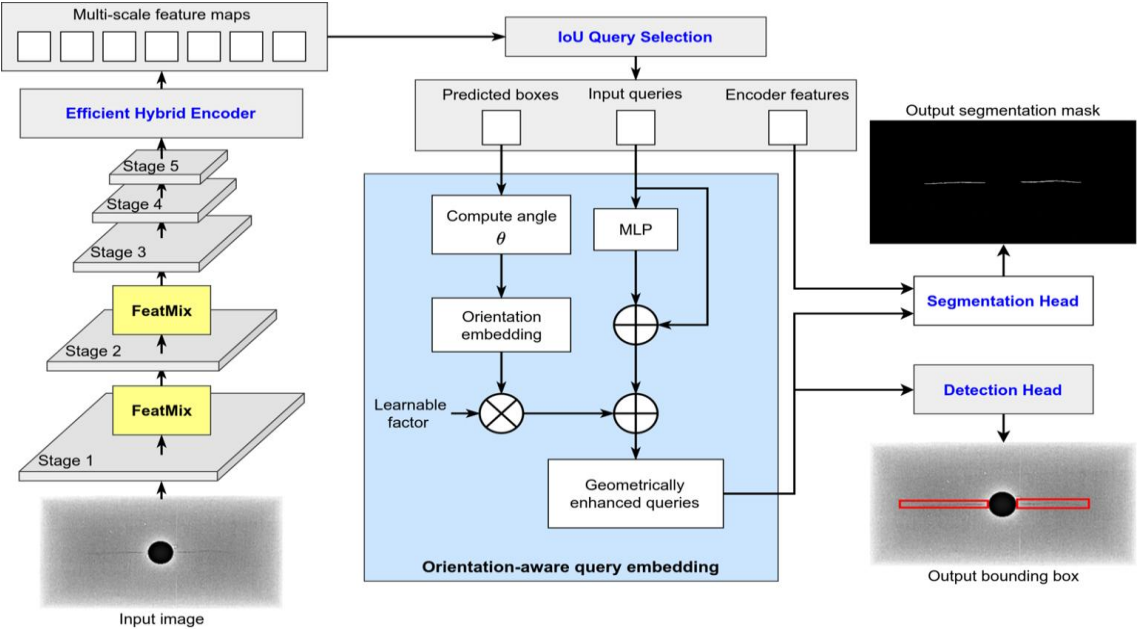
- ❖ To mitigate the simulation-to-real gap, a **FeatMix** module is introduced
- ❖ To address the lack of orientation awareness, an **orientation-aware query embedding** module is introduced

## ❑ An X-ray simulator is used for **synthetic data generation** to address the lack of real training data.



*Comparison of simulated and real data.*

# CrackDETER



Architecture of the proposed crack detection and segmentation model. Grey blocks are from RT-DETR.



# CrackDETER

## FeatMix module

FeatMix is a feature-level augmentation module designed to improve robustness against the synthetic-to-real domain shift.

- ❖ Takes feature maps from the backbone as input.
- ❖ Linearly interpolates the channel-wise mean and standard deviation between two samples within a batch.
- ❖ Rescales the normalized features with the mixed statistics, varying style while preserving semantic content.
- ❖ Forwards the style-augmented features to the next backbone stage.

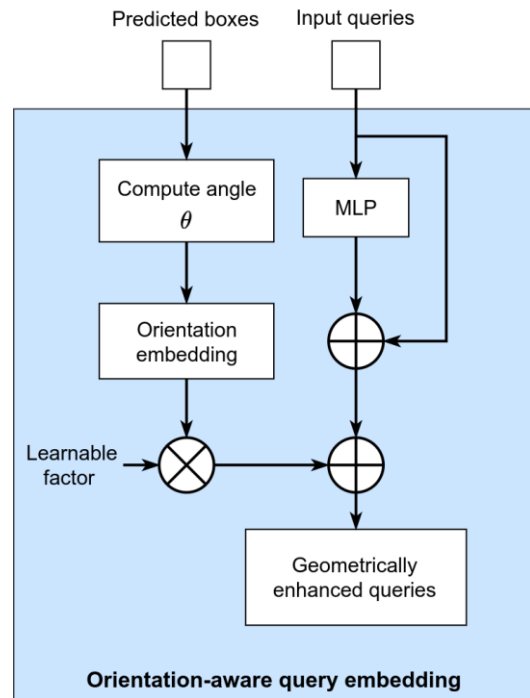


# CrackDETER

## Orientation-aware query embedding module

This module injects crack-direction priors into decoder queries to address the lack of orientation awareness in standard object detection models.

- ❖ The angle  $\theta$  of each predicted bounding box is computed and encoded into an orientation embedding, providing a directional cue.
- ❖ An MLP extracts a complementary orientation cue directly from query features, providing a fallback when the predicted box angle is unreliable.
- ❖ The two branches are fused with a learnable weighting factor and added to the decoder queries, producing geometrically enhanced queries passed to both the detection and segmentation heads.



Structure of the orientation-aware query embedding module. ● ● ●

# Experimental Results

## *Dataset*

Due to the lack of public X-ray crack datasets, simulated data is generated for training and validation, while real data is reserved for evaluating model generalization.

- **Simulated data:** generated using **BAM aRTist**<sup>[2]</sup>, a physics-based radiographic simulation tool.
  - Defect-free 3D models of representative aerospace structures (bolt holes, plain panels, and honeycomb panels) are created.
  - Synthetic crack geometries are generated and inserted via volumetric subtraction.
  - Data augmentation is applied, including Gaussian noise, speckle noise, affine transformations, and contrast variations.
  - Split: 3090 training / 380 validation / 380 testing samples.
- **Inspection data:** a small set of inspection radiographic scans (bolt-hole and honeycomb structures) is used for qualitative case studies to demonstrate generalization beyond simulation.



# Experimental Results

## *Evaluation metrics*

### □ Detection

- ❖  $mAP_{50:95}$ : mean Average Precision averaged over IoU thresholds from 0.5 to 0.95. This is the primary metric reflecting overall detection quality.
- ❖  $mAP_{50}$ : mean Average Precision at IoU threshold 0.5, measuring roughly localization.
- ❖  $mAP_{75}$ : mean Average Precision at IoU threshold 0.75, measuring stricter localization accuracy.

### □ Segmentation

- ❖ Dice: overlap between predicted and ground-truth crack masks, emphasizing correct crack pixels.
- ❖ IoU: intersection over union between predicted and ground-truth masks, penalizing both missed and false crack pixels.
- ❖ Accuracy: proportion of correctly classified pixels across the image.



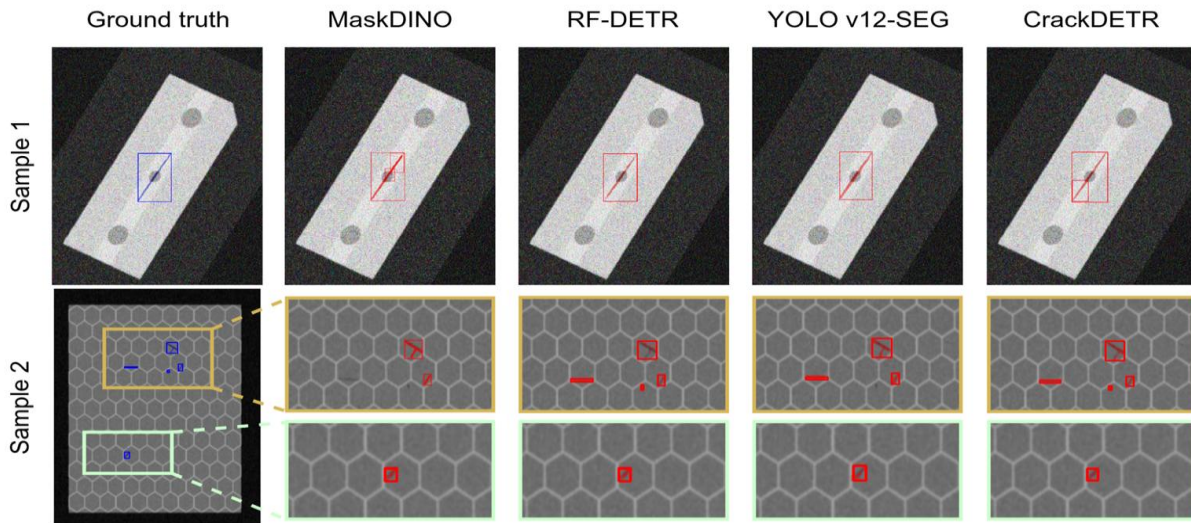
# Experimental Results

Table 1. **Quantitative comparison** of the proposed method and baseline models on the simulated crack dataset.

Model	Detection			Segmentation		
	mAP <sub>50:95</sub>	mAP <sub>50</sub>	mAP <sub>75</sub>	Dice	IoU	Accuracy
MaskDino <sup>[3]</sup>	0.572	0.909	0.663	0.638	0.469	0.990
RF-DETR <sup>[4]</sup>	0.672	0.953	0.736	0.706	0.546	<b>0.998</b>
Yolo v12-SEG <sup>[5]</sup>	0.602	0.902	0.626	0.570	0.399	<b>0.998</b>
CrackDETR	<b>0.687</b>	<b>0.960</b>	<b>0.759</b>	<b>0.804</b>	<b>0.675</b>	0.996

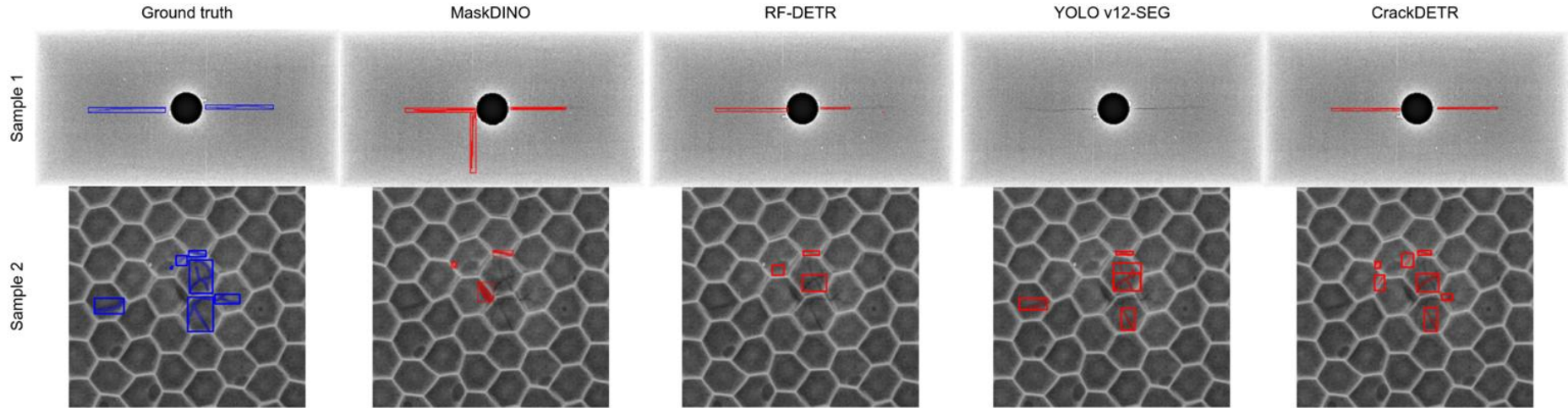


# Experimental Results



- ❑ On Sample 1, all models detect the crack, but CrackDETR produces tighter bounding boxes and more accurate segmentation masks that follow the crack direction.
- ❑ On Sample 2, baselines miss several small cracks or produce false detections, while CrackDETR successfully localizes all cracks with fewer false positives.

# Experimental Results



- ❑ All models show visible performance degradation on real data compared to simulated data, as real cracks exhibit irregular branching and non-uniform width.
- ❑ The proposed CrackDETR remains the most robust, producing the fewest missed cracks and false detections.

# Summary and Future Work

## Summary

- A physics-based synthetic data generation pipeline was developed to address **data scarcity**, modeling representative aerospace geometries and crack shapes.
- **FeatMix** was introduced to mitigate the **domain gap between simulated and real X-ray imaging** through feature-level style augmentation.
- An **orientation-aware query embedding** module was designed to address the **lack of orientation awareness in standard detectors**, improving localization of directional cracks.

## Future Work

- Extend the data generation framework to 3D simulation with physically realistic defect topologies, further enriching crack diversity and enabling volumetric inspection.
- Collect a larger real-world dataset to enable quantitative evaluation of generalization.



# References

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# Thank you!

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