

Deep Learning-Driven X-ray Digital Tomosynthesis (DT) Imaging for Aerospace Composite Inspection

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Abstract. The structural integrity of aerospace-grade Glass Fiber Reinforced Polymer (GFRP) composites is critical, yet conventional non-destructive testing (NDT) methods often struggle to detect subsurface defects reliably due to poor signal-to-noise ratios, low contrast, and complex internal structures. To address these limitations, this study proposes a novel AI-driven framework that integrates low-power X-ray Digital Tomosynthesis (DT) imaging with state-of-the-art deep learning models for defect segmentation in composite materials. Specifically, two state-of-the-art instance segmentation models, YOLOv8 (You Only Look Once, version 8) and Detectron2, are employed to automatically segment flaws in the DT images of the composite specimens. A dedicated dataset of low-power X-ray DT scans of GFRP composite specimens with annotated defects was curated for training and evaluation. The segmentation performance of each model was quantitatively evaluated using metrics such as the Dice similarity coefficient and Intersection-over-Union (IoU), along with inference time measurements. Experimental results demonstrate that YOLOv8 processes images significantly faster (~6.9 ms per image) than Detectron2 (~10.3 ms), enabling near real-time analysis. Conversely, Detectron2 achieves a higher segmentation accuracy (Dice ~86% versus ~74% for YOLOv8), underscoring the trade-off between computational efficiency and segmentation precision. These findings validate the potential of combining low-power DT imaging with deep learning for high-fidelity defect identification, substantially improving the prospects for near real-time composite inspection. Future work will focus on further model optimization (e.g., via quantization and pruning) and the integration of this framework with autonomous robotic inspection systems, thereby extending the capabilities of AI-driven NDT in aerospace applications.

Keywords: Aerospace Composites, Image processing, Defect Segmentation, non-destructive testing, low power X-ray Digital Tomosynthesis imaging, Deep learning

1 Introduction

The aerospace industry increasingly relies on Glass Fiber Reinforced Polymer (GFRP) composites for their high strength-to-weight ratio and durability[1]. However, the complex internal structure can pose significant challenges for non-destructive testing (NDT). Defects such as delamination, cracks, and voids can be introduced during the

manufacturing process, and can serve as initiation points for crack propagation, thereby compromising safety and performance. Traditional NDT methods, including ultrasonic and high-power X-ray imaging currently require subjective visual interpretation of the images. These conventional techniques are time-consuming and are subject to errors, which could result in missing important defects or inclusions. [2], [3]

X-ray imaging has long been used for inspecting composite materials. However, manual interpretation as well as classical image processing techniques such as adaptive thresholding, edge detection, and morphological operations [4] can often fall short. These methods, while effective under controlled conditions, they require significant tuning of parameters and are limited in their ability to handle noise, inhomogeneous material properties, and the variability in defect appearance [5][6][7]. Consequently, there is a critical need for automated, data-driven inspection systems that can reliably identify defects within complex composite structures.

Recent advances in deep learning have revolutionized automated defect detection in NDT [8]. Convolutional neural networks (CNN) architectures such as U-Net [9] and ResNet [10] have shown capability in learning features directly from raw pixel data. Segmentation specific techniques such as U-Net and Mask R-CNN have shown promising results in defect localization and classification [11]. U-Net's encoder-decoder architecture, originally designed for biomedical image segmentation, has been successfully adapted for detecting cracks and delamination in industrial X-ray images [12] and ultrasonic data [13][14]. Similarly, the residual blocks in ResNet enhances defect detection in low-contrast composite materials [15]. Moreover, transfer learning which involves fine-tuning pre-trained models such as Mask R-CNN [16] on smaller, domain-specific datasets has proven effective in achieving high detection accuracy.

Building on these established methods, recent frameworks like YOLOv8 [17] Detectron2 [18] offer significant improvements over traditional architectures. YOLOv8, one of the recent evolutions in the YOLO series, provides an optimized detection pipeline that balances speed and accuracy, making it well suited for real-time applications. Its real-time instance segmentation framework for X-ray data has been adapted for various tasks [19], and transfer learning techniques have been employed to further improve its capability in detecting small defects [20]. Additionally, Detectron2, developed by Facebook AI Research, extends the capabilities of Mask R-CNN by offering a modular and highly customizable framework for precise instance segmentation. These advanced capabilities have been widely used in medical and industrial applications [21]. Although its applications in aerospace inspection are emerging, prior studies in medical imaging and other fields have demonstrated its effectiveness in segmenting complex structures [22][23]. Both frameworks demonstrate robustness in handling low-contrast and noisy X-ray images [24] [25], effectively addressing challenges such as overlapping defect signatures that frequently undermine conventional image processing techniques. Other recent advancements in deep learning, including transformer-based architectures and generative adversarial networks (GANs), which have further enhanced defect detection accuracy [26]. Despite these progressions, challenges remain in achieving robust performance across defect types and composite material heterogeneity, and optimizing AI models for real-time deployment is still an ongoing research endeavor. In the aerospace industry, application varies from the manufacturing stage setup, where

an early detection of defects at components and subassemblies level is crucial, to the aircraft in-service evaluation where the preventive maintenance and life extension of component plays a key role.

In this context, our research proposes an integrated imaging and deep learning framework for high-fidelity, non-invasive defect segmentation in aerospace GFRP composites. This framework is implemented as part of a twin-robot system employing 3D X-ray imaging to enhance aerospace inspection [27]. The process begins with systematic image acquisition at predefined angles and intervals, capturing the intricate internal structure of composite materials and generating a robust dataset that encapsulates subtle variations and potential defect signatures. We employ two state-of-the-art instance segmentation models YOLOv8 and Detectron2 to learn features from the X-ray slices. While Detectron2 offers precise segmentation based on the Mask R-CNN architecture, preliminary evaluations indicate that it may sometimes miss fine details. In contrast, YOLOv8 demonstrates superior performance in handling noisy, low-contrast images, achieving higher detection accuracy and significantly faster inference times essential for real-time inspection applications.

By systematically generating and preprocessing high-quality DT datasets and employing these cutting-edge deep learning models, our integrated framework addresses some limitations of traditional NDT methods especially in improving analysis time, error detection and prompt decision making. The combined approach not only enhances defect detection accuracy but also paves the way for more robust, efficient, and automated inspection systems.

The major contribution in this work include.

- Generate and preprocess GFRP composites image slices datasets with Xray device
- Develop a DL-driven framework for high-fidelity defect segmentation in X-ray DT slices using Yolov8 and Detectron2.
- Comparative analysis of Yolov8 and Detectron2 model performance to evaluate segmentation accuracy measured by performance metrics

The remainder of this paper is organized as follows. **Section 2** describes the methodology, including the data-pre-processing pipeline and the training procedures for our deep-learning models. **Section 3** outlines the experimental workflow, detailing data composition, model configuration, and the performance metrics used. **Section 4** reports further experiment on glass-fiber-reinforced polymer (GFRP) composites, presents the model-validation results, and compares the two models. **Section 5** discusses model performance, highlighting the benefits and limitations observed. **Section 6** concludes the paper by summarizing the key findings and suggesting directions for future research.

2 Proposed Framework

2.1 X-ray Image Acquisition & Preprocessing

X-ray imaging is a non-destructive evaluation technique that utilizes high-energy photons to reveal the internal structure of materials by exploiting differences in X-ray attenuation. When X-rays generated by an X-ray tube pass through an object, they are attenuated to varying degrees depending on the material's density, thickness, and atomic composition [28]. In this work, digital Tomosynthesis was used to develop images as shown in Figure 1, the transmitted X-rays are then captured by a detector, which converts them into digital images. In this study, a composite tube GFRP (Glass Fibre Reinforced Polymer) (length 234 mm, outer diameter 35 mm and a thickness of 5 mm) was scanned. Click or tap here to enter text.

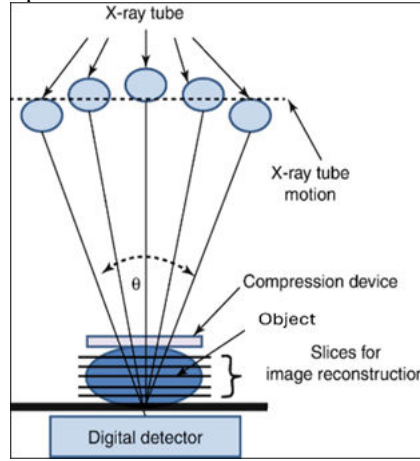


Figure 1: Mechanism of image formation in digital tomosynthesis

The X-ray system used was the Z-series by Adaptix NDT, different images were acquired with source moved to several positions, with total scan time of approximately 5 minutes. A stack of 2D slices was reconstructed using the method and a 3D render was then obtained by the combination of such images as presented in [29], Figure (a) shows the cylindrical tube that was scan for this experiment, Figure 2(b) displays the 3D model of the sample reconstructed from the X-ray DT slices, and Figure (c) presents an individual 2D slice that was subsequently used for training the deep learning model.

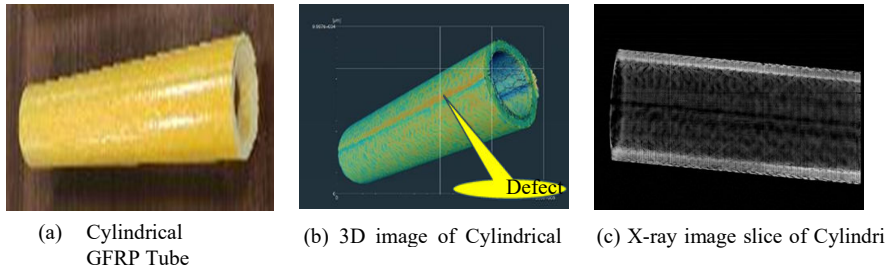


Figure 2: Hollow Cylindrical GFRP tube

2.2 Deep Learning-Based Defect Segmentation

In defect detection, two main deep learning strategies are usually common, one-stage object detectors and two-stage detectors. One-stage detectors like the YOLO series frame defect detection as a single regression problem, predicting bounding boxes and class probabilities in one pass through the network. These models prioritize speed and are well-suited for real-time applications. Researchers have applied YOLO variants to industrial X-ray images with promising [30][31].

To robustly detect defects in the heterogeneous and noisy X-ray images, the core of the framework leverages the strengths of two advanced instance segmentation models, Detectron2 and YOLOv8 to comprehensively capture the multi-scale features inherent in our imaging data, thereby enabling a robust comparative analysis of their performance for inspecting composite structures. They are both PyTorch-based frameworks known for their modularity and precision. YOLOv8 is a notable innovation in YOLO versions which builds on the foundational concepts introduced in earlier YOLO versions [32]. This concept treats object detection as a single regression problem rather than a multi-stage pipeline where it employs a one-stage detection architecture, which allows the network to predict bounding boxes and class probabilities in a single forward pass. YOLOv8 utilizes an extensive stack of deep convolutional layers to extract hierarchical features from input images. These layers enable the model to capture both fine-grained details, critical for detecting small defects and high-level semantic information that are important for recognizing complex structures. An efficient spatial pyramid pooling module is also incorporated and works by pooling features at multiple scales, thereby aggregating contextual information from different regions of the image. These capabilities are crucial for accurately detecting objects and defects that vary significantly in size, from minute cracks to larger delamination. Its optimized architecture ensures rapid inference without compromising the precision of object detection and instance segmentation, making it highly suitable for real-time applications and improving performance in challenging imaging scenarios like those encountered in NDT of GFRP composites.

An alternative utilizes, two-stage detectors such Detectron2 object detection and instance segmentation model that implements the Mask R-CNN architecture, employing Feature Pyramid Network (FPN) that extracts features at multiple scales, enabling the model to detect both fine and coarse details within the X-ray images. The hierarchical feature extraction facilitated by FPN is especially useful for identifying small defects such as micro-cracks, as well as larger anomalies like delamination regions. Furthermore, the modular design of Detectron2 allows extensive customization and fine-tuning. Parameters such as the number of convolutional layers, the scales at which features are extracted, and the learning rates are optimized to handle the varied defect presentations observed in GFRP composites.

Two-stage models tend to be more computationally intensive than YOLO variants, but they often provide higher localization accuracy for difficult examples due to this refined two-step process. The models are trained on annotated X-ray datasets of GFRP composites to automatically learn robust features, effectively segmenting defect regions and structural details from complex, noisy backgrounds. By integrating both

models into our inspection pipeline, we are able to perform a side-by-side evaluation of their performance.

2.3 System Architecture

The system architecture as illustrated in Figure 3, consists of an AI-driven inspection pipeline that takes raw X-ray images of composite materials as input and outputs detected defect locations along with precise segmentation masks.

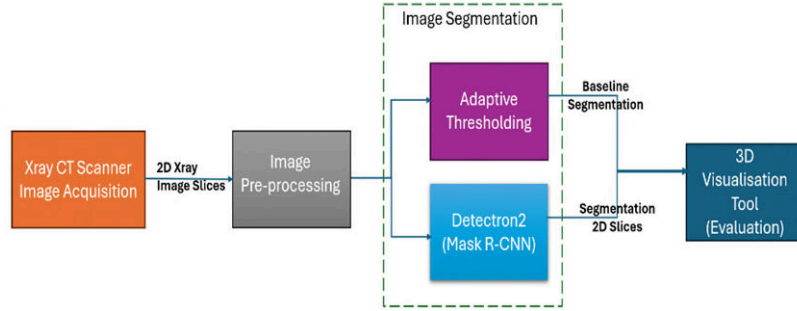


Figure 3: System Architecture

The pipeline integrates the X-ray image acquisition, preprocessing and DL-driven defect segmentation models. The process begins with X-ray scanning, where high-resolution image slices of aerospace GFRP composites are captured at predefined angles to ensure comprehensive coverage of internal structures. These raw X-ray images undergo preprocessing techniques such as normalization and noise reduction to enhance defect visibility. The next stage employs Yolov8 and Detectron2, advanced deep learning frameworks for instance segmentation, to accurately identify and classify defect regions within the composite material. The segmented outputs are visualized and evaluated to facilitate accurate and real-time defect analysis, aiding engineers in decision-making and reducing manual inspection errors. The combination of X-ray imaging and deep learning-based segmentation enhances defect detection accuracy while reducing operational downtime and inspection costs, making it a robust solution for aerospace composite inspection.

3 Experimental Setup

3.1 Dataset Composition & Annotation

The dataset for this study consists of high-resolution X-ray images of GFRP composites that exhibit deep-line real defects (voids), with defect regions manually annotated to create an accurate ground truth. Each raw X-ray image is processed through several steps, including normalization to a 640×640 resolution and noise reduction to

standardize intensity values and minimize imaging artifacts, thereby enhancing defect visibility and ensuring high-quality inputs for the model. Additionally, adaptive equalization techniques are applied to automatically adjust contrast, and data augmentation methods such as rotation, flipping, and mosaic augmentation are employed to boost dataset diversity and improve model robustness.

3.2 Model Training & Hyperparameter Optimization

Two state-of-the-art instance segmentation models—Detectron2 and YOLOv8—were trained and evaluated on the preprocessed X-ray image dataset of GFRP composites. Detectron2 employs a Mask R-CNN architecture, enhanced by a Feature Pyramid Network (FPN) for robust multi-scale feature extraction. This FPN is essential for integrating both fine details and broader context from the input images, making it particularly effective for identifying small defects, such as micro-cracks, as well as larger anomalies like voids. To tailor the model for our specific application, we customized the FPN layers and adjusted the mask head architecture to better capture the subtle variations in defect presentation found in the X-ray images of GFRP composites. In contrast, YOLOv8 is designed with a focus on rapid inference while still maintaining high detection accuracy. Its architecture incorporates deep convolutional layers combined with an efficient Spatial Pyramid Pooling (SPP) module, which allows the network to capture multi-scale features from the input images. These architectural enhancements are critical when dealing with the inherent challenges of low-contrast and noisy X-ray images, ensuring that even minute defects are accurately detected. For both models, the dataset was systematically partitioned into training (70%), validation (15%), and testing (15%) subsets. Key hyperparameters, including learning rate, batch size, and weight decay, were optimized during training. Each model was trained for 100 epochs with periodic evaluation on the validation set to monitor progress and prevent overfitting. The loss functions were carefully calibrated to balance classification, localization, and segmentation tasks. We combined the three components in a weighted sum as shown here; $L_{total} = \alpha L_{cls} + \beta L_{loc} + \gamma L_{seg}$. First, we normalized each term with the GradNorm method, so their initial gradient magnitudes were comparable. Next, we ran a grid search on a held-out validation set and selected weights that maximized mean Dice + mAP. The resulting setting kept the three losses within the same order of magnitude throughout the training, preventing any single task from dominating the optimization.

3.3 Performance Metrics

Accuracy Metrics: Comparing segmentation quality using metrics such as the Dice coefficient and Intersection-over union (IoU) to determine how accurately each model delineates defect regions.

Inference Speed: Assessing the real-time applicability of each model by measuring inference times, which is crucial for high-throughput inspection environments.

Dice Coefficient: Quantifying the overlap between predicted and ground truth masks.

$$\text{Dice} = \frac{2 \times |P \cap G|}{|P| + |G|}$$

where P is the predicted mask, G is the ground truth mask and $|P \cap G|$ is the intersection between the predicted and ground truth mask.

IoU: Intersection-over-Union (IoU)- Assessing segmentation accuracy on a per-instance basis.

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

Average Precision (AP): Calculated across different IoU thresholds.

Precision and Recall: To measure the balance between false positives and false negatives.

4 Experimental Evaluation

We conducted a series of experiments to train and evaluate the performance of the YOLOv8 and Detectron2 models on the task of defect detection in composite X-ray images. The models were trained on a workstation with an NVIDIA RTX 3080 GPU (32GB memory) on a CUDA-enabled GPU platform, leveraging the PyTorch framework. For Detectron2, the training was conducted within its dedicated library, while YOLOv8 was trained using the Ultralytics YOLOv8 repository with the segmentation model variant, yolov8n-seg architecture chosen for a balance of speed and accuracy. Both models underwent periodic evaluation on a designated validation set to monitor performance improvements throughout the training process. They used early stopping based on validation loss to prevent overfitting. The total training time was around 6ms for YOLOv8 and 10ms for Mask R-CNN on our dataset. We evaluated the models using standard object detection and segmentation metrics. For object detection performance, key performance metrics include the Dice coefficient, Intersection-over-Union (IoU), precision, and recall and were computed to assess segmentation accuracy. Based on these metrics, hyperparameters were iteratively adjusted to achieve an optimal balance between accuracy and inference speed. The training procedures were meticulously tailored to address the unique challenges of X-ray imaging for GFRP composites, such as low contrast, noise, and defect heterogeneity. We also report qualitative results by overlaying the predicted masks on the original X-ray images to visually assess the correspondence between the segmented regions and the actual defect shapes. Visual inspection revealed that while the predicted masks largely aligned with the defect boundaries, the Detectron2 model exhibited instances of partially segmented defects, while indicating accuracy of approximately 95% detection accuracy contradiction its performance and efficiency.

We evaluated the performance of the YOLOv8 and Detectron2 Mask R-CNN segmentation models. The two models exhibited a clear trade-off in segmentation accuracy. Detectron2 achieved about 88–89% segmentation accuracy on the X-ray defect dataset, substantially higher than the 77.8% achieved by YOLOv8. This difference is reflected in the Dice similarity coefficient as well where Detectron2 attained ~86% Dice coefficient, outperforming YOLOv8's 74.2%. From visual observations, YOLOv8's instance segmentation was better at precisely matching the defect regions in the ground truth images.

Figure 4(b) indicates that YOLOv8's predicted

masks overlap the true defect areas more completely, capturing finer details of the defect shape. Detectron2's segmentation (based on Mask R-CNN), while high segmentation accuracy, was coarser and left some gaps or extraneous pixels around defect boundaries, leading to a lower overlap with ground truth as shown in Figure 4(a). Segmentation here is slightly less precise as compared to YOLOv8 which provided more exact defect

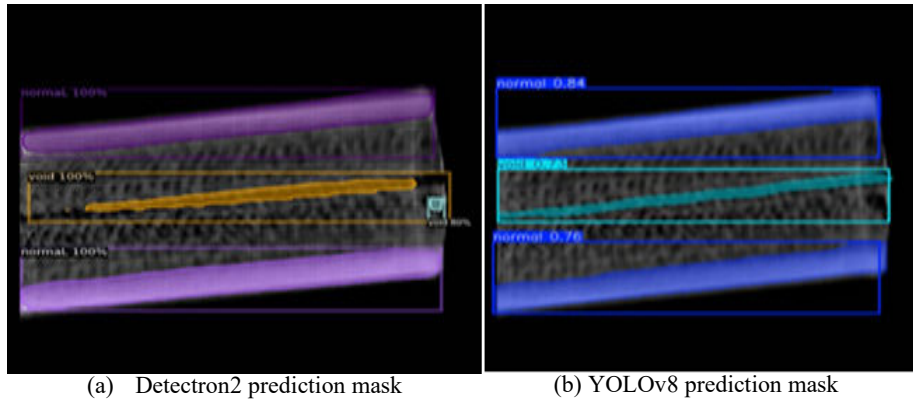


Figure 4: YOLO and Detectron2 segmentation results

segmentation, aligning with its streamlined, real-time design. For inference speed using the same hardware setup, the Detectron2 model required approximately 28 minutes 20 seconds to process the X-ray images while YOLOv8 total processing time ~369s.

In comparison, our custom YOLOv8 model can be easily improved to meet real-time capability, whereas the custom Detectron2 approach would need more improvement for real world application. This comparison is illustrated in **Error! Not a valid bookmark self-reference.** The performance comparison between YOLOv8 and Detectron2 as in **Error! Not a valid bookmark self-reference.** highlights a trade-off between speed and accuracy in defect detection for X-ray DT imaging of composites structural sample. Detectron2 outperforms YOLOv8 in segmentation accuracy (88% vs. 77.8%), Dice coefficient (86% vs. 74.2%), and IoU (86% vs. 74.95%), making it more precise for identifying fine defect structures. However, YOLOv8 significantly surpasses Detectron2 in inference speed, processing images ~4× faster (6.9ms vs. 10.3ms per image) and achieving a total processing time of ~6 minutes compared to Detectron2's 28 minutes plus time interval.

Table 1: Models Performance Comparison

Performance Metrics	YOLOv8	Detectron2	Remarks
Segmentation Accuracy	77.80%	88–89%	Detectron2 achieves higher segmentation precision.
Dice Coefficient	74.20%	86%	Higher Dice score indicates better defect region overlap in Detectron2.
IoU	74.95%	86%	Detectron2 performs better in region matching.
Inference Speed	6.9 ms	10.3 ms	YOLOv8 is significantly faster.
Total Processing Time	~6 min	~28 min 20 sec	YOLOv8 is ~4x faster than Detectron2 for batch processing.
Precision	High	Very High	Detectron2 produces fewer false positives.
Recall	Higher	Slightly Lower	YOLOv8 detects more defects but at the cost of false positives.
Suitability for Real-Time Use	Yes	No	YOLOv8 is better suited for real-time applications.
Best Use Case	Fast, real-time defect detection	High-precision defect segmentation	YOLOv8 for speed, Detectron2 for accuracy.

5 Discussion

The experimental results demonstrate the integrated deep learning framework for defect segmentation in X-ray images of GFRP composites. The performance metrics achieved provide a comprehensive view of the system's capabilities in terms of accuracy, precision, and real-time applicability. While Detectron2 Mask R-CNN (a two-stage detector) excelled in accuracy, it was slower in inference and carries the overhead of proposing regions and refining masks making the configuration at this state far from real-time solution and cannot be used in an on-line inspection loop without drastic modifications. YOLOv8's one-stage CNN architecture, on the other hand, can process approximately 145 frames per second (fps), enabling rapid defect prediction and making it highly optimized for real-time applications. Our findings reinforce that YOLOv8 is well-suited for real-time defect detection, whereas Detectron2 would be limited to off-line analysis or scenarios where speed is not a concern. This distinction is critical in an automated inspection context as research in industrial X-ray inspection study from [33] also emphasizes the need for efficiency, scalability, and real-time analysis. In addition to quantitative metrics, we examined the models outputs on actual composite X-ray images to gauge their practical defect detection ability. Qualitatively, YOLOv8 was more robust in detecting defect regions, whether regular or irregular in shape. However, we observed that Detectron2 would occasionally miss small defect details and yet segmented the defect area with high accuracy (even 100%) but failed to mask the

completed part of the defect as shown in figure 4(a). Such missed detections lower its overall recall, meaning some flaws might go unreported if relying solely on this method.

In aerospace composites, knowing the exact size and shape of a defect is crucial for structural integrity assessments. YOLOv8's masks, while offering consistent coverage of defects, will enable more reliable measurements of defect area from X-ray images, ensuring that specific potential issues are flagged for review. Additionally, in industrial settings, there is often a time-limited requirement for inspection results to facilitate rapid maintenance decisions. Although YOLOv8's inference time was approximately 6 minutes per image in our current configuration, this performance can be improved through further parameter tuning. In contrast, the Detectron2 Mask R-CNN configuration achieved significantly longer inference times, indicating that additional system tuning and optimization are required to meet specific operational priorities. In comparison with existing literature and industrial application limited and sensitive nature of data has been a major factor. The YOLOv8 proposed model with highly specialized datasets can detect >90% of defects and delineate their shapes with IoU/Dice often in the 0.8–0.9+ range, with improved inference speed for early-stage solution development and proof-of-concept, showing possible robust, reliable and fast solution. This is a substantial improvement traditional two-stage or heuristic methods, where quick turnaround is critical. Future work will aim to expand the dataset and adapt the framework to a broader range of composite samples, thereby enhancing the system's generalizability and relevance across related domains.

6 Conclusion

This study demonstrates the potential of integrating X-ray Digital Tomosynthesis imaging with deep learning-based image segmentation for non-destructive evaluation of aerospace composite materials. By combining advanced deep learning segmentation with classical image processing techniques, the proposed module delivers a high-fidelity solution that significantly enhances defect detection accuracy in the samples examined and has the potential to impact on wider composite structures. This solution not only improves defect detection accuracy but also reduces inspection time and increases overall reliability. Experimental evaluations reveal that the system achieves an overall accuracy of 74.95% and a rapid processing speed of approximately 6ms per image making the framework well-suited for real-time applications in dynamic industrial settings, such as robotic inspections. Our comparative analysis between YOLOv8 and Detectron2 underscores that while both models contribute to improved defect segmentation, YOLOv8 stands out for its superior efficiency. Its rapid inference speed and enhanced multi-scale feature extraction allow it to consistently detect defect regions with minimal latency, making it particularly effective for real-time deployment. In contrast, although Detectron2 provides high-quality segmentation masks with precise defect delineation, its relatively slower computational performance limits its applicability in time-sensitive environments.

By leveraging deep learning models specifically optimized for aerospace non-destructive testing, this research sets a new standard for defect analysis and quality assurance in composite materials. The proposed framework not only improves the reliability and accuracy of defect detection but also paves the way for further advancements in automated inspection systems. Future work will focus on optimizing the integration of deep learning techniques, expanding the system to include an interactive 3D visualization interface, and achieving real-time integration with robotic manipulator platforms. Additionally, exploring domain adaptation strategies will be essential to extend the framework's applicability across diverse material types and manufacturing conditions. These efforts aim to further enhance the robustness and scalability of the system, ultimately contributing to safer and more efficient aerospace manufacturing and maintenance workflows.

Future work entails leveraging deep learning models for the use case of small-scale composite aerospace components on existing robotic digital twin system for remotely operated low power X-ray based imaging at Aerospace Integration Research Centre at Cranfield University.

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