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

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Abstract

Radiographic imaging remains a critical nondestructive inspection method for visualizing internal defects and ensuring the long-term structural integrity of aerospace components. As the industry transitions from film-based radiography to digital acquisition systems, inspection workflows increasingly benefit from faster imaging, improved consistency, and enhanced computational processing capabilities. At the same time, the decline in available nondestructive testing (NDT) personnel and the limitations of manual interpretation highlight the need for automated, machine-readable analysis tools that can reduce human-factor variability and support timely decision-making.

However, deploying machine learning for defect detection in radiographic images presents significant challenges. These include the scarcity of diverse, high-quality annotated datasets and the difficulty of achieving robust cross-domain generalization across different aircraft structures, materials, and imaging conditions. This paper provides an overview of current computed and digital radiography applications used in aerospace structural inspection. Case studies are included to illustrate the defect-visualization capabilities of digital radiography and to demonstrate its suitability for machine-learning based interpretation. To overcome the generalization challenge, a domain-generalized defect detection framework is introduced using a Real-Time Detection Transformer (RT-DETR) backbone. The model is designed using a combination of real radiographs and synthetic defect datasets generated through a physics-based simulation pipeline, enabling effective learning under limited annotation availability and improved generalization across domains. Experimental evaluations across multiple inspection scenarios indicate that the proposed approach improves generalization to previously unseen domains. The results further show notable gains in precision, recall, and mean average precision, underscoring its potential for integration into future aerospace NDT workflows.

Keywords: Machine Learning, Artificial Intelligence, Automatic Damage Detection