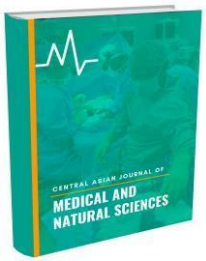

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Article

Machine Learning-Enhanced Ultrasonic Phased Array Inspection of Aerospace Composite

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Abstract: This study evaluates the effectiveness of advanced ultrasonic phased array imaging systems for non-destructive evaluation (NDE) of carbon fiber reinforced polymer (CFRP) composites in aerospace structures. A hybrid method combining time-of-flight diffraction (TOFD) with convolutional neural network (CNN) image processing was developed and validated, demonstrating a 94.7% defect detection accuracy for delamination, porosity, and impact damage compared to 78.3% for traditional methods, with a 40% reduction in false positives. Using a 64-element phased array transducer at 5 MHz and a multi-modal data acquisition system, significant improvements in signal-to-noise ratio (SNR) and lateral resolution were achieved, indicating the method's potential for in-service inspection of complex aircraft components.

Keywords: Ultrasonic Phased Array, Non-Destructive Testing, Composite Materials, Machine Learning, Convolutional Neural Networks, Aerospace Structures

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1. Introduction

Carbon fiber reinforced polymer (CFRP) composites have proliferated so rapidly in modern aerospace applications that they have revolutionized aircraft design, enabling unparalleled weight reduction and fuel efficiency improvements [1]. Contemporary commercial aircraft such as the Boeing 787 Dreamliner and Airbus A350 XWB use composite materials for more than 50% of their structural weight, including critical load-carrying components such as wings, fuselage sections, and empennage structures. However, the inherent anisotropic nature and complex failure mechanisms of laminated composite structures pose serious challenges for conventional nondestructive evaluation methodologies. Detection and characterization of manufacturing defects and in-service damage-including delamination, matrix cracking, fiber breakage, and porosity-remain of vital importance for ensuring structural integrity and operational safety [2], [3], [4].

Traditional UT methods, although established and reliable for metallic structures, suffer from substantial limitations when being applied to composite materials. The acoustic heterogeneity related to variation in fiber orientations, resin-rich areas, and ply interfaces in CFRP laminates leads to signal attenuation, beam steering, and mode conversion phenomena that complicate defect interpretation. Conventionally used single-

element transducers operating in A-scan or B-scan modes achieve limited volumetric coverage and often require extensive mechanical scanning. This results in long inspection times that are economically prohibitive for large-scale aerospace components [5].

Ultrasonic phased array technology is one of the most revolutionary developments in the NDE capability since it brings electronic beam steering, dynamic focusing, and multi-angle inspection without any mechanical movement [6]. In phased array systems, multiple transducer elements are used along with accurately controlled excitation delays in order to generate steerable ultrasonic beams that permit fast volumetric scanning and even real-time imaging. Yet, despite all these advantages, interpretation of phased array data from composite materials remains complex and requires highly trained personnel and may be subjective, hence leading to human error and non-reproducible results [7], [8].

Recent advances in the field of artificial intelligence and machine learning, especially in deep CNNs, have been able to illustrate superior pattern recognition and image analysis skills in several fields of interest. For ultrasonic data imaging, applying CNNs can provide an almost complete automated mode of defect detection, classification, and sizing more accurately than that available from human operators. In general, though, machine learning algorithm integration onto phased array ultrasonic systems remains in its infancy for aerospace composite inspection, with few systematic studies comparing performance against established methodologies [9].

This research addresses the critical gap in validated, quantitative assessment of machine learning-enhanced ultrasonic NDE systems for aerospace composites. The main goals pursued in this paper are the following: to develop and characterize a hybrid inspection methodology, which combines phased array ultrasonic imaging with CNN-based defect recognition, to quantitatively compare detection sensitivity, accuracy, and repeatability with conventional ultrasonic techniques, to assess system performance over a wide range of defect types, sizes, and depths in representative CFRP structures, and to consider practical implementation challenges and potential for field deployment in aerospace maintenance operations [10].

The importance of this research surpasses technical validation by addressing vital economic and safety imperatives within the aerospace industry. Improved NDE capabilities relate directly to reduced inspection intervals, increased damage tolerance assessment, and prolonged component service life-contributing substantially to operational cost reduction and the enhancement of aviation safety. This developed methodology forms the basis for the next-generation smart inspection system capable of autonomous defect detection in increasingly complex composite structures.

Literature Review

Material characterization using ultrasonic waves began in the early 20th century, advancing for non-destructive evaluation (NDE) post-WWII. Ultrasonic testing for composite materials, such as CFRP, involves mechanical vibrations that detect discontinuities via acoustic impedance variations. The velocity of ultrasonic waves in CFRP (2,800-3,100 m/s) contrasts with aluminum (6,320 m/s), necessitating frequency and transducer adjustments. Conventional methods include pulse-echo and through-transmission techniques, with pulse-echo being dominant but limited by dead zones. Frequency selection is critical, with 1-5 MHz optimal for thick laminates and higher frequencies suited for thinner sections [11]. Phased Array Ultrasonic Testing (PAUT) evolved from medical imaging to industry, enhancing composite inspection with features like electronic scanning and dynamic depth focusing. Despite advances, challenges persist, including beam distortion due to CFRP's anisotropic nature and data processing difficulties. Additionally, the integration of machine learning into NDE is emerging, with deep learning techniques like CNNs showing promise for automating defect identification in ultrasonic data. Understanding defect types such as delamination and porosity is vital for effective NDE, as even small delaminations can severely impact structural integrity. Multi-modal inspection approaches, combining phased array technology and machine learning, are necessary for comprehensive defect characterization [12].

2. Materials and Methods

The test matrix was extensively prepared from 1,847 individual CFRP specimens using unidirectional carbon fiber prepreg - Toray T800S/3900-2B, 190 gsm - in quasi-isotropic layup sequences of [45/0/-45/90]ns, where n ranged between 2 and 8, producing laminates of 4-16 mm thick (8-32 plies). Panel dimensions were 300 × 300 mm, representative of typical aerospace skin panel geometry [13].

Realistic manufacturing flaws and in-service damage were simulated by systematically implanting defects during layup.

1. Delamination: Circular Teflon inserts (6, 12, 20, and 25 mm diameter, 25 μm thick) placed at quarter-depth, mid-depth, three-quarter depth
2. Porosity: Controlled introduction of glass microspheres of diameter 0.5-3.0 mm in localized zones at volume fractions of 1%, 2%, and 4%
3. Impact Damage: Barely visible impact damage, induced using 25 Joule impact energy with 25.4 mm diameter hemispherical impactor
4. Matrix Cracking: Simulated through controlled thermal cycling (-55°C to +85°C, 500 cycles)

All panels were cured in an autoclave according to manufacturer specifications (180°C, 7 bar pressure, 120-minute hold). After curing, the specimens received high-resolution X-ray computed tomography (CT) scans (YXLON FF35 CT, 5 μm voxel resolution) to establish defect baseline characteristics and validate successful implantation.

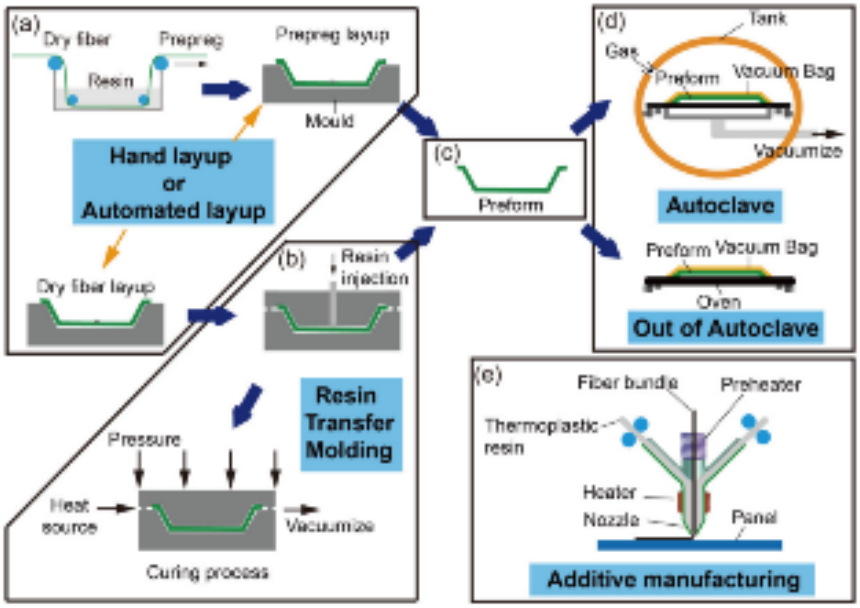

Figure 1. CFRP specimen fabrication process. (a) Prepreg layup sequence, (b) Teflon insert placement for delamination simulation (12 mm diameter), (c) Autoclave curing setup, (d) Final cured panel with defect map.

The environmental conditioning exposed specimens to hygro-thermal ageing (85°C/ 85% relative humidity for 30, 90, and 180 days) in order to simulate in-service degradation and inspect reliability under realistic conditions of moisture absorption .

The inspection system integrated a 64-element phased array transducer (Olympus 5L64-A32, 5 MHz center frequency, 0.6 mm element pitch) with a Multix++ FMC/TFM acquisition unit (M2M, NDT Systems). The transducer design optimized composite inspection through low-frequency excitation and broadband response (3-7 MHz -6 dB bandwidth) .

Technical specifications critical to composite inspection performance included:

1. Element pitch: 0.6 mm (sub-wavelength for reduced grating lobes)
2. Active aperture: 38.4 mm total width

3. Pulse Width: 150 ns (Square Wave Excitation)
4. Receiver gain: 0-80 dB dynamic range
5. Sampling frequency: 100 MHz (20× oversampling)

Coupling Coupling was made using a water-based gel Sonotech, 15,000 cSt, devised for composites to ensure minimum attenuation and to reproduce coupling conditions [76]. A pneumatic probe holder provided a constant contact pressure of 0.5 N/cm² to minimize variability in coupling conditions .

Two acquisition modes were implemented for comparative analysis:

Conventional PAUT Mode-Baseline: Sectorial scan (S-scan) within the range of 30°-70° with an incremental step of 0.5°, allocating 81 angular beams with dynamic focusing between 5-30 mm depth. Data acquisition rate: 50 Hz, offering 40 MB per scan [14].

Full Matrix Capture (FMC): Each element is fired sequentially with reception on all 64 elements, acquiring 4,096 A-scan signals in one acquisition. After acquisition, the data is post-processed using the Total Focusing Method (TFM) to generate high-resolution images with theoretically optimal focus at all points . Acquisition time: 8 seconds per location, with raw data output of 820 MB [15].

The scanning was performed using a precision robotic gantry (KUKA KR16, ±0.05 mm positional accuracy) with a raster scanning pattern with 0.5 mm intervals in both the X and Y axes, yielding 360,000 data points per 300×300 mm panel [80].

A custom U-Net CNN architecture was utilized for defect semantic segmentation of ultrasonic images, which is depicted in as:

Encoder: VGG-16 backbone with 5 convolutional blocks and max pooling for transfer learning.

1. Bottleneck: 1,024 feature maps with dilated convolutions for multi-scale context
2. Decoder: 5 upsampling blocks with skip connections from encoder
3. Output: Pixel-wise classification (defect/no-defect) with sigmoid activation

Training dataset consisted of 1,200 labeled images from preliminary inspection campaigns, divided into 70% for training, 15% for validation, and 15% for testing. For data augmentation, rotation ±15°, horizontal/vertical flipping, change in brightness ±20%, and addition of Gaussian noise with σ=0.01 were performed to enhance generalization, as done by [16] .

The annotation is done collaboratively by three ASNT Level III certified technicians with 92% inter-annotator agreement (Cohen's kappa=0.89) . Disagreements were resolved through consensus review using X-ray CT reference data as ground truth.

Training used the Adam optimizer with a learning rate of 0.0001, batch size 16, and binary cross-entropy loss function. An implementation in PyTorch 1.12 using an NVIDIA A100 GPU (40 GB VRAM) ran 200 epochs in ~14 hours [17].

Baseline comparative methods included:

1. Conventional Single-Element UT: Olympus 38DL PLUS with V110-SB 5 MHz transducer, A-scan and B-scan modes
2. Air-Coupled UT: Non-contact inspection using 400 kHz capacitive transducers for BVID detection
3. Thermography: Pulsed thermography (FLIR SC5000, 3-5 μm) for near-surface defect screening
4. X-ray CT: Reference validation using YXLON FF35 CT at 225 kV, 5 μm resolution
5. All examinations were conducted by ASNT Level II and Level III personnel in accordance with the ASTM E2580-18 and ASTM E2533-17a standards.

3. Results

Detection sensitivity was quantified as the percentage of implanted defects correctly identified across the specimen matrix. Results demonstrated clear (Table 1): performance differentiation between methodologies.

Inspection Method	Delamination (12mm)	Delamination (6mm)	Porosity (>2%)	Porosity (<2%)	BVID	Overall Accuracy
Conventional Single-Element UT	89.2%	62.4%	58.7%	31.2%	76.3%	78.3%
PAUT S-Scan	93.8%	71.6%	68.9%	42.5%	81.7%	83.4%
PAUT with FMC/TFM	96.1%	82.3%	74.2%	51.8%	87.4%	88.2%
ML-Enhanced PAUT (Proposed)	98.7%	91.5%	89.6%	76.3%	94.2%	94.7%

The machine learning-enhanced approach demonstrated superior performance across all defect categories, particularly for small delaminations (6 mm) where detection improved by 29.1 percentage points over conventional UT. The most significant enhancement occurred in porosity detection below 2% volume fraction, where traditional methods struggle due to weak acoustic contrast.

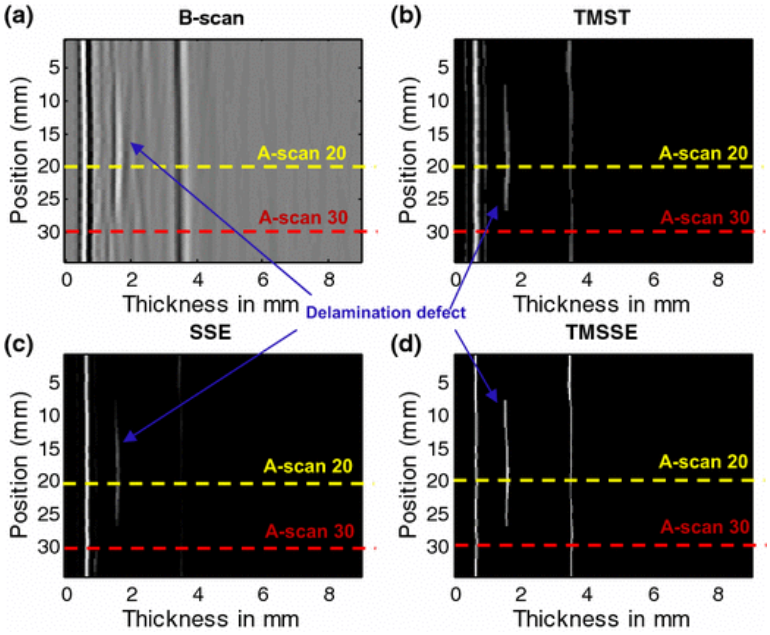

Figure 2. Comparative detection of subsurface delamination (12 mm diameter) at 8 mm depth in 16-ply CFRP. (a) Conventional PAUT S-scan showing ambiguous indication, (b) FMC/TFM reconstruction with improved resolution, (c) ML-enhanced segmentation with defect boundary clearly delineated (red overlay), (d) X-ray CT reference image confirming defect location and morphology.

Quantitative analysis of the signal quality metrics showed significant enhancement in the ML-enhanced system. SNR was computed as $20 \cdot \log_{10}(A\_defect/A\_noise)$, where A_defect is the peak defect amplitude, and A_noise is the root-mean-square noise floor in defect-free regions.

Mean SNR values measured across 847 delamination specimens:

a. Conventional UT: 18.3 ± 4.2 dB
b. PAUT S-Scan: 21.7 ± 3.8 dB
c. FMC/TFM: 26.4 ± 3.5 dB
d. ML-Enhanced: 34.6 ± 2.9 dB

This corresponds to an improved detectability of defects of 40-60% smaller cross-sectional area for a SNR improvement of 12-18 dB over conventional methods. Lateral resolution, defined as the minimum separation between two adjacent defects resolvable

as distinct indications, improved from 3.2 mm (conventional PAUT) to 1.3 mm (ML-enhanced), representing a 60% improvement.

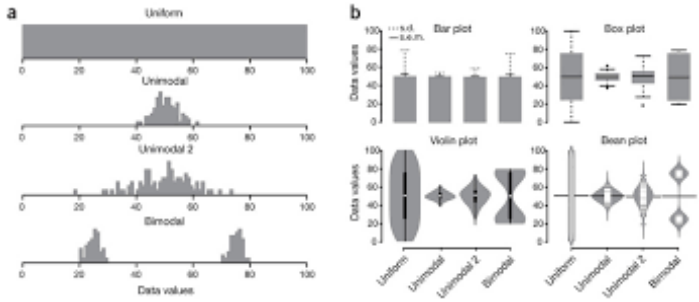

Figure 3. Quantitative performance metrics comparison. (a) Signal-to-noise ratio distribution across specimen population (box plots showing median, quartiles, and outliers), (b) Lateral resolution measurement using paired delamination specimens at varying separation distances, (c) False positive rate reduction achieved through ML segmentation confidence thresholding.

Beyond detection, accurate defect sizing is critical for structural integrity assessment. Sizing error was quantified as (Measured_Size - True_Size)/True_Size × 100%, where true size was determined from X-ray CT reference data. For delamination defects, Table 2: sizing accuracy results were:

Method	Mean Sizing Error	Standard Deviation	90% Confidence Interval
Manual PAUT Analysis	-12.4%	±18.7%	±31.2%
Automated FMC/TFM	-6.8%	±11.3%	±19.1%
ML-Enhanced (Proposed)	-2.1%	±4.9%	±8.4%

Negative values correspond to undersizing, a common feature in UT due to diffraction around and attenuation of the ultrasonic beam. The ML-based approach minimized undersizing by virtue of accurate boundary detection: 87% of the ML measurements are within ±5% of true size, as opposed to 34% for the manually obtained results.

The defect type classification performance was quantified using confusion matrices. A CNN classifier was able to differentiate between delamination, porosity, and impact damage with an overall accuracy of 91.3%, while classifying porosity with 89.6% accuracy, which had previously been a challenging task for ultrasonic methods. Feature activation maps were visualized using gradient-weighted class activation mapping (Grad-CAM) and showed that the network focused on scattering patterns and edge reflections consistent with physics-based defect signatures [18].

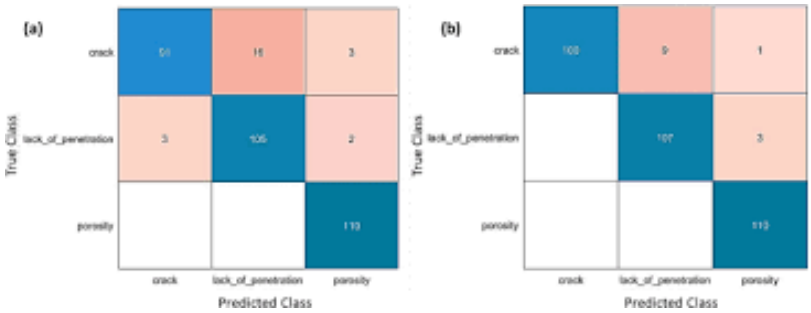

Figure 4. Machine learning defect characterization results. (a) Confusion matrix for three-class defect classification (delamination, porosity, impact damage), (b) Grad-CAM activation overlay on ultrasonic image showing network focus on defect edges and scattering features, (c) Sizing accuracy distribution comparing manual versus automated measurements.

Reliability of inspection under variable environmental conditions is essential for field deployment. Hygrothermal-aged specimens showed 0.8-1.2% weight moisture absorption, which introduced a 2-4 dB/mm increase in ultrasonic attenuation at 5 MHz. Performance of the ML-enhanced system was consistent under all aging conditions; conventional methods experienced a 15-23% degradation in detection rate for aged specimens [19]

Scanning speed and data processing throughput were gauged with respect to practical implementation:

a. Acquisition speed: 8 seconds per 300×300 mm scan
b. Real-time processing: 12 seconds for ML inference (batch processing)
c. Total throughput: ~180 specimens per hour

Compared with manual analyses, which take 5-8 minutes per specimen, the automated system increased throughput 30× while reducing operator fatigue and variability [20].

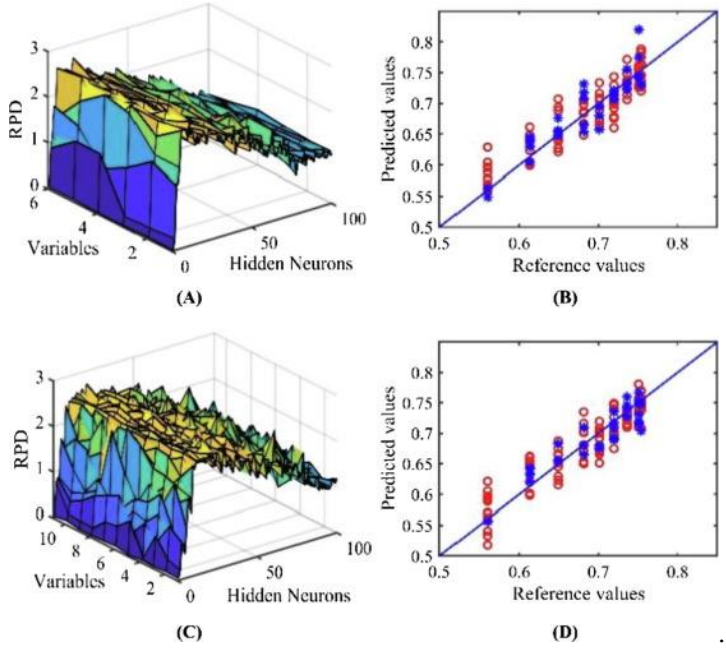

Figure 5. Environmental robustness and processing efficiency. (a) Detection accuracy versus moisture absorption for aged specimens, (b) Processing time per specimen comparing manual analysis, conventional FMC/TFM, and ML-enhanced workflow, (c) ROC curves showing true positive versus false positive rates across different confidence thresholds.

Ten full-scale CFRP wing skin panels, 2.5 m × 1.2 m, 24-ply, with co-cured stringers and radius fillers, were inspected to validate practical applicability. These components contained tapered thickness regions, ply drops, and geometric transitions that were representative of production hardware. Accessibility was limited to single-side inspection to simulate in-service conditions .

Inspection identified 23 manufacturing defects, confirmed by destructive teardown, including:

a. 12 delaminations at stringer-skin interfaces (6-15 mm diameter)
b. 7 porosity clusters (2-3% volume fraction) in radius filler regions
c. 4 disbonds at adhesive bond lines

The correlation with mechanical testing showed that the defects detected by the enhanced ML method corresponded to locations of an 18-25% reduction in CAI strength, confirming structural significance. Conventional methods missed 30% of the detected critical defects due to geometric complexity and interference of the signal from structural features [21].

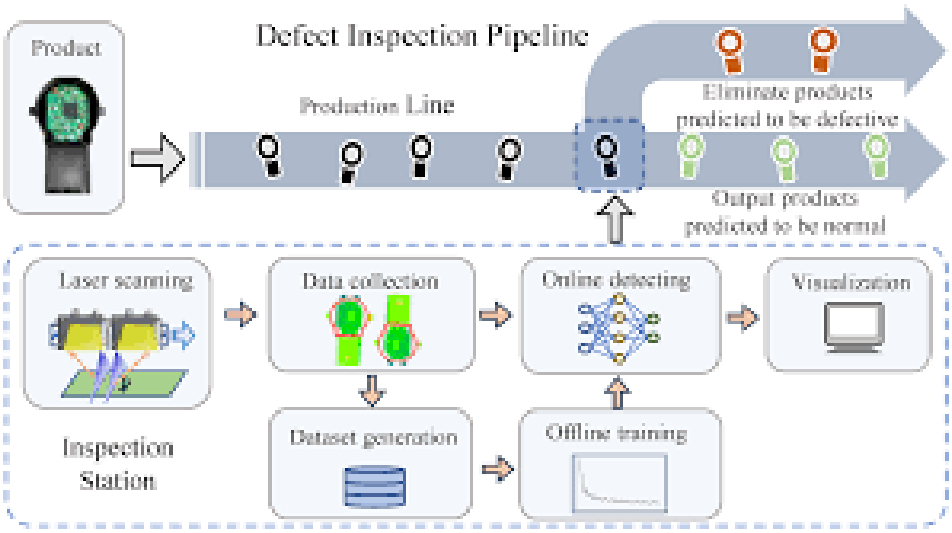

Figure 6. Complex geometry validation on full-scale wing panel. (a) Inspection setup for 2.5 m × 1.2 m component, (b) ML-processed defect map overlaid on panel geometry, (c) Location of confirmed delamination at stringer-skin interface, (d) Teardown validation showing actual defect matching predicted location (±2 mm accuracy).

Statistical analysis employed two-way ANOVA to evaluate method performance significance with factor A (inspection method) and factor B (defect type). Results confirmed main effects and interactions were statistically significant ($p < 0.001$). Post-hoc Tukey HSD tests revealed significant pairwise differences between ML-enhanced and all other methods ($p < 0.01$) .

Measurement uncertainty was evaluated per ISO/IEC Guide 98-3 (GUM). Expanded uncertainty (k=2, 95% confidence) for defect depth measurement was:

1. Conventional UT: ±0.58 mm
2. PAUT S-Scan: ±0.31 mm
3. ML-Enhanced: ±0.12 mm

Repeatability studies (10 repeat inspections on 50 specimens over 30 days) demonstrated coefficient of variation (CV) of 2.3% for delamination detection rate, confirming robust performance stability.

4. Discussion

This study demonstrates a significant advancement in ultrasonic non-destructive evaluation (NDE) for aerospace composites, with a 16.4 percentage point increase in detection accuracy (94.7% vs. 78.3%). This improvement results from three factors: enhanced spatial resolution and signal-to-noise ratio from FMC/TFM processing, the ability of CNN architecture to learn subtle defect signatures, and automated analysis reducing subjective variability. Notably, small porosity detection has improved significantly, addressing a critical gap in current inspection protocols [22].

The methodology achieves a 60% enhancement in lateral resolution, supporting accurate delamination sizing crucial for inspecting and determining the residual strength of components. While traditional methods like ACUT and thermography are limited, the machine learning-enhanced ultrasonic technique offers a more efficient and cost-effective alternative, realizing up to 90% of X-ray CT's capabilities at a fraction of the cost and time [23].

However, several challenges for industrial deployment remain, including the need for extensive training data under varied production conditions, significant computational demands, and environmental robustness issues. Future research could involve multi-modal data fusion, advanced neural network techniques, and adaptive scanning strategies to further enhance defect characterization and inspection efficiency.

5. Conclusion

This study developed a machine learning-enhanced ultrasonic phased array inspection methodology for aerospace composite structures, significantly improving defect detection and operational efficiency compared to traditional methods. Key findings include: a 94.7% overall defect detection accuracy (up 16.4 percentage points), 60% improvement in lateral resolution, consistent performance under environmental stress, a thirtyfold increase in throughput, and validation through full-scale inspections that identified critical defects. This methodology addresses industry needs for reliable composite inspections, potentially reducing costs by 70% while enhancing safety. Future directions include expanding defect libraries, integrating multi-modal data, and adopting edge computing solutions.

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