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Innovations in Defect Detection: Integrating AI and NDT Techniques in Composite Materials

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ABSTRACT

This paper proposes an innovative approach integrating vibration mode analysis and artificial intelligence (AI) algorithms to improve defect detection in composite materials. Recognizing the limitations of traditional NDT techniques in complex environments, this research demonstrates how the integration of AI, including CNNs and unsupervised learning techniques, enables more accurate and faster identification of structural anomalies. Experimental results confirm a significant improvement in performance, particularly in terms of accuracy and reliability, compared with conventional methods. By exploring applications in critical sectors such as aeronautics and renewable energies, this article highlights the future prospects of this methodological combination and proposes research directions to enhance the robustness of fault detection systems.

1. INTRODUCTION

The splendid houses of composite substances, together with light-weight, excessive tensile strength, and adaptability, lead them to crucial in an extensive variety of commercial sectors. In aeronautics, using composite substances extensively reduces plane weight, main to more strength performance and decrease emissions whilst retaining the structural integrity required for safety. Wind turbine blades product of composite substances display more suitable sturdiness and long-time period overall performance in renewable strength structures, as they could face up to severe environmental situations. Similarly, the car enterprise advantages from those substances to fabricate light-weight but strong vehicles, enhancing gas performance and passenger safety. In excessive-overall performance sports, composite gadget along with bicycles and rackets combines lightness and strength, presenting athletes an aggressive edge. Recent research has additionally highlighted the improvement of bio composites with more suitable mechanical houses, along with PMMA-primarily based totally composites mixed with polyamide and polyvinylpyrrolidone, that have promising packages in superior cloth design [1].

Despite those advantages, composite substances face large demanding situations because of inner defects along with delaminations, cracks, porosities, and inclusions. These anomalies, frequently invisible to the bare eye, can significantly compromise structural integrity and cause catastrophic disasters in vital packages. For example, undetected delamination in aircraft additives can bring about in-flight failure, whilst defects in wind turbine blades can degrade overall performance or necessitate highly-priced repairs. Studies have proven that the conduct of composites below low-speed effect and fatigue situations is vital for making sure sturdiness, mainly in traumatic commercial packages [2]. Ensuring the reliability, protection, and sturdiness of composite structures calls for early and correct detection of such defects.

Conventional non-unfavorable testing (NDT) strategies, along with ultrasonic inspection, radiography, and infrared thermography, frequently war to hit upon diffused or complicated anomalies in the heterogeneous systems of composites. These strategies are regularly hindered via way of means of constraints associated with environmental situations, structural geometry, or illness size. Consequently, revolutionary processes are urgently had to cope with those boundaries and meet the growing needs of cutting-edge industries.

Artificial intelligence (AI) blended with superior NDT techniques has emerged as a promising technique to those demanding situations. AI excels in processing big volumes of complicated records and figuring out diffused styles that traditional strategies may miss. For instance, superior algorithms like convolutional neural networks (CNNs) can't handily pick out microscopic anomalies in X-ray pictures however additionally are expecting illness propagation in actual time. Additionally, unsupervised gaining knowledge of techniques, along with clustering, permit the identity of unknown defects without requiring pre-classified records. These technological improvements now no longer handiest beautify detection accuracy however additionally enhance operational performance via way of means of lowering fees and inspection times.

This article delves into the synergy among vibration mode evaluation and synthetic intelligence algorithms for illness detection in composite substances. It evaluates the overall performance of those included strategies in comparison to traditional strategies, highlights their applicability in vital sectors like aerospace and renewable strength, and proposes guidelines for destiny studies to cope with chronic demanding situations on this field.

2. COMPOSITE MATERIALS AND COMMON DEFECTS

2.1 Characteristics of composite materials

Composite materials possess outstanding properties, combining different phases such as a reinforcement material (typically high-strength fibers like carbon, glass, or aramid) and a polymer resin matrix. This combination results in materials with significantly better mechanical properties than traditional ones. These include lightweight structures that reduce overall mass while maintaining strength, as well as high tensile and compressive strengths, making them essential in modern industry.

The utilization is witnessed across various industries owing to their flexibility. Composites, for example, appeal to the aviation sector for their weight loss capability while also increasing the strength of the aircraft structural points very vital for the vehicle. Parveez et al. [3] carried out the detailed study of the scenario of the composite materials being utilized for the aircraft structures where their value was the highest highlighted. In the argument by Wu [4], the highest and the very first value of the use of the carbon-fiber composites is the consideration that the structures and the aerodynamics of the aircraft improve, something very fundamental for the conservation of energy through less consumption and the enhancement of the efficiency of the craft.

In the renewable energy sector, significant progress has been made in defect detection for composite wind turbine blades, leveraging advanced AI techniques and non-destructive testing (NDT) methods. For instance, one study proposes a semi-supervised anomaly detection method that identifies surface defects using drone-captured images, enhancing inspection accuracy and efficiency [5]. Another research project focuses on predicting fatigue damage in composite blades under uncertain wind loads through stochastic degradation models, enabling proactive maintenance and improved reliability [6]. Furthermore, an innovative perception system based on polarized computational imaging offers automatic defect detection in composite laminates, significantly improving the precision of blade inspections [7]. These advances are critical for enhancing the reliability, lifespan, and performance of wind turbine blades in renewable energy systems.

In high-demand sectors such as automotive and sports equipment, the application of high-performance fiber-reinforced polymer composites continues to expand, as highlighted by Alam et al. [8]. These materials combine lightweight characteristics with exceptional strength, making them ideal for creating durable, high-performance structures. The study indicates potential applications in diverse sectors, including the medical field, thanks to enhanced processability and performance [9].

These advancements enhance the capabilities of composite materials, improving efficiency, performance, and safety across various sectors such as aerospace, renewable energy, automotive, and sports.

2.2 Types of composite materials and their characteristics

Typology of Defects: Composite materials, renowned for their advanced performance attributes, are susceptible to a variety of defects that can compromise their structural integrity and functionality. Understanding these defects is essential for effective quality control and maintenance (see Figure 1).

Delamination: Delamination is a critical defect where layers within a composite material separate due to poor bonding or impact damage. This can result in a significant reduction in the load-bearing capacity of the material. According to the article "Mécanique de la rupture des composites: délaminage et fissuration" [10], delamination often occurs due to the inherent properties of composite interfaces and is a major concern in structural applications. Detecting delamination early is crucial for preventing failures in aerospace and automotive applications [11]. Additionally, Sobri et al. [12] explored the advancements in carbon fiber reinforced polymers (CFRP), emphasizing improvements in manufacturing processes and material properties.

Cracks: There are a number of reasons for the development of cracks which are mechanical stress, thermal cycles, or impact events causing potential structural degradation. The article then goes on with a detailed study of the mechanics of cracking in composites, enumerating which ones are the most common and how the stresses that appear either in use or in the production process can become the reasons of the structural defect [10]. The techniques like digital image correlation and acoustic emission are in the stage of development that will allow us to better detect and analyze cracks in composites.

Table 1. Key characteristics and applications of composite materials

Material Type	Key Characteristics	Applications
Carbon Fiber-Reinforced Polymer (CFRP)	Lightweight, high tensile and compressive strength, thermal resistance	Aerospace, automotive, sports equipment
Glass Fiber-Reinforced Polymer (GFRP)	Cost-effective, good impact resistance, chemical stability	Construction, piping, automotive
Natural Fiber Composites	Renewable, biodegradable, moderate strength	Automotive interiors, construction panels
Hybrid Composites	Tailored properties by combining different fibers	Military, transport, renewable energy

Table 1 presents the key characteristics and applications of composite materials, highlighting their advantages in various industries.

Inclusions: Inclusions are foreign particles or contaminants that become embedded within the composite matrix during manufacturing. These inclusions create stress concentrations that can weaken the material. Identifying inclusions often involves using advanced imaging techniques, such as scanning electron microscopy (SEM) and X-ray computed tomography (CT).

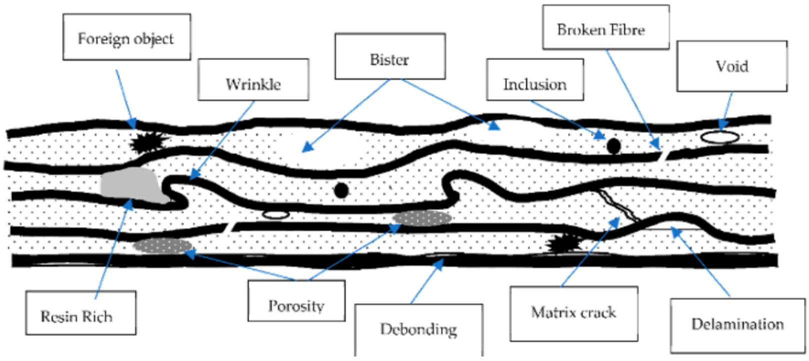

Figure 1. Common manufacturing defect in composites [12]

Porosities: Porosities, or voids within the composite matrix, are a common defect resulting from incomplete resin infiltration or gas entrapment during the curing process. These voids can significantly reduce the material's mechanical properties and overall performance. According to recent studies, porosities can lead to reduced tensile strength and stiffness, making their detection critical for ensuring the quality of composite materials.

Impact Damage: Impact damage can involve a range of defects, including matrix cracking, fiber breakage, and delamination. This type of damage is caused by external forces and can lead to a significant reduction in the material's structural integrity. Advanced non-destructive testing methods, including laser scanning and acoustic emission, are used to assess the extent of impact damage.

Fiber Misalignment: When the fibers of reinforcement are misplaced not in the right direction, fiber misalignment takes place. The defect can make the mechanical performance of a composite in risk, which can mean that the strength and stiffness of it are compromised. The evaluation of fiber misalignment typically involves methods such as X-ray diffraction and ultrasonic inspection.

Matrix Cracking: Matrix cracking involves cracks forming in the resin matrix due to excessive stress or thermal expansion. These cracks can propagate and compromise the composite's load-carrying capacity. Matrix cracking is often studied using microscopy and acoustic emission techniques to understand its impact on material performance.

Resin Rich Zones: Resin rich zones occur when there is an excess of resin in certain areas of the composite, leading to uneven mechanical properties and potential delamination. These zones can be detected using advanced imaging techniques, including infrared thermography and laser scanning.

Impact of Defects

Defects in composite materials can have profound effects on their mechanical properties and overall lifespan, impacting their performance in critical applications.

Delamination: Delamination severely affects the load-bearing capacity of composite materials. It creates weak planes within the material, leading to reduced shear strength and potential structural failure. The presence of delamination can significantly decrease the material's ability to withstand loads, particularly in aerospace and automotive applications where structural integrity is paramount. Studies show that delamination can lead to a marked decrease in tensile strength and stiffness, often requiring costly repairs or replacements [13].

Cracks: Cracks in composite materials, whether due to mechanical stress or impact, can propagate and lead to catastrophic failures if left unaddressed. Cracks reduce the material's ability to handle stress, affecting its fatigue life and overall durability. The propagation of cracks can lead to increased maintenance costs and reduced service life, as the material may no longer meet the required performance standards [14].

Inclusions: The presence of inclusions can compromise the material's structural integrity, leading to premature failure under operational loads. Inclusions within the composite matrix are the reason for the creation of stress concentrations which may, in turn, cause localized failures. These intruders of foreign origin may, to a great extent, change the uniform distribution of stress and strain in the structure. This can again result in decreased the mechanical functions and potential weak spots [15].

Porosities: Porosities, or voids, in the composite matrix can significantly weaken the material by reducing its density and mechanical strength. These voids can act as stress concentrators, leading to reduced tensile strength, stiffness, and impact resistance. Studies indicate that even small levels of porosity can substantially affect the material's performance, potentially leading to a reduced lifespan and higher susceptibility to environmental damage [16, 17].

Impact Damage: Impact damage, including matrix cracking and fiber breakage, affects the material's ability to bear loads and resist further damage. Impact-induced defects can compromise the material's structural integrity, leading to decreased performance and increased maintenance needs. The extent of impact damage often dictates the necessity for repairs or replacements, which can be costly and time-consuming.

Fiber Misalignment: Fiber misalignment reduces the composite's mechanical performance by disrupting the intended load distribution. This misalignment can lead to a decrease in tensile and compressive strength, affecting the overall stability and load-bearing capacity of the material. Misalignment often results in reduced performance and increased risk of failure under load [9].

Matrix Cracking: Matrix cracking affects the material's load-carrying capacity by compromising the integrity of the resin matrix. These cracks can propagate and lead to further degradation of the material's mechanical properties, reducing its overall durability and lifespan. Effective monitoring and repair are necessary to manage the impact of matrix cracking on composite materials [18].

Resin Rich Zones: Resin rich zones can lead to non-uniform mechanical properties within the composite, affecting its overall performance. These areas can have reduced strength and increased susceptibility to delamination, impacting the material's reliability and service life. Detecting and managing resin rich zones is crucial for maintaining the material's intended performance [19].

Overall, defects in composite materials can significantly impact their mechanical properties and service life. Early detection, accurate assessment, and effective repair strategies are essential for ensuring the reliability and longevity of composite structures.

3. NON-DESTRUCTIVE TESTING (NDT) TECHNIQUES

3.1 General overview of Non-Destructive Testing (NDT)

Non-Destructive Testing (NDT) plays a crucial role in the inspection and evaluation of composite materials, ensuring their structural integrity and reliability without causing damage. Various NDT methods are employed to detect and characterize defects, each offering unique advantages depending on the type of composite material and the specific application.

Ultrasonic Testing (UT): Ultrasonic testing is one of the most widely used NDT methods for inspecting composite materials. The method is highly effective for evaluating the thickness of composite layers and identifying flaws that are not visible on the surface (see Figure 2) [20].

Radiography (X-ray and Computed Tomography): Radiographic testing uses X-rays or gamma rays to penetrate the composite material and capture images of its internal structure. X-ray computed tomography (CT) provides 3D imaging, allowing for detailed visualization and analysis of internal defects (see Figure 3) [22].

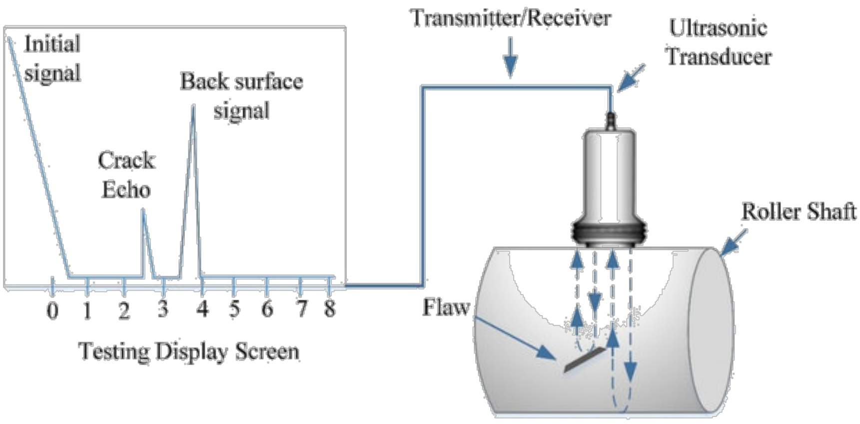

Figure 2. A diagram that displays the test screen and compression probe of the ultrasonic testing unit (UT) [14, 21]

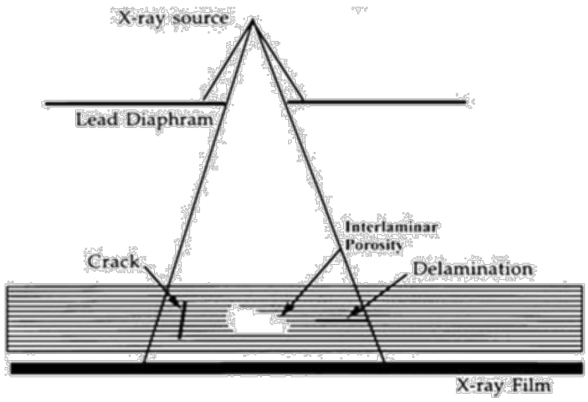

Figure 3. Schematic radiograph of a typical composite with typical flaws [23]

Thermography: Infrared thermography is a non-contact NDT method that detects temperature variations on the surface of the composite material. These variations are often caused by internal defects, such as delamination or impact damage, which disrupt the material`s thermal conductivity (see Figure 4) [24].

Acoustic Emission (AE): Acoustic emission testing monitors the sound waves generated by the release of energy from within the material, typically during loading or stress. These sound waves are indicative of crack growth, fiber breakage, or delamination. AE is a sensitive method for detecting dynamic changes in the material and can provide real-time monitoring of defect progression. It is often used in structural health monitoring of composite components in service (see Figure 5) [26].

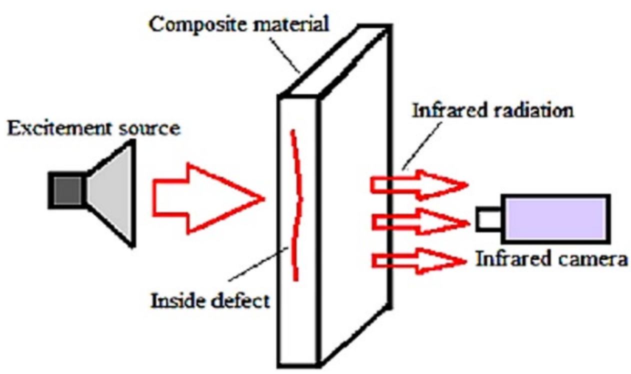

Figure 4. Active infrared thermography [25]

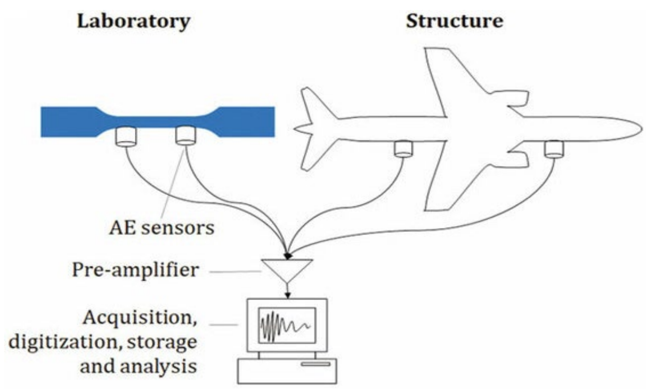

Figure 5. Schematic representation of a typical AE system [27]

Shearography: Shearography provides a full-field inspection, making it suitable for large composite structures and complex geometries. It is commonly used in the aerospace and automotive industries for quality control and maintenance inspections (see Figure 6) [28].

Resonant Frequency Testing: The natural vibration frequencies of a composite structure are measured through resonant frequency testing. Defects such as delamination, cracks, or material degradation can be indicated by changes in these frequencies. For a comprehensive assessment, this method is often used in conjunction with other NDT methods to assess material properties that change globally [30].

Magnetic Resonance Imaging (MRI): Even though this is not standardly performed, MRI scan has been developed to check the state of all the magnetic types of the materials. With the help of this imaging technique, the internal architecture can be seen in great detail, and thus, the imperfections, such as voids, inclusions, and fiber orientation, can be discovered. Composite materials which MRI can be used for in the R&D area are also done in a detailed way [31].

3.2 Vibration mode analysis for defect detection

The structural vibration characteristics can be examined using vibration mode analysis, which is a powerful technique for detecting defects in composite materials. Natural frequencies and mode shapes are the focus of this method's study.

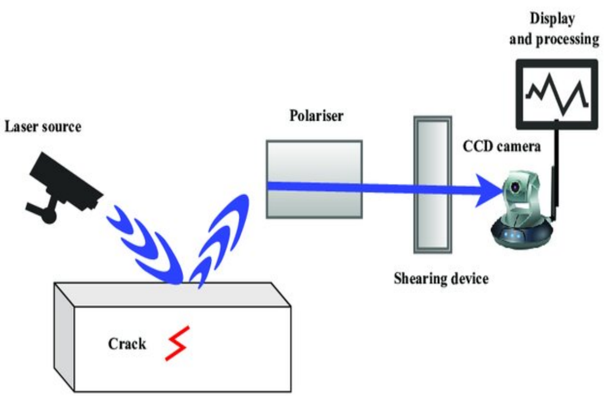

Figure 6. Schematic representation of a shearography test [22, 29]

3.3 Theoretical principles

- **Vibration Modes and Natural Frequencies**

The vibration of an elastic structure can be described by the following differential equation, derived from the principles of structural dynamics: The fundamental Eq. (1) governing these vibrations is:

$$\frac{\partial^2 u(x,t)}{\partial^2 t} + \omega^2 u(x,t) = 0 \tag{1}$$

where,

- $u(x,t)$ is the displacement as a function of position x and time t.
- ω represents the natural frequency of the structure [32].

This equation is based on the fundamental laws of dynamics and the constitutive relations between internal forces and deformations.

- **Dynamic Equilibrium and Mass and Stiffness Matrices**

Defects in composite materials, such as cracks or delaminations, alter the mechanical properties of the structure, thereby affecting its natural frequencies. This modification can be modeled by the following Eq. (2):

$$M\ddot{x} + C\dot{x} + Kx = F(t) \tag{2}$$

where,

- M: Mass matrix (positive definite).
- C: Damping matrix.
- K: Stiffness matrix.
- x: Displacement vector
- F(t): External force vector.

For free vibrations (no external forces, $F(t) = 0$) and undamped systems ($C = 0$), the Eq. (3) simplifies to [33]:

$$M\ddot{x} + Kx = 0 \tag{3}$$

- **Solving Free Vibrations: Eigenvalues and Eigenvectors**

Assuming a harmonic solution of the form $x(t) = \phi\sin(\omega t)$ where ϕ is the mode shape vector, we obtain Eq. (4) [34]:

$$[K - \omega^2 M]\phi = 0 \tag{4}$$

This is an eigenvalue problem where,

- ω^2: Eigenvalues, corresponding to the squares of the natural frequencies.
- ϕ: Eigenvectors, representing the associated mode shapes.

The natural frequencies are found by solving Eq. (5):

$$\det(K - \omega^2 M) = 0 \tag{5}$$

The mode shapes (ϕ) are calculated for each eigenvalue. This equation is used to compute natural frequencies and mode shapes based on material properties and structural geometry.

- **Effects of Defects on Vibratory Modes**

Defects, such as cracks or delaminations, alter the physical properties of the structure:

- The stiffness matrix (**K**) is locally reduced due to the defect,
- These modifications affect the natural frequencies (ω) and mode shapes (ϕ).

For a defective structure, the Eq. (6) becomes:

$$(K_d - \omega_d^2 M)\phi_d = 0 \tag{6}$$

where, K_d and ω_d represent the stiffness matrix and natural frequencies modified by the defect. Differences between ω and ω_d, and between ϕ and ϕ_d, provide insights into the location and severity of the defect.

- **Finite Element Simulation (FEM)**

To model the vibrations of composite structures, the finite element method (FEM) is employed. The procedure involves:

1) Constructing the global mass M and stiffness K matrices from local element contributions.
2) Solving $(K - \omega^2 M)\phi = 0$ to compute natural frequencies and mode shapes.

3) Introducing defects (e.g., cracks, delaminations) into the model and recalculating the dynamic parameters to observe changes.

- **Experimental Validation and Data Analysis**

The experimentally measured natural frequencies ω_{exp} and theoretical values ω_{th} are compared using the following metric Eq. (7):

$$\Delta\omega = \frac{\omega_{exp} - \omega_{th}}{\omega_{th}} * 100\% \tag{7}$$

Significant variations indicated the presence of defects.

Additionally, mode shapes can be compared using the Modal Assurance Criterion (MAC) Eq. (8):

$$MAC = \frac{|\phi_{exp}^{T}\phi_{th}|^2}{\left\|\phi_{exp}\right\|^2 \|\phi_{th}\|^2} \tag{8}$$

where, MAC measures the similarity between experimental and theoretical mode shapes. A low correlation suggests alterations due to defects.

3.4 Measurement methods

- **Excitation and Detection**

Excitation: The structure can be excited using methods such as impact testing (hammer test) or harmonic vibrations (shaker test).

Detection: Accelerometers or strain gauges measure vibrational responses. The recorded signals are analyzed to identify natural frequencies and vibration modes [35].

- **Data Analysis**

Fourier Transform (FT): FT is used to convert time-domain signals into the frequency domain to identify peaks corresponding to natural frequencies. This transformation is crucial for analyzing vibrational data [36].

Modal Analysis: This technique determines the modal shapes and resonance frequencies. Differences between experimental results and theoretical predictions can indicate defects. Modal analysis compares measured modal characteristics with theoretical predictions [37].

- **Advanced Techniques**

Experimental Modal Analysis (EMA): Comparing experimental results with theoretical simulations is the basis of an advanced technique for evaluating modal characteristics. Observing discrepancies in mode shapes and frequencies is used in this method to detect defects [38].

Thermographic Imaging: Thermal anomalies associated with structural defects can be detected when it is combined with vibration analysis [39].

3.5 Comparative overview and analysis of non-destructive testing (NDT) techniques

A type of strategies are applied for disorder detection in composite substances, every imparting particular benefits and barriers tailor-made to particular applications. Vibration Mode Analysis is a way that detects defects through reading herbal frequencies and mode shapes of a structure, correctly figuring out cracks and delaminations in laminated composite panels. This approach is distinctly touchy to structural adjustments, non-invasive, and appropriate for complicated geometries, aleven though it calls for precise modeling and is touchy to boundary situations and noise [40-42].

Ultrasound Testing, which makes use of high-frequency sound waves to come across inner flaws or thickness versions, is extensively implemented in examining wind turbine blades and plane components. It boasts immoderate accuracy, deep penetration, and real-time effects but requires a hint medium and is restricted thru manner of approach of ground roughness and geometry [43-47].

Infrared Thermography detects subsurface imperfections through looking at warmth fluctuations on a cloth's floor as a result of thermal emissions. It is a non-touch, speedy inspection technique that covers massive areas, making it appropriate for figuring out delaminations in car composites. However, it has confined penetration intensity and is laid low with ambient temperature and floor emissivity [48-50].

Table 2. Comparative overview and analysis of non-destructive testing (NDT) techniques

Technique	Principle	Main Applications	Advantages	Limitations	Relevant Studies
Vibration Mode Analysis	Detects defects by analyzing the natural frequencies and mode shapes of a structure, based on changes in vibration patterns.	Detection of cracks and delaminations in laminated composite panels	High sensitivity to structural changes, non-invasive, suitable for complex geometries.	Requires detailed modeling, sensitive to boundary conditions and noise.	[40-42]
Ultrasound Testing	Detects internal flaws or thickness variations in a material by using high-frequency sound waves.	Inspection of wind turbine blades, aircraft components	High accuracy, deep penetration, real-time results.	Requires contact medium, limited by surface roughness and geometry.	[43, 44]
Infrared Thermography	Observes heat fluctuations on the surface of a material to spot subsurface imperfections based on thermal emissions.	Identification of delaminations in automotive composites	Non-contact, fast inspection, covers large areas.	Limited penetration depth, affected by ambient temperature and surface emissivity.	[45-47]
Radiography (X-ray)	X-rays are employed to create internal images of a material, which reveal density variations that indicate defects.	Detection of porosities and cracks in aerospace structures	High resolution, able to detect internal defects, widely used.	Safety concerns with radiation, limited by material thickness.	[48-50]
Magnetic Particle Testing	Detects defects on both sides and near-sides of ferromagnetic materials by utilizing magnetic fields.	Surface defect detection in ferromagnetic materials for pipelines	Highly sensitive to surface defects, easy to apply, cost-effective.	Limited to ferromagnetic materials, shallow penetration.	[51]
Eddy Current Testing	Detects defects in conductive materials by inducing eddy	Corrosion and crack detection in conductive	Non-contact, effective for detecting surface cracks	Limited to conductive materials, sensitivity	[51-56]

	currents using electromagnetic fields.	alloys (e.g., aircraft and automotive parts)	and corrosion.	decreases with depth.	
Acoustic Emission Testing	Specifies transient elastic waves that are triggered by sudden structural changes, such as crack formation and growth.	Real-time monitoring of structural health in bridges and industrial pipelines	Sensitive to active defects, real-time monitoring, can cover large areas.	Requires continuous monitoring, can be affected by environmental noise.	[57-62]
Dye Penetrant Testing	Displays surface defects on non-porous materials by using a visible or fluorescent dye.	Surface crack detection in metal components	Simple and inexpensive, effective for surface cracks.	Limited to surface defects, requires pre-cleaning, not suitable for porous materials.	[63, 64]

Figure 7. Graphic mind map representing a classification of techniques adapted to different types of materials

Radiography (X-ray) employs X-rays to generate inner photographs of substances, revealing density versions indicative of defects including porosities and cracks in aerospace structures. This technique affords high-decision imaging and is extensively used, however it comes with protection issues associated with radiation and barriers because of cloth thickness [48-50].

Magnetic Particle Testing makes use of magnetic fields to come across floor and near-floor defects in ferromagnetic substances, including the ones utilized in pipelines. It is distinctly touchy to floor defects, cost-powerful, and clean to apply, however it's miles confined to ferromagnetic substances and gives shallow penetration [51].

Eddy Current Testing induces eddy currents via electromagnetic fields to come across defects in conductive substances, including corrosion and cracks in plane and car parts. This non-touch technique is powerful for floor cracks and corrosion detection however is confined to conductive substances, and its sensitivity decreases with intensity [51-56].

Acoustic Emission Testing video display units temporary elastic waves brought about through structural adjustments like crack formation and growth. It is touchy to energetic defects, helps real-time tracking, and might cowl massive areas, making it best for structural fitness tracking of bridges and commercial pipelines. However, it calls for non-stop tracking and may be laid low with environmental noise [57-61].

Dye Penetrant Testing, a easy and cheaper technique, is powerful for detecting floor cracks on non-porous substances the usage of a seen or fluorescent dye. While cost-green and clean to apply, it's miles confined to floor defects, calls for pre-cleaning, and is improper for porous substances [63, 64].

By understanding the principles, applications, advantages, and limitations of these techniques, researchers and practitioners can choose the most appropriate method or combination of methods for specific industrial applications. The preceding Table 2 has been designed to simplify and clarify the advantages, making them easier to understand and apply.

3.6 Taxonomy of Non-Destructive Testing (NDT) for materials

The diagram Figure 7 represents a comprehensive mental map illustrating various non-destructive testing (NDT) techniques applicable to a wide range of materials, including metals, composites, polymers, wood, glass, ceramics, smart materials, and other specialized materials. This classification visually organizes NDT methods to enable quick identification of the most suitable techniques for each material category, tailored to their unique properties and defect detection needs.

Composite materials, in particular, demand specialized NDT approaches due to their intricate structures, often composed of laminated layers or embedded fibers. These complexities necessitate the use of advanced techniques to ensure accurate detection of defects and maintain material integrity in critical applications. Among the key methods, three-dimensional tomography and radiography stand out for their ability to identify internal volume defects such as porosities and inclusions. These techniques provide high-resolution, detailed imaging that is indispensable for analyzing the internal structure of layered composites.

Infrared thermography, leveraging heat to detect surface-level anomalies, is another essential method. It excels in identifying delaminations and cracks quickly and efficiently over large areas, making it especially valuable in industries such as aerospace and automotive. Acoustic emission analysis further complements this suite by monitoring real-time sound waves generated by defects under stress. This technique is particularly effective for detecting micro-cracks or early failure initiation, enabling preventive measures to avoid catastrophic failures.

Vibration analysis, meanwhile, assesses changes in stiffness and structural integrity by evaluating the material's vibratory responses. This method is highly sensitive to variations in structural properties, making it a critical tool for diagnosing defects in laminated and hybrid composite systems. Each of these NDT techniques offers distinct advantages, including varying detection depths, resolutions, and sensitivities, making them suitable for different types of composite material applications.

By combining multiple NDT methods, a comprehensive and accurate fault diagnosis can be achieved. This multi-technique approach not only enhances detection reliability but also provides a deeper understanding of material behavior under different conditions. The visual framework presented in the diagram serves as a valuable reference for selecting optimal NDT techniques based on material type, defect nature, and inspection requirements, supporting advancements in quality assurance and structural health monitoring across diverse industries.

4. APPLYING ARTIFICIAL INTELLIGENCE IN NDT

4.1 Introduction to AI in NDT

The integration of synthetic intelligence (AI) in non-adverse testing (NDT) has emerged as a transformative technology, improving disorder detection and cloth characterization. AI permits the processing of massive datasets gathered from diverse NDT techniques, inclusive of vibration mode analysis, ultrasonics, and infrared thermography. Machine learning (ML) and deep learning (DL) algorithms significantly improve the accuracy of anomaly detection, defect propagation prediction, and real-time optimization of inspection processes [58-61].

AI's primary advantages include its ability to identify complex patterns and automate defect detection tasks that traditional methods struggle to address. For instance, Convolutional Neural Networks (CNNs) utilize convolutional layers to extract hierarchical features from radiographic images, enabling the identification of microscopic defects with improved accuracy and reduced false-negative rates. This leads to improved inspection reliability and precision. Additionally, AI systems trained on vibrational data employ unsupervised clustering algorithms, such as DBSCAN, to group similar defect patterns, even in noisy datasets, facilitating the classification of defect types and streamlining the evaluation of composite materials [65-67].

Moreover, supervised learning algorithms, including neural networks, automate ultrasonic signal analysis by mapping signal features to defect types, enabling continuous, real-time inspections without human intervention [68-70]. To detect unknown anomalies, unsupervised learning techniques like clustering (e.g., k-Means, DBSCAN) proactively identify defect patterns by segmenting high-dimensional data into meaningful clusters, addressing challenges posed by noisy or unlabeled data [71-73]. This synergy between supervised and unsupervised approaches demonstrates the transformative potential of AI in enhancing NDT processes.

4.2 The algorithms used

Artificial intelligence is turning into extra vital withinside the detection of defects in composite materials. The improvement of state-of-the-art techniques for figuring out and classifying anomalies has been made viable via way of means of current advances in computing and records processing. AI algorithms which can be primarily based totally on neural networks, deep learning, and sign processing strategies can offer effective answers for illness detection with progressed precision and efficiency.

Review the main AI algorithms applied in defect detection, such as neural networks, deep learning, and signal processing methods. Convolutional Neural Networks (CNNs) are commonly used for defect recognition in composite material images by leveraging their ability to capture complex spatial features [74]. They have recently been extended with techniques like attention mechanisms, which enhance feature localization, improving the precision in defect detection tasks [75]. Similarly, Long Short-Term Memory (LSTM), a type of recurrent neural network, is effective for defect detection in time series by enabling the modeling of data sequences [76]. Enhanced LSTM models, such as Bi-LSTM, have been used to capture bidirectional dependencies, further refining defect prediction [77]. Capsule Networks (CapsNet) represent an advance in enhancing neural networks' ability to recognize spatial relationships between features [78].

Regarding signal processing methods, the Fourier Transform remains a fundamental tool for frequency domain signal analysis, widely used for identifying recurring defects [79]. Wavelet Transform, on the other hand, is effective for detecting defects localized in both time and frequency, which is crucial for analyzing non-stationary signals [80]. Recent research incorporates adaptive wavelet transform for better noise reduction and defect resolution [81].

Random Forests (RF) are distinguished for their versatility and the possibility of handling datasets with plenty of variables, which is why developers often choose them for creating automated systems for defect detection [82]. Gradient Boosting Machines (GBM) give a better performance by amalgamating several weak models to get a stronger model that increases the detection accuracy [83]. XGBoost, which is a variant of GBM, is one of the most demanded software for defect classification as a result of its speed and the exactness of the performance with large datasets [84].

For the clustering mechanism, we use k-Means which apart from its simplicity turns out to be the most effective way of grouping non-labeled data through the identification of similar defects [85]. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) can effectively be used for detecting the defect structures in noisy data without prior knowledge of the clusters number [86]. Improvements in DBSCAN, for example, hierarchical DBSCAN, have been able to achieve a higher success rate in the identification of vulnerabilities in the noisy environments [87].

To make it easier to find defects, dimensionality reduction algorithms, such as Principal Component Analysis (PCA), are often employed to simplify multidimensional data analysis [88]. t-SNE is a particularly effective method for visualizing complex data, making it easier to detect defect clusters [89]. Recently, UMAP (Uniform Manifold Approximation and Projection) has gained attention for its efficiency in preserving local and global structures in defect visualization.

Autoencoders use unsupervised learning to compare the input and its reconstruction for anomaly detection and they are among the most impressive ways to detect unlabeled faults [90]. Besides, Generative Adversarial Networks (GANs) are mainly used for not only the generation of synthetic data but also for the detection of defects by the generation of very good counterexamples [91].

Reinforcement Learning (RL) methods, such as Q-Learning, allow learning optimal policies for defect detection by interacting with a dynamic environment [92]. Deep Q-Networks (DQN), which combine Q-Learning and deep neural networks, are particularly effective for systems where data evolves over time [93]. Advanced RL frameworks, such as multi-agent reinforcement learning, have shown potential in collaborative defect detection.

Semi-Supervised Learning uses methods like Label Propagation, which relies on a small set of labeled data to label unlabeled data, which is especially useful when manual labeling is costly [94]. Co-Training leverages multiple views of the data to train distinct models, thus enhancing the robustness of defect detection systems in heterogeneous datasets [95].

Bayesian Techniques such as Bayesian Networks (BN) model probabilistic relationships between variables to predict the presence of defects, which is particularly useful in uncertain environments [96]. Gaussian Processes (GPs), as a non-parametric method, provide flexible modeling of potential anomalies in materials [97].

Finally, Transfer Learning is increasingly used to adapt pre-trained models to new defect detection tasks. Fine-Tuning Deep Networks allows adjusting an existing model for a new application, reducing the need for large amounts of specific data [98]. Domain Adaptation is crucial for generalizing a model across different domains, making defect detection systems more robust against variations in experimental conditions [99].

4.3 Case study of different algorithms

As shown in Table 3, different algorithms exhibit varying levels of accuracy and efficiency in detecting defects in composite materials.

4.4 Performance analysis of classification models in fault detection

In the context of defect detection in composite materials, Cheng et al. [71] conducted an in-depth evaluation of the performance of various classification algorithms based on neural networks [100] (see Table 4). The study highlighted models such as CNN, GhostCNN, ECACNN, Unet, deepCrack, MCuePushU, and ECAGhostCNN, comparing their classification accuracy and average execution time per image. The results reveal that the ECAGhostCNN model provides a remarkable balance between accuracy (93.75%) and speed (10.53ms), outperforming standard models like CNN (71.25% and 19.98ms) and GhostCNN (77.5% and 10.07ms). While MCuePushU achieves the highest accuracy (98.52%), its average execution time (549ms) limits its use in real-time applications. Furthermore, models like Unet (90.21%) and deepCrack (93.15%) demonstrate notable robustness, but their higher computation times make them less suitable for scenarios requiring rapid responses. These results highlight the importance of a trade-off between accuracy and efficiency, with the ECAGhostCNN model standing out as an optimal solution for practical real-time defect detection applications.

Table 3. Case studies of different algorithms for composite defect detection

Case Study Context / Application Description	Experimental Setup	Data Collection	Processing Methods	Algorithm Advantage	Disadvantages	Applicable Scenarios	Ref
Defect detection in composite materials using Convolutional Neural Networks (CNNs)	High-resolution radiographic imaging systems; composite panels subjected to simulated stress conditions to induce defects.	Industrial-grade radiographic equipment; standardized exposure settings; pre-processed images for noise reduction.	Transfer learning with CNNs; hierarchical feature extraction from 10,000 labeled samples.	High accuracy in hierarchical feature extraction; ability to detect subtle defects like voids and cracks.	Requires large labeled datasets; computationally intensive.	Ideal for surface and internal defect detection in aerospace composites using imaging data.	[72]
Vibration analysis in wind turbine blade composites using Support Vector Machines (SVM) and PCA	Test rig simulating operational conditions; accelerometers mounted on blades to measure vibration responses.	Signals recorded at 10 kHz over multiple cycles; raw data filtered to remove high-frequency noise.	SVM and PCA integration for defect classification with high accuracy.	Robust to high-dimensional data; reduces computational complexity through PCA.	Sensitive to parameter tuning; less effective with non-linear patterns.	Effective for fault detection in high-dimensional vibration datasets in renewable energy applications.	[91]
Real-time monitoring of composite structures in bridges using Fourier and Wavelet Transforms	Monitoring systems with piezoelectric sensors installed on bridge girders.	Data logged over six months; signal anomalies flagged for analysis.	Fourier and Wavelet Transforms for signal decomposition; noise reduction algorithms to enhance defect clarity.	Effective in analyzing non-stationary signals; decomposes data into time-frequency components for detailed analysis.	Computationally intensive; requires careful parameter optimization.	Suitable for long-term structural health monitoring of bridges and large infrastructures.	[92]
Detection of complex defect patterns in composite materials using Capsule Networks (CapsNet)	Laboratory experiments on composite laminates with artificially introduced defects (delaminations, inclusions).	Optical and thermal imaging systems; controlled lighting and temperature conditions.	Augmented datasets used to improve robustness; spatial feature recognition with CapsNet.	Captures spatial hierarchies in defect features; resilient to varying orientations of input data.	Limited adoption; computationally demanding for large datasets.	Ideal for detecting complex, multi-layered defects in composite laminates.	[92]
Unsupervised detection of defects in composite materials using K-means clustering	Non-uniform pressure applied on composite sheets to simulate defects; vibration sensors placed on test samples.	50,000 unlabeled vibration samples under varying conditions.	Fine-tuned K-means clustering to optimize inter-cluster distances and identify defect clusters.	Identifies hidden patterns in unlabeled data; effective for noisy datasets.	Assumes predefined cluster numbers; struggles with non-spherical clusters.	Effective for initial exploration of unlabeled datasets in vibration-based defect detection.	[94]
Structural health monitoring systems using Artificial Neural Networks (ANNs)	SHM systems installed on aircraft components (fuselage, wings) to detect fatigue-related defects.	Ultrasonic testing data collected using phased array probes; time-of-flight data recorder.	Non-linear pattern detection in ultrasonic signals with ANNs; dataset includes 5,000 labeled instances.	Flexible in modeling complex non-linear relationships; improves sensitivity to subtle ultrasonic anomalies	Requires extensive computational resources; performance depends on labeled data quality.	Suitable for fatigue defect detection in aerospace structural components using ultrasonic data.	[95]
Defect detection in composite materials through vibration signal analysis using Sequential Neural Networks (SNNs)	Vibrational test bench simulating real-world operational conditions; sensors mounted to collect vibration data.	Vibrational signals captured at high frequency; pre-processed to remove outliers and reduce noise.	Sequential Neural Networks trained to analyze temporal dependencies in vibration patterns and detect anomalies.	Excellent in modeling temporal data; improves real-time defect detection in dynamic environments.	High training time; requires large amounts of sequential data.	Ideal for real-time anomaly detection in dynamic operational conditions of composite materials.	[96]

Table 4. Performance analysis of classification models in fault detection [100]

Model Name	Classification Accuracy (%)	Average Runtime	Key Strengths	Key Limitations
CNN	71,25	19,98	Simplicity, relative speed	Limited accuracy
GhostCNN	77,5	10,07	Good speed	Average accuracy
CNN + PP	66,2	87	-	Low overall performance
ECACNN	88,75	21,3	Good accuracy	Slightly high execution time
Unet	90,21	166,7	High accuracy	High computation time
deepCrack	93,15	141	Good accuracy	High execution time
MCuePushU	98,52	549	Best accuracy	Very high execution time
ECAGhostCNN	93,75	10,53	Excellent accuracy/time trade-off	-

5. SYNTHESIS OF CURRENT KNOWLEDGE

5.1 Summary of advances

In current years, huge development has been made withinside the subject of disorder detection in composite materials, drastically thru using non-detrimental testing (NDT) and synthetic intelligence (AI). Recent literature highlights the growing integration of NDT techniques, including ultrasonic analysis, infrared thermography, and electromagnetic methods, with AI algorithms to beautify the accuracy and performance of disorder detection.

Recent traits display a fashion in the direction of the software of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and pill networks (CapsNet) to investigate complicated records from NDT inspections. These algorithms permit for multi-scale function extraction and modeling of temporal dependencies, that are critical for figuring out diffused defects in composite structures.

Unsupervised gadget mastering methods, including K-way clustering, have additionally received recognition for anomaly detection without the want for classified records, allowing early disorder identity in eventualities with confined records. Additionally, random forests (RF) and help vector machines (SVM) stay extensively used for his or her robustness in coping with noisy and imbalanced records.

Recent sources, such as Calvo et al. [96] on carbon fiber composites, provide an in-depth perspective on advancements in NDT techniques and their integration with AI for industrial applications. Recent chapters in collective works, such as "Advances in Composite Materials for Aerospace Applications", emphasize the importance of these technologies in improving the reliability and safety of composite structures used in critical sectors like aerospace and automotive [97].

Finally, the study by Calvo et al. [96] highlight the use of sequential networks for vibration analysis, demonstrating the effectiveness of sequential neural architectures for real-time anomaly detection in composite materials. This convergence of NDT and AI technologies represents a key trend in the industry, with applications that continue to evolve and expand into new domains.

5.2 Gaps in research

Although tremendous advances were made withinside the discipline of illness detection in composite substances the use of non-damaging testing (NDT) strategies and device mastering algorithms, numerous gaps stay in modern-day research. NDT strategies inclusive of ultrasound, infrared thermography, and electromagnetic strategies preserve to stand obstacles in precision and in detecting diffused or small defects. These strategies can occasionally produce fake positives or negatives, in particular in complicated environments or systems with difficult geometries.

Just the same, the collaboration of non-destructive testing data with machine learning algorithms still progresses, some of the issues having to with letting the machines to be clever with a limited resource of a given type of training data. As an example, a survey by Saberironaghi et al. [98] brings an insight into deep learning- based approaches, highlighting specific aspects of the situation like model complications and the demand for huge, labeled datasets. In the related research sector, Wei et al. [99] also contribute to the point by discussing the more kneaded constraints and difficulties of the machine learning models such as the one regarding overfitting and the other one of weak generalization. Comparable to the above study, Jo et al. [100] have conducted a detailed review of the research where deep learning-based methods are used. Here, the authors are persistently mentioning the complicated situation regarding model complexity and the need for the large, annotated datasets. Ghaleh et al. [101] focus on the real-life issues that occur while machine learning is put into action in the industrial sector, and Dikmen et al. [102] offer a recent overview of obstacles and associated possibilities, including matters like the variability of defects and on top of that the difficulty of assembling representative datasets. The increasing gaps which have been brought about by a continuous increased capability to have faults prediction and detection problems in vital industrial activities will be the ones that need an urgent intervention by being redesigned and improved the current ones to make them more reliable and efficient.

5.3 Opportunities for future research

One significant research needs to be tackled will be the non-destructive testing (NDT) of these materials. One way to go about is to work on developing some other non- destructive testing (NDT) methods that enable control with more accuracy. Similar research can be directed at improving the techniques already used to make these nondestructive investigations more precise or inventing brand new technologies that can cover the unnoticeable or small cracks. Not only that, the development of artificial intelligence (AI) algorithms integrating with the NDT data would be a step towards AI-m4b. The upcoming research could focus on the creation of new algorithms that require fewer perfect data and are able to generalize effectively to different kinds of defects and material conditions. The study may also focus on generating diversified and representative datasets that are a must for training high-precision models. Also, trying advanced data fusion methods, which allow the outcomes of different NDT techniques, as well as AI, to be combined and thus result in more precise and comprehensive defect assessments may be a fruitful way out. On the other hand, the use of transfer learning and semi- supervised learning methods can be helpful when the limitations are connected with the lack of data and its low quality. In the end, the ability to come up with reliable and accurate diagnostic solutions for dealing with noisy and incomplete data is paramount for obtaining accurate results to the defect detection methods.

6. FUTURE PROSPECTS AND RECOMMENDATIONS

6.1 Emerging trends

Recent improvements in disorder detection for composite substances screen numerous key rising trends. A enormous fashion is the combination of synthetic intelligence (AI) with clever sensors to decorate disorder detection and monitoring. Chen et al. [93] highlight the benefits of AI-integrated smart sensors in advancing defect detection capabilities by providing more accurate and detailed monitoring of composite materials. This integration allows for real-time analysis and early detection of potential issues, improving the overall reliability of monitoring systems. Similarly, the study discusses how combining AI with smart sensors can further enhance defect detection accuracy, particularly by enabling adaptive and intelligent responses to detected anomalies [103, 104]. This approach not only increases the precision of defect detection but also offers the capability for predictive maintenance and early intervention. Another first-rate fashion is the usage of the Internet of Things (IoT) for real-time illness detection. Li et al. [105] offer a complete evaluate of ways IoT technology are reworking illness detection with the aid of using permitting non-stop tracking and records collection. IoT enables the mixing of sensor records with superior analytical tools, bearing in mind real-time evaluation and extra knowledgeable decision-making concerning the situation of composite materials. These trends underscore the growing importance of leveraging advanced technologies to improve the effectiveness and efficiency of defect detection in various industrial applications.

6.2 Challenges to overcome

Despite enormous development in automatic disorder detection systems, numerous demanding situations stay that want to be addressed to develop the sector further. One of the number one demanding situation is the nice and amount of information to be had for schooling gadget studying fashions. High-nice annotated information is important for schooling correct and dependable fashions, but acquiring such information is frequently hard and resource-intensive. For instance, Li et al. [105] emphasize the undertaking of obtaining large, various datasets essential for schooling deep studying fashions effectively. Another predominant undertaking is the combination of various technology and methodologies. Combining numerous non-detrimental testing (NDT) strategies with superior synthetic intelligence (AI) fashions frequently calls for complicated information fusion processes that may be hard to enforce and optimize. Chen et al. [93] presents the issues involved in integrating AI with smart sensors that even face problems with the data synchronization and the device interoperability. The processing of data from automated systems in real-time is the presentation of significant computational difficulties. Whereas ensuring that systems are not only capable of apprehending information but also of reacting to it contextually is a significant challenge. Niu et al. [104] articulate that it's real-time processing that is the main spoiler of the overall efficiency of fault detection systems. Lastly, the effectiveness of autonomous systems is still affected by the strength and reliability of their operation in the real-world environments the mechanisms are adapted to. The question is how the systems are able to adapt to the changes in the material conditions and the peculiar operating environments without making them work inefficiently. For the mass for adoption can be possible only by constant work on the subjects as the research of data acquiring technological devices, systems integration, real-time processing and environmental adaptability.

6.3 Recommendations for future research

To advance the field of automated defect detection in composite materials, several key areas warrant further exploration. Firstly, improving data acquisition techniques is essential. Future studies have to recognition on growing superior techniques for gathering high-quality, annotated datasets which can be consultant of various real-international conditions. This may want to contain the usage of artificial facts technology or leveraging switch gaining knowledge of to mitigate the demanding situations related to confined facts availability, as cautioned through Li et al. [105]. Secondly, there may be a want to beautify the combination of AI with non-unfavorable testing (NDT) techniques. Research has to intention at optimizing facts fusion methodologies to mix a couple of NDT modalities effectively, thereby enhancing the general accuracy and reliability of disorder detection systems. Chen et al. [93] recommends exploring new algorithms and architectures that can better handle the complexities of multi-modal data integration. Additionally, future research should prioritize the development of real-time processing capabilities. This includes not only improving computational efficiency but also ensuring that systems are robust enough to operate effectively in dynamic and unpredictable environments. Niu et al. [104] highlight the potential of edge computing and decentralized AI as promising approaches to achieve real-time processing in industrial settings. Finally, expanding the application scope of automated defect detection systems is crucial. Research ought to discover the usage of those structures in new commercial sectors, which includes aerospace, automotive, and renewable energy, in which the detection of cloth defects is important for protection and performance. This enlargement can also contain the combination of those structures with rising technology just like the Internet of Things (IoT) and superior robotics to allow greater complete and adaptive tracking solutions. The suggestions suggest a future where automated defect detection systems are not only more precise and efficient but also widely applicable across different industries.

7. CONCLUSION

This take a look at explored advances withinside the detection of defects in composite substances through integrating non-unfavorable testing (NDT) strategies and synthetic intelligence (AI). The originality of this paintings lies withinside the in-intensity evaluation of blended techniques for overcoming the restrictions of conventional illness detection approaches, in particular in complicated environments and for heterogeneous composite structures. By highlighting the possibilities provided through superior algorithms, which includes convolutional neural networks (CNNs) and unsupervised getting to know approaches, this studies opens up new potentialities for faster, greater correct and dependable detection.

However, numerous demanding situations remain, in particular with reference to records quality, the generalization of AI fashions and the control of complicated real-global environments. In this respect, this take a look at proposes numerous guidelines for destiny paintings. Firstly, the improvement of greater strong algorithms able to managing imperfect or noisy records is essential. Secondly, the introduction of greater numerous and consultant databases may be vital to enhancing the overall performance of getting to know fashions. Finally, the mixing of recent technologies, which includes clever sensors and the Internet of Things (IoT), may want to revolutionize real-time tracking and predictive renovation of composite structures.

In conclusion, this paintings contributes to strengthening the expertise and skills of AI-greater NDT structures in crucial applications, substantially withinside the aerospace, car and renewable power industries. Further studies in those regions couldn't simplest enhance the protection and performance of composite structures, however additionally foster persevered innovation withinside the improvement of superior substances and sensing structures.

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