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A Comprehensive Review of Artificial Intelligence for Image- and Signal-Based Non-destructive Testing in Aerospace Structures

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Abstract

Ensuring the structural integrity of aerospace components requires inspection techniques that can detect diverse surface and subsurface flaws in increasingly complex materials and geometries. Although conventional non-destructive testing (NDT) remains essential, its dependence on manual interpretation and limited automation has created a demand for more objective and scalable solutions. This review presents a structured synthesis of artificial intelligence advancements in non-destructive testing, organized around the two dominant data paradigms: image-based and signal-based inspection. Image modalities, such as radiography, infrared thermography, and visual inspection, generate spatial information well-suited to convolutional networks, segmentation models, and vision transformers. Signal modalities, including ultrasonics, acoustic emission, eddy currents, and vibration analysis, generate temporal or spectral data that can be effectively modeled by recurrent neural networks (RNNs), hybrid CNN-LSTM architectures, and emerging transformer models. The review compares these modalities, evaluates their diagnostic performance, and highlights challenges related to dataset scarcity, inconsistent annotation standards, domain shift, interpretability, and certification. Particular attention is given to multi-modal fusion strategies that integrate spatial and temporal cues through attention-enabled hybrid models to improve robustness and decision reliability. Practical aerospace scenarios such as composite panel inspection, ultrasonic C-scan analysis, radiographic porosity detection, and structural health monitoring are examined to illustrate operational readiness. Despite significant progress, most models rely on controlled datasets, lack standardized evaluation protocols, and provide limited insight into uncertainty or failure modes. Advancements in open benchmarks, explainable and physics-informed architectures, and digital-twin-enabled deployment are essential for achieving trustworthy, certifiable AI-based NDT. Overall, the review provides a concise road-map for developing intelligent and interpretable NDT systems for next-generation aerospace applications.

Keywords: Artificial Intelligence; Deep Learning; Non-Destructive Testing; Aerospace Structures; Signal-Based Analysis; Structural Health Monitoring

1. Introduction

The aerospace industry's pursuit of higher performance, fuel efficiency, and structural reliability has driven the widespread adoption of advanced materials such as lightweight composites, fiber–metal laminates, and high-strength alloys [1, 2]. While these materials provide superior strength-to-weight ratios and durability, they introduce complex defect types, including delamination, voids, matrix cracks, and porosity, that can compromise structural integrity if left undetected [1, 3].

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Ensuring the long-term health of aerospace structures requires rigorous, continuous monitoring that can detect both surface and subsurface flaws with high reliability [4, 5]. Non-destructive testing (NDT) is central to aerospace manufacturing, maintenance, and safety assurance, underpinning the structural integrity and operational reliability of aircraft and spacecraft [2, 6]. Conventional techniques, such as ultrasonic testing (UT), radiography (RT), infrared thermography (IRT), and acoustic emission (AE), remain indispensable throughout the component life cycle from raw material validation to post-incident assessment [6, 7]. However, these methods are often constrained by reliance on human interpretation, leading to variability, fatigue-induced errors, and time-intensive workflows [4, 8]. To overcome these limitations, artificial intelligence (AI) has emerged as a transformative tool, enhancing defect detection sensitivity, reducing inspection time, and enabling automated decision-making [9–11]. AI-enabled approaches, particularly those leveraging machine learning and deep learning, can objectively process large volumes of inspection data, supporting predictive maintenance and real-time diagnostics [5, 12, 13]. Within the aerospace NDT field, two primary paradigms are evident. Image-based techniques, including radiography, thermography, and visual inspection, produce spatially rich data that is well-suited to computer vision architectures, such as convolutional neural networks (CNNs) and transformers [5, 14]. Signal-based techniques, encompassing ultrasonic testing, eddy-current testing (ECT), vibration analysis, and acoustic emission monitoring, generate sequential data optimally handled by temporal models such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and hybrid architectures [15, 16].

Despite the promise of AI-driven NDT, several challenges remain. Data scarcity, inconsistent datasets, and proprietary benchmarks hinder model generalization and reproducibility [17, 18]. Many AI models also lack interpretability, complicating trust and certification in safety-critical applications [8]. Modality-specific limitations, such as sensitivity to noise, limited penetration depth in imaging, or reduced resolution in signal analysis, further restrict reliability. Collectively, these factors underscore the need for standardized evaluation protocols, open annotated datasets, and cross-modal integration strategies that combine spatial and temporal features to enhance diagnostic accuracy [2, 19].

This review addresses these gaps by providing a comprehensive, comparative analysis of image- and signal-based NDT methods within aerospace applications, evaluating AI architectures, performance strengths and weaknesses, dataset availability, and practical deployment considerations. The paper highlights opportunities for multi-modal fusion, integrating complementary spatial and temporal features, and examines real-world inspection scenarios such as composite panel evaluation, ultrasonic C-scan imaging, and radiographic detection of subsurface flaws. By critically assessing current methodologies and their operational constraints, this review establishes an integrative framework that guides future research toward robust, interpretable, and certifiable AI-driven NDT solutions. This review differs from prior surveys by providing an integrated comparison of image-based and signal-based NDT data structures and their alignment with corresponding AI architectures, offering a unified framework that links sensing modality, model selection, and diagnostic performance. Unlike earlier reviews that focus on either specific techniques or general AI trends, this work synthesizes multi-modal fusion strategies, evaluates real aerospace inspection scenarios such as composite panel thermography, ultrasonic C-scan analysis, and radiographic defect characterization, and highlights certification-oriented challenges, including interpretability, dataset standardization limitations, and deployment constraints. Collectively, the novelty lies in delivering a comprehensive, aerospace-specific mapping of NDT modalities, multi-modal pathways for AI methods, and practical implementation considerations that guide researchers and practitioners toward robust and certifiable AI-enabled inspection workflows.

2. Methods

This study was conducted as a structured, comprehensive review aimed at synthesizing recent advancements in artificial intelligence and machine learning for non-destructive testing in the aerospace industry. Because the field encompasses diverse sensing modalities and AI architectures, a narrative survey approach was adopted to integrate heterogeneous findings, identify methodological trends, and highlight knowledge gaps, rather than conducting a formal systematic review. To ensure broad and representative coverage, relevant publications were identified through Scopus, Web of Science, IEEE Xplore, and ScienceDirect using combinations of keywords such as "artificial intelligence," "deep learning," "non-destructive testing," "ultrasonics," "radiography," "thermography," "eddy current testing," and "structural health monitoring." The review focused on peer-reviewed journal articles and major conference papers published between 2015 and 2025, reflecting the period in which modern deep learning and transformer-based approaches gained traction in NDT applications [16, 17, 11, 18].

Studies were included if they examined an AI or ML technique applied to an imaging or signal-based aerospace inspection modality. Work limited to hardware design, non-technical commentary, or studies without empirical analysis was excluded. Although the review did not follow a formal systematic protocol, titles, abstracts, and full texts were screened to ensure relevance and technical substance [7, 9]. For each publication, information was extracted on the sensing modality, AI methodology, dataset characteristics, defect category, validation strategy, and reported limitations.

These details supported a thematic synthesis organized around three core dimensions: (1) how imaging and signal-based modalities differ in data structure and AI suitability [5, 14, 15], (2) challenges related to dataset availability, annotation quality, and domain shift [17, 8, 19], and (3) emerging trends such as multi-modal fusion, interpretability, and deployment in real-world aerospace environments [12, 13, 20, 21]. For clarity, this review uses "non-destructive testing (NDT)" as the standard term throughout; when other acronyms (NDE, NDI) occur in cited titles, they are preserved in the references but not adopted in the running text. The final synthesis emphasizes comparative analysis, critical evaluation, and practical relevance for aerospace stakeholders, consistent with the goals of a comprehensive survey.

3. Overview of Non-destructive Testing (NDT) Techniques in Aerospace

Non-destructive testing (NDT) underpins every stage of the aerospace lifecycle, from manufacturing and assembly to routine maintenance and structural health monitoring (SHM), by enabling material and component evaluation without impairing serviceability [2, 4]. Non-destructive testing is essential for ensuring the safety, reliability, and longevity of aerospace structures, particularly with the increasing use of advanced composites and hybrid materials [19, 22]. The increasing complexity of airframe architectures, advanced composites, and multi-material assemblies has amplified the need for inspection techniques capable of detecting a broad spectrum of defects, including porosity, delaminations, corrosion, fatigue cracks, inclusions, and bond-line degradation [5, 23]. As no single method provides universal coverage, aerospace inspection relies on a portfolio of complementary techniques that differ in terms of penetration depth, resolution, contrast mechanisms, and suitability for specific material systems. Traditional manual inspection pipelines, while effective, are increasingly challenged by the complexity of modern materials, the need for rapid inspection cycles, and the risk of human error [24–26]. From a data standpoint, NDT modalities naturally fall into two categories: image-based and signal-based. This distinction is particularly relevant for AI integration, as it defines whether inspection data are spatial, temporal, or spectral, and therefore determines the families of algorithms that can be applied.

3.1. Image-Based NDT Techniques

Image-based NDT techniques generate two- or three-dimensional representations of structural conditions and are inherently compatible with computer vision and deep learning. Three modalities dominate aerospace usage: infrared thermography, radiography, and visual inspection.

Infrared Thermography (IRT)

Infrared thermography maps surface temperature distributions to reveal subsurface disruptions in heat flow caused by delaminations, disbonds, and impact damage [2, 13]. Active thermography, utilizing flash lamps, lasers, or ultrasonic stimulation, enhances defect contrast, making IRT particularly effective for composite skins and sandwich structures. Its non-contact operation, rapid coverage, and sensitivity to hidden anomalies make it especially useful in aircraft maintenance environments.

Radiography (RT)

Radiographic testing utilizes X-rays or gamma rays to visualize internal discontinuities that arise from differences in attenuation through the material [7, 27]. Aerospace applications range from weld inspection to porosity detection in composite or metallic components [2, 23]. Computed tomography (CT) provides volumetric reconstructions, offering detailed insight into complex geometries, though at the cost of higher exposure controls and specialized facilities.

Visual Inspection (VI)

Visual inspection, conducted manually via borescope or using imaging sensors, remains one of the most widely used NDT techniques for detecting corrosion, cracking, and surface damage. When automated through deep learning and high-resolution imaging, VI supports objective, repeatable, and large-scale diagnostics [1, 28]. In modern maintenance operations, it increasingly serves as the first line of data acquisition for AI-driven defect recognition. Collectively, image-based NDT offers high spatial fidelity and intuitive visual interpretation, albeit with limited penetration depth, particularly in dense or multilayered materials.

Signal-Based NDT Methods

Signal-based NDT techniques measure a material's mechanical, acoustic, or electromagnetic response to induced stimuli. These modalities yield time-series or frequency-domain signatures that encode subsurface or evolving structural conditions [29]. They are indispensable for detecting internal or dynamically progressing damage.

Ultrasonic Testing (UT)

Ultrasonic testing (UT) uses high-frequency acoustic waves for internal flaw detection, thickness evaluation, and laminate integrity assessment [3, 7, 10]. Pulse–echo, phased-array, and nonlinear approaches support the characterization of cracks, voids, matrix degradation, and porosity [23, 27]. UT offers exceptional depth resolution, although it requires coupling materials and careful probe alignment.

Acoustic Emission (AE)

Acoustic emission (AE) sensing monitors transient elastic waves generated by actual damage events, such as crack propagation, delamination onset, or fiber breakage, providing early warning capability in fatigue-critical components [3, 7]. AE is widely used in full-scale structural testing and operational health monitoring of airframe assemblies.

Vibration Analysis

Changes in modal shapes, natural frequencies, and acceleration spectra provide insight into stiffness reduction or damage development [16]. Vibration-based methods are valuable for global damage detection, but they require controlled conditions due to their sensitivity to environmental and boundary variations.

Eddy Current Testing (ECT)

Eddy current testing (ECT) detects near-surface discontinuities in conductive materials using electromagnetic induction. Variations in impedance or phase response reveal surface cracking, corrosion, or fastener-hole degradation [3, 7, 30]. Although widely used in aluminum aircraft structures, penetration depth is limited by conductivity and excitation frequency. Signal-based methods thus provide depth-resolved and quantitative insight into subsurface conditions and dynamic damage processes, making them central to structural health monitoring [16].

3.2. Integrated Perspective and Rationale for AI

Both image- and signal-based techniques address complementary diagnostic needs within aerospace operations. Image modalities excel in wide-area, rapid scanning for surface-level anomalies, whereas signal-based methods provide the depth penetration and sensitivity required for bonded joints, thick laminates, and metallic structures. The growing volume and complexity of these datasets—thermal sequences, radiographic images, ultrasonic waveforms, and eddy-current phase maps—render manual interpretation increasingly challenging. This motivates the integration of AI-driven modeling to automate feature extraction, reduce operator dependence, and standardize decision-making [7, 31]. The next section builds on this foundation by examining how AI techniques spanning classical machine learning to deep learning transformers are reshaping the landscape of aerospace NDT.

4. Artificial Intelligence in Aerospace Non-destructive Testing

Artificial intelligence has become a central driver of innovation in aerospace non-destructive testing by reducing operator subjectivity, enhancing defect classification accuracy, and enabling automated large-scale inspection across diverse modalities [32, 33]. Both image-based and signal-based techniques generate complex data that are increasingly difficult to interpret reliably through manual inspection alone. AI provides a systematic means of learning spatial, spectral, and temporal patterns directly from raw inputs, thereby eliminating the need for extensive feature engineering and improving diagnostic consistency across various materials, defect types, and inspection configurations [2, 31]. Classical machine learning approaches such as support vector machines, k-nearest neighbors, and random forests remain relevant for structured datasets or small-sample environments where interpretability and computational simplicity are required [6, 32]. However, deep learning now dominates the aerospace NDT landscape due to its ability to learn multi-level representations that capture subtle defect signatures in both images and signals [5, 8, 13, 16, 19, 22].

AI-enabled NDT systems generally follow a sequential workflow from data acquisition to decision output. Figures 1 and 2 illustrate the contrast between traditional workflows and end-to-end deep learning systems, adapted from the authors in [16, 20]. Traditional approaches rely on manually crafted features and expert-driven classification protocols, which limit scalability and introduce variation across inspectors. Deep learning approaches unify feature extraction, representation learning, and decision-making within a single trainable architecture, enabling improved generalization and automated deployment across both manufacturing and maintenance environments.

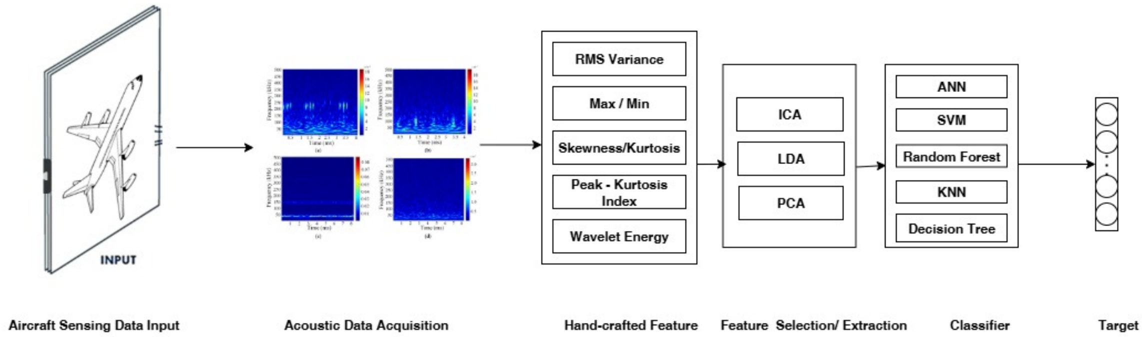

Figure 1: Traditional machine learning–based NDT workflow showing data acquisition, handcrafted features, feature extraction/selection, and classifier output (adapted from [16]).

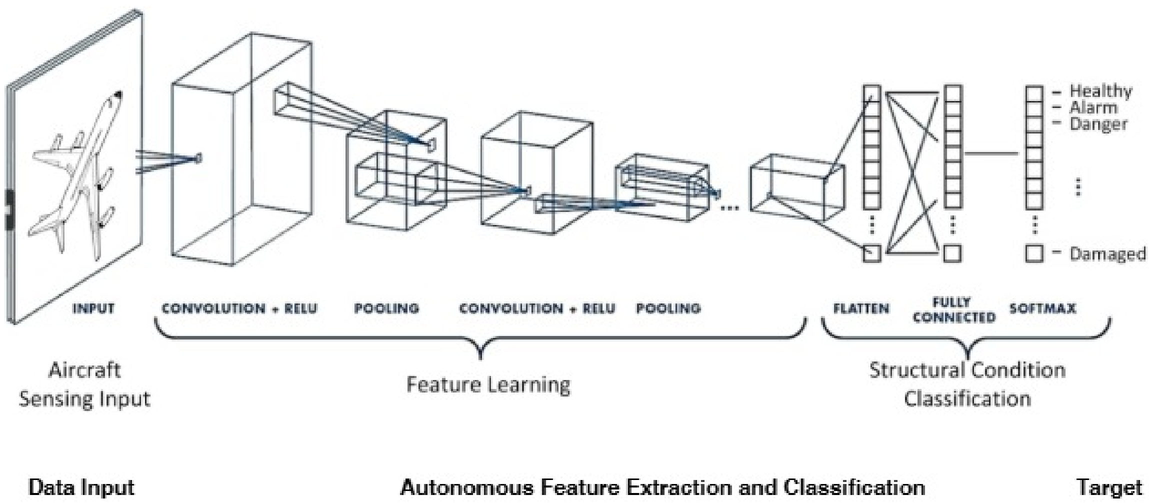

Figure 2: Deep learning–based end-to-end NDT workflow illustrating autonomous feature extraction and structural condition classification (adapted from [20]).

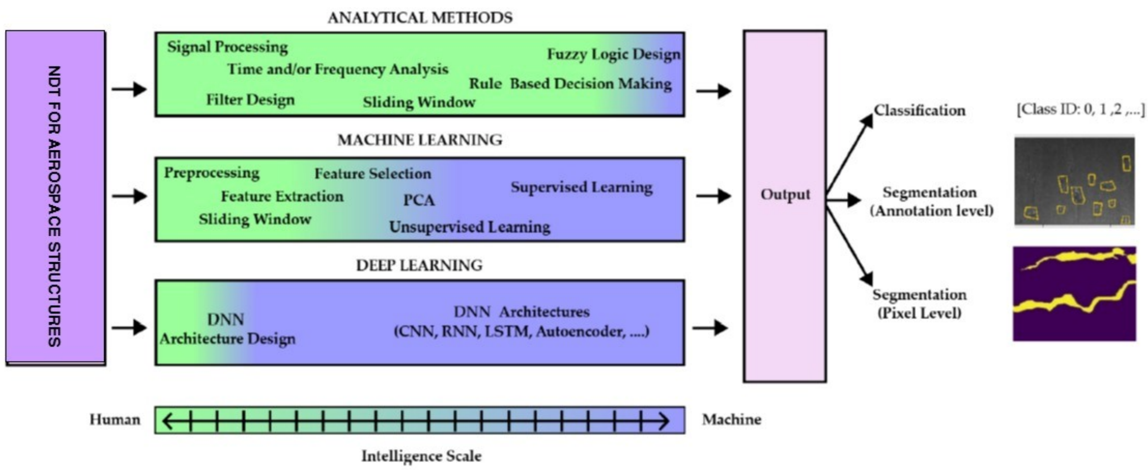

Figure 3: Relationship among analytical methods, machine learning, and deep learning for aerospace NDT, illustrating classification and segmentation pathways (adapted from [29]).

4.1. AI-Driven Image-Based NDT

Image-based NDT modalities such as radiography, infrared thermography, and visual inspection produce two-dimensional or three-dimensional spatial data that are highly compatible with computer vision techniques. Early studies relied on handcrafted texture descriptors and classical classifiers that performed adequately on small, well-controlled datasets [6, 34]. However, deep convolutional neural networks and advanced segmentation architectures provide significantly stronger performance by learning spatial hierarchies and detecting small or low-contrast anomalies that are difficult for humans or classical algorithms to observe [2, 34–36]. CNN-based models excel at defect recognition in radiography and surface imaging, while U-Net and Mask R-CNN architectures support pixel-level segmentation of cracks, porosity regions, or delamination zones. Vision transformers extend these capabilities by capturing long-range contextual information and improving global consistency in thermographic sequences [29]. These models are particularly effective in active thermography, where temporal heating profiles must be interpreted to distinguish genuine subsurface defects from environmental or surface-related variations. In vibration-based SHM, one-dimensional CNNs have demonstrated superior noise immunity and generalization compared to traditional algorithms [37–39]. Generative adversarial networks (GANs) are also gaining significant attention in aerospace NDT. GAN-based frameworks synthesize additional defect images, enhance low-contrast regions, or perform domain translation to reduce variability introduced by different equipment or excitation sources [13, 40, 41]. This improves model generalization and reduces dependency on scarce or expensive defect datasets [8]. GAN-augmented datasets have improved defect detection performance, especially for underrepresented flaw types [8]. To contextualize the distribution of responsibilities between inspectors and AI systems, Figure 3 presents a conceptual illustration adapted from [29], showing the transition from fully manual inspection to semi-autonomous and fully autonomous workflows.

4.2. AI-Driven Signal-Based NDT

Signal-based methods such as ultrasonic testing, acoustic emission, eddy current testing, and vibration analysis generate time-series data that encode critical information about material integrity and structural condition. These data formats require models that can capture temporal dependencies, spectral features, and long-range correlations. Recurrent neural networks, particularly long short-term memory (LSTM) and gated recurrent unit (GRU) architectures, are widely used for modeling ultrasonic A-scans, guided waves, or acoustic emission burst sequences [15, 42]. RNNs and LSTMs are effective for time-series and waveform-based NDT, such as acoustic emission and ultrasonic signal analysis. They capture temporal dependencies and have been used for defect classification and fatigue prediction, with reported accuracies above 90% in several studies [19, 22, 38]. Hybrid CNN–LSTM models combine spatial–spectral filtering with temporal memory mechanisms, enabling accurate detection of internal cracks, porosity, weld defects, and evolving fatigue processes [38]. Transformer-based models, originally developed for natural language processing, have recently demonstrated strong performance in signal-based NDT due to their ability to capture global relationships and reduce sensitivity to noise [29, 43]. Transformers address limitations of recurrent networks by processing entire sequences simultaneously, improving robustness in environments with varying defect sizes or inconsistent signal quality. Transformers demonstrate promise in deconvolving complex ultrasonic signals, improving thickness gauging in environments with corrosion or noise, and enhancing feature extraction from long-range temporal dependencies [43]. Early studies show that transformers outperform CNNs in capturing long-range dependencies [43]. Attention mechanisms have also been shown to be useful for multi-modal fusion (image + signal), as well as volumetric signal analysis. Classical methods remain important when computational resources are limited or when interpretability is required. Support vector machines and ensemble classifiers perform effectively on engineered feature sets derived from ultrasonic peaks, acoustic emission frequency descriptors, or eddy current phase curves. A summary of representative AI architectures and their corresponding signal-based NDT modalities is provided in Table 1, which reflects typical diagnostic objectives across aerospace materials and components.

4.3. Integration Perspective

The application of AI in aerospace NDT has evolved from isolated algorithmic demonstrations to integrated systems capable of real-time inference and onboard evaluation. Modern approaches integrate imaging, acoustics, and electromagnetic sensing with unified decision-making links enabling multi-modal defect characterization and enhanced reliability across diverse operational conditions. Transfer learning and data augmentation help mitigate limitations in defect data availability, while GPU-accelerated inference and embedded processors support deployment in maintenance hangars, manufacturing lines, and field operations [4, 5]. These advancements indicate a shift toward predictive and autonomous inspection capabilities that can operate continuously with minimal human intervention. Figure 4 shows the key machine learning and deep learning algorithms employed for X-ray image-based NDT of aerospace welds and structures. These algorithms, graphically summarized in Figure 4, illustrate the shift toward intelligent, scalable inspection solutions that utilize AI.

Table 1: Representative AI architectures used in signal-based NDT modalities.

Technique	Signal Domain	Typical AI Models	Diagnostic Objective
Ultrasonic Testing (UT)	Time-of-flight / frequency	LSTM, Transformer, CNN–LSTM	Crack detection, thickness estimation
Acoustic Emission (AE)	Burst signals / time-series	Autoencoder, LSTM, GRU	Fatigue monitoring, early damage detection
Eddy Current Testing (ECT)	Impedance / phase response	CNN, SVM	Surface crack and corrosion characterization
Vibration Analysis	Frequency spectrum / acceleration	CNN on spectrograms, Transformer	Rotor and bearing fault diagnosis
Hybrid Systems	Fused UT, AE, vibration	Attention-based fusion networks	Prognostics and health monitoring

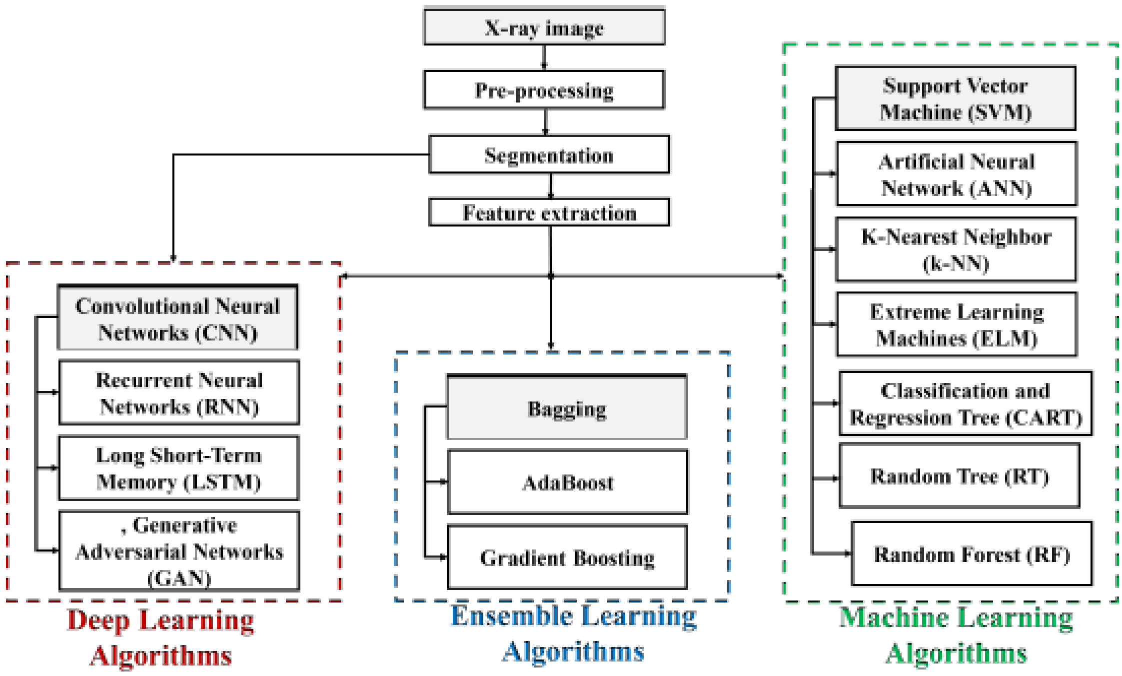

Figure 4: Machine learning, ensemble learning, and deep learning algorithms used for X-ray image-based NDT of aerospace structures (adapted from [14]).

4.4. Application Scenarios for AI-Driven Non-destructive Testing

Recent studies from 2018 to 2025 have demonstrated a surge in the practical applications of advanced AI models, such as CNNs, LSTMs, Transformers, GANs, and Physics-Informed Neural Networks (PINNs), in real-world aerospace NDT scenarios across multiple modalities and component types. In ultrasonic testing of composite bonded structures, a hybrid CNN-BiGRU model with attention mechanisms achieved 97.7% accuracy in defect identification, effectively overcoming the signal attenuation and noise challenges inherent to ceramic matrix composites used in aircraft thermal protection [44]. Similarly, a hybrid CNN-LSTM model with attention was applied to ultrasonic signal classification for multilayer composite adhesives, achieving 98.57% accuracy and highlighting the value of automated feature extraction and hyperparameter optimization for delamination detection [45]. For impact detection and characterization in composite fuselage panels, CNNs trained on ultrasonic wave data from piezoelectric sensors enabled the accurate localization and categorization of impacts, with detection rates exceeding 99.4%. These systems demonstrated scalability from coupon-level inspections to complex subcomponents, although additional work is needed to address operational and environmental variability [20]. In the context of digital radiography and visual inspection, Mask R-CNN architectures combined with data augmentation were deployed for automated aircraft maintenance inspections, improving the F1-Score to 67.5% for dent detection on aircraft wings. However, field deployment remains challenging due to environmental variability and generalization requirements [28].

Physics-informed neural networks (PINNs) have been applied to ultrasonic array imaging and pulsed thermography, enabling precise interface reconstruction in complex curved components and defect detection in carbon fiber-reinforced polymers, with reported average relative errors below 1% and computation times under one second. However, gradient ill-conditioning and data scarcity can constrain performance [46–48]. For structural health monitoring under fatigue loading, CNN-based frameworks using radar data achieved F1-scores between 91% and 100% in wind turbine blade damage detection, underscoring the adaptability of deep learning to electromagnetic modalities and large-scale composite structures [49]. Additionally, digital twin platforms integrating ConvLSTM networks have enabled real-time, location-specific damage prediction in piezoelectric composite aircraft wing panels, addressing the need for in-situ monitoring and microstructure-dependent analysis [50]. Across these studies, common trends include the integration of attention mechanisms for feature selection, the use of hybrid and physics-informed models to incorporate domain knowledge, and the adoption of data augmentation or generative models (e.g., GANs) to address data imbalance and improve robustness. Practical deployment, however, remains constrained by the need for large, high-quality labeled datasets, challenges in generalizing across varying operational conditions, and the computational demands of real-time inference. Collectively, these advances highlight the growing maturity and practical relevance of AI-driven NDT in aerospace, while emphasizing the ongoing need for robust validation, interpretability, and field-ready solutions [28, 44, 48].

Table 2: Summary of AI-Based Aerospace NDT Studies (2015–2025).

Reference	NDT Modality	AI/ML Model	Dataset Used	Performance	Limitations
[8]	Digital radiography of aerospace welds	U-Net segmentation	Real aerospace weld radiographs with virtual flaw augmentation	High sensitivity; accurate defect sizing; low false call rate	Annotation inconsistencies; limited real-world data diversity
[24]	Ultrasonic inspection of CFRP aerospace composites	Autoencoder + DBSCAN	CFRP samples with embedded aerospace-grade defects	AUC: 0.922 (simple), 0.879 (complex)	Sensitive to geometry; limited field validation
[51]	Laser ultrasonic testing of aerospace laminates	Deep autoencoder	Composite laminate with six programmed defects	>90% balanced accuracy; F1 > 0.75	Small dataset; limited defect variations
[44]	Ultrasonic inspection of CMC for aircraft thermal protection	CNN–BiGRU with attention	Aerospace-grade CMC panels	97.7% accuracy	Operational noise and generalization not tested
[28]	Aircraft visual inspection (surface dent detection)	Mask R-CNN with augmentation	Real wing and fuselage images	F1 = 67.5%	Illumination and environmental sensitivity
[46]	Ultrasonic array imaging for curved components	Physics-informed neural network (PINN)	Simulated and experimental CFRP samples	<1% average relative error	Gradient instability; limited robustness
[48]	Pulsed thermography of CFRP composites	PINN reconstruction	CFRP panels with real impact defects	<1% error	Requires high-fidelity physical models
[49]	Radar-based SHM for composite structures	CNN classifier	Experimental radar data	F1: 91–100%	Environmental sensitivity; modal variability
[14]	Digital X-ray radiography	Custom CNN; ResNet-50/101; patch-based CNN	539 helicopter rotor-hub X-rays plus 657 new-sensor images	Best: 98.07%; patch: 96.15%; CV: 92.34–95.00%	Requires ROI cropping; limited labeled data
[2]	Multi-modal aerospace NDT (thermography, radiography, UT)	Deep learning (reviewed examples)	Multiple datasets (survey)	Various	Environmental sensitivity; lack of standardization

To provide a consolidated overview of existing literature and support the comparative analysis in the following sections, Table 2 summarizes key peer-reviewed studies applying artificial intelligence to non-destructive testing of aerospace materials and components. The table highlights representative image-based and signal-based modalities, the AI models employed, dataset characteristics, reported performance, and stated limitations.

5. Comparative Analysis of Image-Based and Signal-Based NDT Techniques

Aerospace inspection environments require the combined strengths of imaging and signal-based non-destructive testing techniques to capture the full spectrum of structural anomalies encountered across composite and metallic systems. Image-based approaches, including infrared thermography, radiography, and visual inspection, provide spatially resolved information that is intuitive for human interpretation and well aligned with computer vision models [13, 27]. These techniques excel at detecting surface-breaking defects and near-surface delamination, delivering rapid coverage across large areas with minimal contact requirements [2]. However, their penetration depth is limited, and thermal or radiographic contrast may diminish significantly in thick or absorptive aerospace composites. Signal-based techniques, such as ultrasonic testing, acoustic emission, vibration monitoring, and eddy current testing, complement image-based methods by providing enhanced sensitivity to subsurface and volumetric damage. Ultrasonic testing, in particular, can detect internal voids, barely visible impact damage, and debonding in multilayered structures with high depth resolution [7, 10]. Acoustic emission and vibration-based diagnostics capture dynamic characteristics associated with fatigue crack growth and stiffness degradation, enabling *in situ* monitoring under operational loads [3, 16]. While powerful, signal-based approaches can be sensitive to coupling conditions, boundary variability, and operator technique, which complicates standardization. A consolidated comparison of strengths, limitations, and AI compatibility across the two categories is shown in Table 3. This comparison highlights that each modality occupies a specific niche but rarely provides complete defect characterization when deployed in isolation.

Table 3: Comparative characteristics of image- and signal-based NDT techniques.

Attribute	**Image-Based Techniques (IRT, RT, VI)**	**Signal-Based Techniques (UT, AE, ECT)**
Primary Output	2D/3D spatial images	1D time-series or frequency data
Penetration Depth	Shallow (surface/near-surface)	Deep (subsurface to volumetric)
Resolution	High spatial resolution; limited depth	High depth resolution; moderate spatial
Inspection Speed	Fast; wide-area coverage	Moderate; localized measurements
Typical Defects	Surface cracks; delamination; corrosion	Subsurface cracks; voids; fatigue damage
AI Models	CNN; U-Net; Vision Transformer	LSTM; GRU; Transformer; CNN–LSTM
Data Volume	Large (image-heavy)	Moderate (signal sequences)
Automation Potential	High, especially with visual AI	High, with continuous monitoring systems

5.1. Data Modalities and AI Model Compatibility

The primary distinction between image and signal modalities lies in their structural format. Image-based NDT produces two-dimensional or three-dimensional spatial fields that are ideal for convolutional neural networks, segmentation models, and vision transformers, which capture spatial gradients and morphological structures associated with cracks or porosity [35, 36]. Radiographic and thermographic datasets often contain high-resolution textures, making them particularly responsive to attention-based vision models [8]. Signal-based modalities generate one-dimensional time series or frequency spectra that reflect wave propagation, impedance shifts, or vibration signatures. These data require models capable of learning sequential and spectral dependencies, including LSTM networks, gated recurrent units, and transformer-based architectures [15, 42]. Hybrid CNN–LSTM models provide an intermediary approach by capturing spatial–frequency patterns before temporal modeling, often improving performance in ultrasonic and acoustic emission applications [4, 38].

5.2. Empirical Capabilities and Operational Constraints

Empirical performance varies significantly across NDT modalities. Image-based systems provide rapid scanning and intuitive spatial interpretation but often experience contrast degradation in noisy environments, complex geometries, or thermally unstable conditions [13]. In contrast, signal-based techniques offer strong penetrability and reliable characterization of subsurface defects, particularly in ultrasonic and acoustic emission applications. However, their performance depends on consistent measurement conditions and can be influenced by geometric complexity or material heterogeneity [46]. In aerospace maintenance settings, the coexistence of large-area surfaces, multi-material assemblies, and intricate component geometries frequently necessitates the combined use of image and signal modalities. Recent research has focused on multi-modal integration, where complementary data sources are processed together within unified AI frameworks to improve defect characterization and decision reliability [29]. This trend reflects a broader shift toward adaptive, evidence-driven inspection workflows that can synthesize information across various sensing domains.

6. Challenges, Limitations, and Research Opportunities in AI-Augmented NDT

Despite notable advances, the deployment of AI-enabled NDT in aerospace remains constrained by foundational challenges linked to data availability, model robustness, interpretability, and certification pathways. These constraints originate from both the physical characteristics of NDT modalities and the operational demands of high-reliability aerospace environments.

6.1. Dataset Availability, Representation, and Limitations

A recurring limitation across the literature is the scarcity of large, diverse, and well-annotated datasets that reflect true operational conditions.

Ultrasonic C-Scan and B-Scan Data

Ultrasonic inspection datasets are heavily proprietary, limiting public availability and reducing cross-study comparability [25, 38]. Annotation quality is inconsistent, particularly for composite structures where defect morphology is complex. Although virtual flaw synthesis and simulation frameworks assist with data augmentation, models trained exclusively on simulated data exhibit domain shift when deployed in real aerospace components [8, 24].

Radiography and Thermography Datasets

X-ray and thermographic datasets for aerospace components remain rare, often exhibit sparse defect diversity, and lack consistent labeling standards [37]. Thermographic sequences are sensitive to heating conditions and environmental noise, complicating robust learning across multiple platforms [8]. Transfer learning partially mitigates these issues but does not fully account for structural heterogeneity.

SHM Benchmark Signals

Benchmark datasets in structural health monitoring exist but provide limited representation of environmental variability, operational noise, or progressive damage evolution [37, 52]. These gaps restrict model robustness under realistic conditions, particularly for vibration and acoustic emission applications.

Cross-Cutting Issues

Across all modalities, dataset accessibility, annotation protocols, and documentation standards vary widely [24]. The absence of metadata describing noise characteristics, equipment parameters, and environmental conditions restricts reproducibility and prevents the development of standardized evaluation benchmarks [25, 38].

6.2. Model Robustness, Validation, and Domain Generalization

Many studies demonstrate high performance under controlled laboratory conditions but show inconsistency in field deployments. Mismatched validation strategies, such as testing on idealized simulated datasets, lead to overestimated accuracy and hinder real-world reliability [37, 44]. Domain shift is particularly problematic in ultrasonic inspections where component curvature, layup orientation, and surface condition alter waveform characteristics [24].

Few studies evaluate models under varying noise levels, environmental conditions, or cross-aircraft structural differences, leaving substantial gaps in robustness assessment [8]. This challenge underscores the need for adaptive and physics-informed learning frameworks that can maintain performance across diverse conditions.

6.3. Interpretability, Uncertainty Quantification, and Trustworthiness

Deep learning models often operate as opaque classifiers without explicit reasoning. In aerospace, this limits operational acceptance and slows certification. Explainability methods highlight important features or regions, but their physical interpretability remains limited [53]. Uncertainty quantification approaches, such as deep ensembles and Bayesian neural networks, enhance confidence calibration but require sufficient data diversity for accurate estimation [26].

6.4. Certification, Standardization, and Operational Constraints

Certification of AI-based NDT remains challenging because most machine learning models fail to meet the requirements for traceability and deterministic behavior specified in NAS 410 and EN 4179. Deep networks adjust large numbers of parameters during training, making their decision logic difficult to document in a form acceptable for aerospace qualification [2, 8]. Model drift caused by sensor changes or environmental variation can reduce reliability over time, requiring continuous monitoring and scheduled revalidation [54]. Recent studies emphasize the need for strict version control, including dataset versioning and secure tracking of deployed model weights, to meet audit and reproducibility expectations [2, 21].

6.5. Future Research Directions

Three research trajectories emerge as particularly critical. Multi-modal and Hybrid Fusion continues to gain traction in aerospace NDT because it integrates complementary information from ultrasonic testing, thermography, radiography, and other sensors to improve defect detectability in composite and metallic structures [2, 21, 55]. Image-level and feature-level fusion techniques enhance contrast and reduce ambiguity for subsurface defects, especially when combining phased-array ultrasonics with pulsed thermography or X-ray imaging [21]. Recent work demonstrates that hybrid deep learning architectures, such as CNN–RNN or transformer-based fusion networks, capture correlated spatial–temporal patterns from heterogeneous inspection data and outperform single-modality models in classification and defect segmentation tasks [42, 54]. Despite these advantages, recent controlled studies on multi-modal still produce systematic uncertainties in defect sizing and depth estimation, with evaluations reporting increased mean absolute error in deep-layer flaws and inconsistent detection rates across varying laminate thicknesses [18, 21, 55]. Comparative reviews further emphasize that NDT fusion remains an emerging field with few standardized benchmarks or harmonized evaluation metrics, making cross-study comparison difficult and limiting confidence in operational deployment [54]. These gaps highlight the need for unified fusion protocols, consistent metrics, and broader validation on field-acquired aerospace datasets.

Physics-Informed and Domain-Adaptable Models

Hybrid data–physics frameworks, including physics-informed neural networks and model-assisted learning, enhance generalization and reduce dependency on large datasets [46].

Autonomous and Real-Time Inspection

Robotic platforms integrating embedded AI and onboard inference can deliver consistent, repeatable inspections. Edge computing, model compression, and standardized digital workflows will be essential for realizing deployable systems [29].

7. Conclusion

Artificial intelligence has revolutionized non-destructive testing in aerospace by enabling automated feature extraction, enhanced defect detection, and improved diagnostic reliability across both image-based and signal-based modalities.

While image-based techniques offer intuitive spatial interpretation and high-throughput surface inspection, signal-based approaches provide deep material penetration and sensitivity to internal and dynamic damage mechanisms. Their complementary nature has driven the adoption of multi-modal frameworks that integrate thermal, radiographic, ultrasonic, and vibration signals into unified decision pipelines. However, major challenges persist. Dataset scarcity, inconsistent annotation standards, limited domain generalization, and weak interpretability continue to restrict operational deployment. The lack of standardized benchmarks and certification pathways further complicates adoption in safety-critical aerospace environments. These constraints underscore the need for coordinated research on multi-modal datasets, physical multi-modal design, uncertainty-aware algorithms, and interpretable decision support systems. The trajectory of future development points toward autonomous, explainable, and certifiable NDT tools that combine the strengths of advanced sensing, deep learning, and digital twin platforms. Achieving this vision requires close collaboration between AI researchers, NDT experts, aerospace manufacturers, and regulatory bodies. With continued multi-modal evaluation, AI-driven NDT will become a foundational component of next-generation aerospace maintenance and structural health monitoring systems.

Declaration of Competing Interests

The author declares no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

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Author Contributions

The sole author carried out the conceptualization, methodology design, literature investigation, comparative analysis, manuscript drafting, and critical revision of the work. The author approves the final version of the manuscript and is fully accountable for all aspects of its accuracy and integrity.

Data Availability Statement

No new data were generated or analyzed in this study. All sources referenced are publicly available in the cited literature.

AI-Use Disclosure

AI tools were used to assist with formatting; all substantive analysis, interpretation, and conclusions were developed exclusively by the author.

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