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Review

Recent Advances in AI and Signal Processing for PZT-Based Structural Health Monitoring

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Abstract

Structural health monitoring (SHM) systems fundamentally rely on effective sensing technologies for reliable damage detection and structural condition assessment. Among the available sensing approaches, piezoelectric (PZT)-based transducers are widely used in civil engineering due to their dual actuation–sensing capability, high sensitivity, low cost, and suitability for real-time monitoring. However, SHM performance not only depends on the sensing hardware, but also on the signal processing techniques that extract meaningful damage-related information from measured responses. Recently, Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown strong potential to enhance automation and improve the performance of SHM systems. This paper provides a critical review of signal processing and data-driven learning approaches for PZT-based guided-wave (GW) SHM and nondestructive testing (NDT), with applications to metallic, composite, and concrete structures. The review covers developments from early ML-based GW SHM methods to recent advances in DL, hybrid frameworks, and physics-informed approaches. Although emphasis is placed on civil infrastructure, developments in other fields such as aerospace and energy engineering are also reviewed due to their role in validating GW-based SHM methodologies. The fundamental theory of PZT sensing and guided wave propagation is introduced to establish the required background for monitoring techniques. Classical signal processing methods are then reviewed, followed by AI-based SHM frameworks, with particular emphasis on hybrid approaches that integrate physics-based signal processing with data-driven models to improve robustness, accuracy, and generalization. Key challenges such as environmental variability, sensor degradation, limited labeled data, and model transferability are discussed, along with future research directions including physics-informed machine learning (PIML), transfer learning, explainable AI, and baseline-free SHM. The review highlights that hybrid and physics-informed frameworks offer strong potential for field deployment by improving robustness, reducing data dependency, and enhancing generalization capability. A key contribution of this work is the comparative synthesis of signal processing, ML, DL, and hybrid methodologies across different material systems and structural types, together with a structured discussion of the challenges and future research directions for real-world implementation.

Keywords: structural health monitoring (SHM); structures; civil engineering; nondestructive testing (NDT); piezoelectric (PZT) sensors; signal processing; machine learning; deep learning

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1. Introduction

Modern SHM systems integrate sensing, signal interpretation, and data-driven analysis within a unified monitoring framework. This is particularly important as raw sensor measurements alone are often insufficient for assessing the health state of structures. Thus, a structured review of the underlying principles and methodologies is required to properly frame subsequent discussions. In this section, the fundamental concepts of SHM, sensing technologies, and GW-based approaches are introduced, providing the basis for the detailed examination of signal processing, ML, and hybrid frameworks presented in the remainder of the paper.

1.1. Background of SHM

As the population of aging infrastructure continues to grow globally, the demand for SHM is steadily increasing. SHM, through its capability for the continuous real-time monitoring of fatigue cracks, corrosion, delamination, and material degradation, addresses this challenge by mitigating catastrophic failures, extending service life, and enhancing structural safety [1]. Historically, engineers relied on visual assessments and periodic inspections to identify potential structural problems and undertake corrective actions when necessary [2]. While these techniques remain widely adopted, they are not fully objective. Despite being implemented with care, they are often labor-intensive, prone to uncertainty, and may fail to accurately detect or localize damage in some cases [3]. In contrast, SHM techniques offer real-time or continuous monitoring, allowing for the earlier detection and localization of subtle damage prior to its progression into critical conditions [4]. This paradigm shift enables engineers to move from reactive, repair-based maintenance toward proactive and predictive infrastructure management. Accordingly, advanced SHM techniques have been developed to overcome the limitations of traditional approaches, enhanced through the integration of sensing technologies, ML algorithms, and real-time data analytics, leading to improved accuracy, reduced false alarms, and more cost-effective maintenance strategies. A variety of SHM techniques have been implemented in civil infrastructure such as buildings, bridges, and transportation networks. Typical applications include the monitoring of fatigue damage in long-span bridges [5], assessment of reinforced concrete buildings [6], application of SHM to pipeline evaluation for material degradation, or leakage [7], etc. Nevertheless, SHM systems are subject to several inherent limitations, such as limited sensing range, sensitivity to environmental conditions, sensor durability challenges, high initial deployment costs, and the complexity of data processing.

1.2. Limitations of Conventional Methods

Despite their prevalence in infrastructure monitoring, conventional inspection and maintenance methods are associated with several challenges that constrain their effectiveness in ensuring structural safety and long-term serviceability [8]. The most prevalent of these methodologies is visual inspection, which is heavily reliant on human expertise and subjectivity. This makes it susceptible to human errors, inconsistencies across inspectors, and challenges in the early detection of hidden and developing damage that are visually imperceptible. Another key limitation is that conventional inspection methods are non-continuous. Structural evaluations are normally performed at discrete points in time, e.g., annual or periodic inspections, which means that damage that takes place between inspection cycles is left undetected. The non-continuous nature of these monitoring approaches limits the timely detection of rapidly evolving damage mechanisms, including fatigue cracking, corrosion progression, and composite delamination [3,8,9].

Also, traditional inspection and maintenance techniques are typically expensive. They involve the labor-intensive inspection of bridges or other transportation systems, traffic or service interruptions while inspecting bridge systems, or expensive maintenance/repair that occurs later in the deterioration timeline. Often, reactive maintenance decisions rather than proactive maintenance decisions result in a higher lifecycle cost and decreased reliability of the structure. These limitations underscore the need for advanced automated monitoring approaches capable of continuous, objective, and real-time damage detection. This demand has led to the development of SHM systems utilizing embedded and/or surface-mounted sensor technologies (e.g., PZT sensors), enabling continuous structural condition monitoring and improved maintenance planning. Recent statistical investigations of bridge collapses further emphasize the importance of SHM-based monitoring for aging infrastructure. A comprehensive study of bridge failures in Italy from 2000 to 2023 reports that a large proportion of collapses are associated with progressive deterioration mechanisms and insufficient condition assessment, highlighting the need for improved monitoring and data-driven maintenance strategies [10].

1.3. SHM Techniques

SHM techniques can be broadly classified, based on monitoring strategy, into active and passive approaches. Passive SHM utilizes the structure's natural or operational response without external excitation, including ambient vibration, acoustic emission, impact detection, and changes in modal properties such as natural frequency and damping ratio. Active SHM, in contrast, employs externally applied input signals, with the corresponding response analyzed for damage detection and characterization [11]. Common active SHM techniques include GW testing, electromechanical impedance (EMI) testing, ultrasonic pulse methods, impulse-echo testing, and controlled-vibration excitation. Passive SHM techniques can be used to continuously monitor a large structure, while active SHM typically provides high sensitivity to localized and early stage damage. SHM techniques are often more appropriately classified according to the NDT principles or the specific physical sensing mechanisms employed to characterize structural behavior, rather than solely by the active–passive distinction. Using this classification, there are a number of different types of SHM techniques: vibration-based techniques, wave propagation techniques, impedance-based techniques, electromagnetic methods, optical/vision-based methods, static response-based techniques, thermal techniques, and chemical/environmental sensing techniques, as shown in Figure 1.

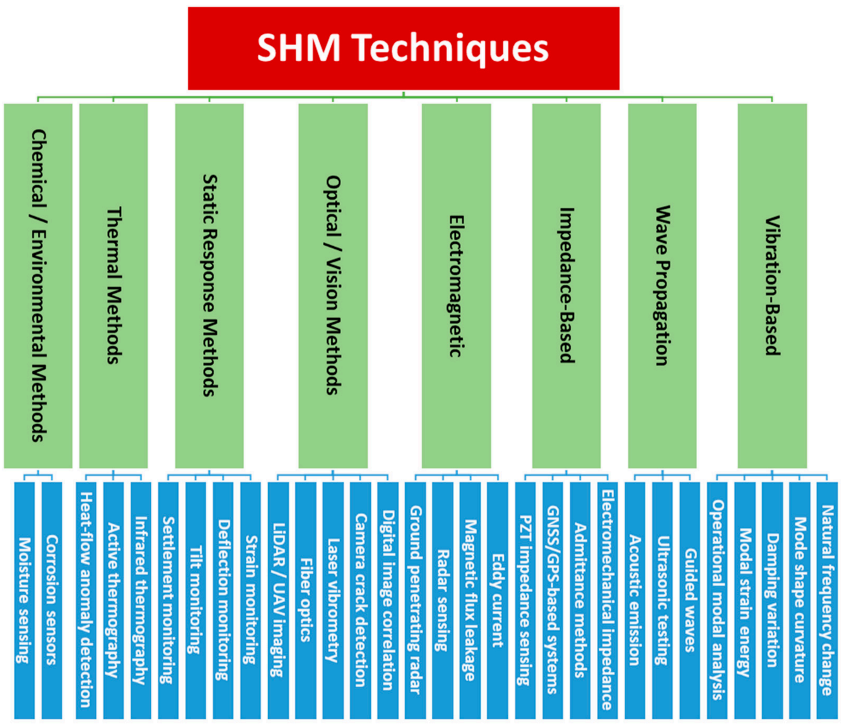

Figure 1. SHM technique categories based on the NDT technique employed.

Among the active SHM approaches, the GW technique is one of the most widely adopted, due to its efficiency in assessing large structural areas for damage detection [12,13]. In contrast to point-based methods that provide localized measurements, guided waves can propagate over long distances, allowing for an interrogation of structural regions along their path and enabling the detection of damage such as cracks, corrosion, debonding, delamination, and voids. Therefore, a much larger area can be inspected using a smaller number of sensors, resulting in reduced cost and simplified installation. Since guided waves are highly sensitive to changes in material and geometric properties, they provide an effective means for detecting damage at the early stages of development. Another advantage is their applicability to a wide range of structural types, including plates, beams, pipes, shells, laminated composites, and concrete members. The transducers used to generate guided waves are compact piezoelectric devices that can be readily integrated into long-term monitoring systems. In addition, guided wave responses contain rich information in the time, frequency, and mode domains, which can be exploited to identify the damage.

1.4. Role of Sensors in SHM

Sensors used in SHM can measure both structural and environmental parameters that are associated with damage initiation, deterioration, or abnormal structural behavior. Accordingly, SHM sensors are typically classified based on the physical quantities they measure. For example, strain sensors are widely used to monitor deformation and stress redistribution, with common implementations including resistive strain gauges [14] or fiber Bragg grating sensors [15]. Other vibration/dynamic response type sensors are used to measure the acceleration [16] and vibration characteristics of structures to capture modal changes; these sensors include accelerometers, velocimeters, and seismometers [17,18]. Displacement sensors are used to measure relative movement, deflection, and crack opening; representative examples include linear variable differential transformers (LVDT) [19], laser displacement sensors [20], and GNSS/GPS sensors [21] on large structures. Sensors for measuring temperature are commonly used to monitor the effects of temperature and humidity on structural performance as well as on the response signal received by the sensors; thermocouples [22], resistance temperature detectors (RTD) [23] and humidity sensors [24] are examples of these types of sensors. Sensors measuring acoustic wave propagation are used to interrogate structural condition and/or detect events by generating and receiving stress waves; typical examples include piezoelectric transducers [25], acoustic emission sensors [26] and ultrasonic probes [27]. Load and force sensors, such as load cells and pressure sensors, are included to monitor the applied or external actions or the support reactions on the structures [28]. Recent developments have also extended SHM sensing frameworks beyond conventional sensor networks toward large-scale and data-driven monitoring paradigms. Emerging SHM approaches are increasingly shifting toward distributed and indirect sensing strategies that improve spatial coverage while reducing reliance on dense sensor deployments. Crowdsensing and drive-by monitoring methods exploit instrumented vehicles or mobile platforms to infer structural responses indirectly from vibration or wave-based measurements, enabling the efficient monitoring of transportation infrastructure such as bridges [29]. Self-sensing materials, particularly conductive cement-based composites, further extend the sensing capabilities by enabling structural components to act simultaneously as load-bearing elements and sensors through the conversion of mechanical deformation into measurable electrical or piezoresistive signals [30]. At a larger scale, satellite-based remote sensing techniques, including interferometric synthetic aperture radar (InSAR) and SBAS-DInSAR, enable the non-contact deformation monitoring of infrastructure networks across regional and urban scales, supporting long-term risk assessment and prioritization [31]. Collectively, these approaches complement conventional sensor networks by enabling multi-scale and infrastructure-wide monitoring capabilities. A summarized overview of the classifications of SHM sensors is shown in Figure 2. Within this framework, PZT sensors belong to the wave propagation and acoustic sensing category and represent one of the most versatile and widely used transducer technologies in SHM [7].

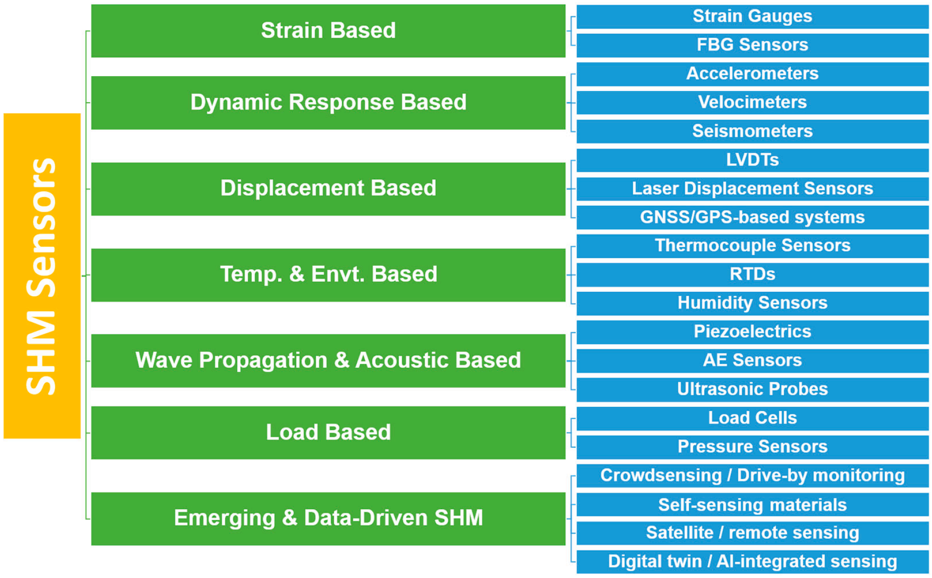

Figure 2. Classification of SHM sensors.

1.5. Motivation for Signal Processing and Machine Learning

Although PZT-based SHM systems provide fundamental information on structural condition, the measured signals are often complex, noisy, and influenced by factors other than damage, such as environmental variations, operational loading, boundary reflections, and sensor noise. Signal interpretation in wave based monitoring is complicated by multiple effects such as attenuation, dispersion, and multimodal propagation [32]. In addition to this, micro-cracks and other types of early-stage defects, such as debonding, rust or local stiffness reductions, only create small changes in signal amplitude, phase, frequency content, arrival time, or other aspects of the signal [11,33]. These subtle damage-sensitive characteristics may be obscured by variations in environmental and operational conditions. Consequently, signal processing methods are required to transform raw measurements into meaningful features that can be correlated with the presence and progression of structural damage. Examples of typical signal processing objectives include: reducing the amount of noise present in a signal; extracting useful features from a signal; estimating time-of-flight; analyzing frequency characteristics; and identifying nonlinear indicators of damage. Signal processing techniques that are commonly employed include: Fourier transforms; wavelet analysis; filtering; and correlation techniques. More recently, the application of ML techniques to automate structural condition assessment has received increased interest [34,35]. Machine learning is capable of learning patterns from measured data and assisting with NDT by minimizing the reliance placed on human interpretation. Consequently, the combination of signal processing and ML is establishing itself as a strong candidate for intelligent and reliable SHM systems [36,37].

1.6. Literature Search and Selection Methodology

To ensure comprehensive and representative coverage of the field, a systematic literature search strategy was adopted. Relevant studies were identified through major scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, Engineering Village (Compendex), and Google Scholar. Searches employed combinations of keywords and Boolean operators related to GW-based SHM, including "guided wave", "Lamb wave", "structural health monitoring", "piezoelectric sensor", "signal processing", "machine learning", "deep learning", "physics-informed learning", and "NDT". The review primarily focused on studies published between 2015 and 2026, capturing the rapid advancement of data-driven and hybrid SHM frameworks, while earlier foundational works were included where necessary to establish the theoretical background.

Retrieved publications were screened through a multi-stage process involving duplicate removal, title and abstract screening, and full-text evaluation. Studies were selected based on their relevance to AI-based GW SHM for civil engineering structures, including metallic, composite, and concrete systems. Priority was given to peer-reviewed journal articles and high-impact conference papers reporting experimentally validated methods, novel algorithms, comprehensive reviews, or significant methodological advances. Studies were excluded if they were unrelated to SHM, focused on non-GW sensing techniques, lacked sufficient methodological detail or validation, or duplicated findings reported elsewhere. Particular emphasis was placed on contributions advancing signal processing methods, ML and DL frameworks, and hybrid or physics-informed approaches. The final set of publications was organized according to the major themes addressed in this review, including GW fundamentals, signal processing, ML, DL, hybrid frameworks, physics-informed learning, structural applications, implementation challenges, and future directions. Studies summarized in the review tables were categorized according to their primary methodological contribution, structural application, learning framework, and SHM objective, such as damage detection, localization, classification, quantification, prognosis, or condition monitoring. Where multiple topics were addressed, studies were assigned to the category most relevant to the corresponding discussion.

This review therefore aims to provide a comprehensive and balanced assessment of recent developments in PZT-based guided wave SHM, while maintaining transparency in the literature selection and classification process. Figure 3 shows a summary of the review methodology adopted in this study.

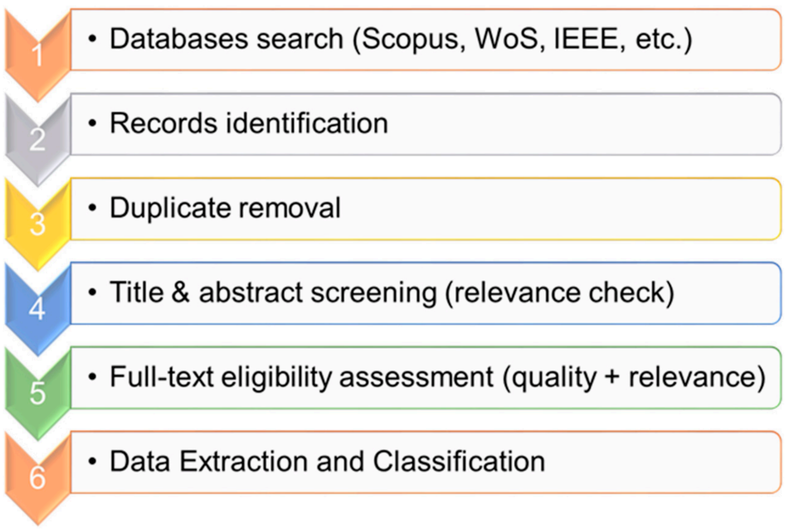

Figure 3. Review methodology adopted in this study.

1.7. Comparison with Existing Review Studies

In recent years, several review articles have been published on GW-based SHM, ML, signal processing, and piezoelectric sensing. However, these studies generally address specific components of the SHM workflow, such as guided wave modeling, signal processing techniques, machine learning algorithms, or application-oriented implementations. As a result, a fully unified perspective linking signal processing, ML, DL, and physics-informed approaches within a complete PZT-based GW-SHM framework remains limited. Representative studies are summarized in Table 1, which outlines their scope, strengths, limitations, and key contributions.

Table 1. State-of-the-art literature review of recent GW-based SHM review studies and the proposed review.

Ref.	Scope	Strengths	Limitations	Key Contribution
[38]	• *ML GW NDT & SHM*	• *Broad overview of GW NDT methods* • *Clear classification of phased array, laser ultrasonics, and nonlinear techniques* • *Includes ML and DL trends in SHM*	• *Limited integration of physics-informed ML and DL frameworks* • *Limited nonlinear GW* • *Limited consideration of material diversity beyond laminated composites* • *Limited comparative assessment of DL methods under data-scarce SHM conditions*	• *Recent GW-based SHM advances with emphasis on ML*
[39]	• *ML GW-based SHM*	• *Comprehensive ML workflow overview* • *Links GW physics with data-driven models* • *Engineering-oriented perspective*	• *Lack of a unified taxonomy and systematic comparison of ML approaches* • *Limited integration of signal processing, ML, and physics-based methods within a unified framework*	• *Reviews ML-enabled GW-based SHM across the full pipeline (modeling, data acquisition, preprocessing, ML, physics-based ML)* • *Outlines future research directions*
[40]	• *ML GW-based SHM for pipelines*	• *Comprehensive review of GW theory and pipeline NDT applications* • *Includes transducers, wave modes, and ML/DL methods* • *Discusses practical engineering implementation*	• *Application-specific focus on pipelines with limited cross-structure generalization* • *Limited comparative evaluation of ML/DL techniques across different SHM applications*	• *GW-based SHM corrosion detection techniques including Lamb & SH waves, transducer technologies, and emerging ML/CNN-based approaches* • *Summarizes current progress and future prospects*
[41]	• *GW-based SHM with emphasis on ML integration and physics-based approaches*	• *Comprehensive pipeline* • *Clear ML classification* • *Links physics and data-driven methods*	• *Focuses mainly on linear GW-based SHM, with limited coverage of nonlinear effects* • *Limited assessment of DL architectures under data-scarce SHM scenarios* • *Insufficient validation under complex in-service operational conditions*	• *Structured multi-stage framework linking GW-based SHM with ML and physics-informed learning strategies*
This work	• *PZT-based GW SHM integrating signal processing, ML, DL, hybrid and physics-informed approaches*	• *Unified framework linking signal processing, ML, DL and physics-informed methods* • *Comparative assessment across metallic, composite and concrete structures* • *Discussion of practical deployment challenges*	• *Focused on PZT-based GW SHM*	• *Provides an end-to-end perspective from sensing and signal processing to intelligent decision-making and future research directions*

As indicated in Table 1, most existing reviews concentrated on isolated aspects of GW-based SHM, including sensing technologies, signal processing methodologies, ML-based diagnostic models, or application-specific case studies. While these contributions are valuable, they typically lack a holistic integration of the full SHM pipeline and provide limited comparison across methodologies and structural applications.

To further clarify the positioning of the present review with respect to the existing literature, Table 2 provides a comparative overview in terms of methods covered, structural applications, and practical insights and the challenges covered in each study. As shown in Table 2, most previous works focused on either ML- or DL-based approaches in isolation, or emphasized specific structural domains without systematically integrating multiple material systems and learning paradigms. In contrast, the present review provides a unified framework that connects signal processing, ML, DL architectures, hybrid learning strategies, and physics-informed approaches within a comprehensive PZT-based GW-SHM workflow.

Table 2. Taxonomy-based review of recent GW-based SHM review studies and the proposed review.

Ref.	Methods Covered	Structures Considered	Practical Insights	Challenges Discussed
[38]	• *GW* • *Phased Array Ultrasonics* • *Laser Ultrasonics* • *Nonlinear Ultrasonics* • *ML* • *DL*	• *Laminated composite structures (primary)* • *Composite-based engineering structures*	• *GW NDT overview* • *ML/DL integration trends* • *Ultrasonic technique classification* • *Composite SHM focus*	• *Wave propagation complexity in anisotropic media* • *Mode conversion and dispersion effects* • *Signal attenuation and scattering* • *High sensitivity to environmental and operational variability*
[39]	• *GW* • *Rayleigh–Lamb modeling* • *TMM/GMM/FEM /WFE/SAFE/SFEM* • *Signal processing (time/frequency/time–frequency/wavenumber)* • *ML* • *DL concepts within ML framework* • *Supervised/Unsupervised/ Semi-supervised/ Reinforcement learning* • *Physics-based ML*	• *SHM/NDT systems for large engineering structures* • *In-service GW-based SHM/NDT applications*	• *End-to-end ML-based GW-SHM/NDT workflow* • *Integration of GW physics with ML models* • *Complete pipeline (data acquisition–processing–ML–diagnosis)* • *Physics-informed + data-driven fusion* • *Structured ML-SHM methodology*	• *Lack of unified ML taxonomy for GW-SHM/NDT* • *Limited integration of physics-based models with ML* • *Insufficient benchmarking of ML methods in SHM* • *High complexity of GW signal interpretation in real conditions*
[40]	• *GW propagation* • *Lamb and shear horizontal modes* • *Dispersion analysis* • *Reflection and transmission analysis* • *Signal processing time frequency wavenumber domain* • *Mode selection* • *ML-based defect classification* • *DL CNN-based corrosion quantification* • *Imaging-based evaluation*	• *Steel pipelines* • *Coated pipelines* • *Buried pipelines* • *Pressure pipelines* • *Curved pipeline sections* • *Corroded and pitted regions*	• *Long range inspection capability* • *Single point excitation enables large coverage* • *High sensitivity to corrosion and wall loss* • *Multimodal GW information enhances diagnostic capability* • *Efficient for pipeline monitoring applications*	• *Dispersion effects* • *Multimodal interference* • *Mode conversion at defects* • *Low sensitivity to small and shallow corrosion* • *Signal attenuation over distance* • *Environmental and operational condition effects* • *False alarms in baseline based SHM*
[41]	• *GW* • *FEM SAFE SFEM TMM GMM Wave modeling* • *Sensor optimization* • *Signal processing* • *ML SHM* • *DL SHM* • *Physics-based ML* • *Classification learning methods*	• *Steel plates* • *Composite structures* • *Pipelines rods* • *Laminated structures*	• *GW enables long range SHM* • *High sensitivity to internal defects* • *ML improves detection performance* • *Sensor layout enhances monitoring efficiency* • *Physics based models improve interpretability* • *Suitable for large scale structural monitoring*	• *Wave dispersion and mode conversion* • *High computational complexity of models* • *Limited training data* • *Environmental variability affects signals* • *Multimodal signal complexity* • *Integration gap between physics and ML models*

Table 2. *Cont.*

Ref.	Methods Covered	Structures Considered	Practical Insights	Challenges Discussed
This work	• *Linear and nonlinear GW* • *Signal processing (time/frequency /time–frequency features)* • *Classical ML (SVM, KNN, RF, ANN)* • *Deep learning (CNN, LSTM, Autoencoders)* • *Hybrid frameworks (signal processing + ML/DL)* • *Physics-informed ML concepts*	• *Metallic structures* • *Composite structures* • *Concrete structures* • *Full-scale civil infrastructure (field applications)*	• *Comprehensive review of GW-based SHM evolution from ML to DL* • *Comparison of classical ML, DL, and hybrid pipelines* • *Identification of key application domains* • *Discussion of real-world deployment* • *Discussion of gap and future directions (XAI, transfer learning, digital twins, PIML)*	• *Lack of standardized datasets* • *Poor real-world generalization* • *Environmental and operational variability* • *Sensor degradation and noise* • *Limited field validation* • *High computational cost of DL models* • *Weak interpretability in DL methods*

Furthermore, unlike previous studies, the present work systematically compares methodological developments across metallic, composite, and concrete structures, highlighting transferable concepts, implementation challenges, and data-driven limitations in practical SHM deployment. Based on these identified gaps, this review aims to provide a structured and comprehensive assessment of PZT-based GW-SHM by jointly examining signal processing techniques, ML and DL methodologies, and physics-informed learning strategies across multiple structural domains.

1.8. Scope and Contribution of This Review

The recent evolution of PZT-based sensor technologies has generated considerable interest in SHM through the integration of traditional signal processing and data-driven methodologies. Building upon the gaps identified in the existing literature, this review aims to provide a comprehensive assessment of PZT-based GW SHM systems. The review focuses on three main aspects: (i) signal processing techniques for extracting damage-sensitive information from PZT measurements, (ii) ML and DL methods for automated damage detection, localization, and classification, and (iii) hybrid and physics-informed frameworks that combine physical knowledge with data-driven learning.

The remainder of this paper Is organized as follows. Section 2 presents the fundamentals of PZT-based SHM systems, including the operating principles of piezoelectric sensors and their role in structural monitoring. Section 3 reviews major signal processing methods used for extracting damage-sensitive information from PZT measurements. Section 4 discusses linear and nonlinear guided wave techniques. Section 5 discusses ML techniques for PZT-based SHM, including automated damage detection and classification, examines hybrid approaches that integrate signal processing and ML models, and highlights emerging AI trends in GW-based SHM. Section 6 summarizes key engineering applications of PZT-based SHM systems. Section 7 outlines the main technical and practical challenges associated with current implementations. Section 8 highlights emerging research trends and future directions. Finally, Section 9 presents the main conclusions of the review.

2. Fundamentals of PZT-Based SHM

NDT techniques employ various sensing technologies to acquire structural response data for condition assessment. Piezoelectric transducers are among the most widely used in guided wave applications. Interpreting the resulting measurements requires an understanding of how sensing mechanisms interact with wave propagation within structural media. This section introduces these key concepts to support the subsequent discussion on signal processing and data-driven analysis.

2.1. Piezoelectric Effect

PZT (lead zirconate titanate) is a perovskite ceramic material composed of lead, zirconium, titanium, and oxygen, typically formulated as Pb(Zr,Ti)O_3. PZT materials exhibit a coupled electromechanical behavior through the piezoelectric effect, whereby mechanical deformation generates an electrical response (direct effect) (Figure 4a) while an applied electric field induces mechanical strain or vibration (inverse effect) (Figure 4b).

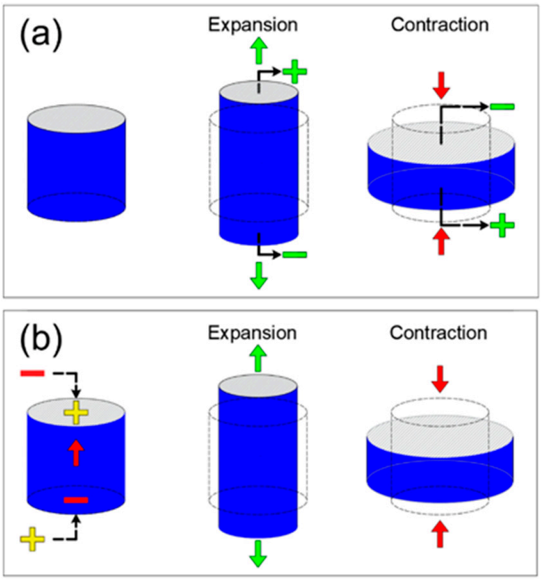

Figure 4. Schematic of mechanical deformation due to coupled electromechanical behavior in PZT transducers in (**a**) direct and (**b**) indirect configuration (redrawn from [42]).

This dual functionality enables a single PZT element to operate as both an actuator and a sensor [42]. Due to their dual actuator–sensor capability, PZT transducers are widely used in active SHM systems, where guided waves are transmitted through a structure and the resulting responses are analyzed to detect and characterize damage. Therefore, PZT transducers have been extensively used in NDT applications, such as detecting cracks [43], delaminations [44], corrosion [45], loose bolts [46], and evaluating interfacial debonding in both composite materials and reinforced structures [47,48].

The widespread adoption of PZT sensors in SHM is attributed to several advantages. Their small size and low mass allow for easy surface bonding or embedding with minimal influence on structural behavior. In addition, their capability for high-speed signal generation and acquisition supports real-time or near real-time structural assessment [49]. Moreover, PZT sensors exhibit high sensitivity to stiffness changes, wave scattering, and nonlinear effects induced by damage, enabling the detection of very small defects that may not be captured by conventional inspection methods [50,51].

However, the placement of PZT transducers directly influences the quality of the acquired signals and therefore affect feature extraction, ML model performance, and the reliability of AI-based damage assessment.

2.2. Types of PZT Sensors

SHM applications utilize PZT sensors in a wide range of geometries and packaging configurations, allowing adaptation to local structural conditions and monitoring objectives. In addition to classification based on geometry, PZT transducers can also be categorized according to their installation method and application, including surface-mounted, embedded, and packaged configurations. Typical geometries include rectangular, square, circular/round, and ring type (see Figure 5a–d).

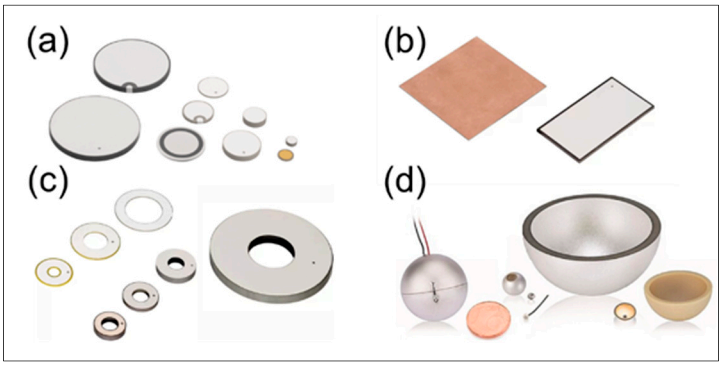

Figure 5. PZTs in different shapes: (**a**) disks, (**b**) plates, (**c**) rings, and (**d**) hollow spheres, hemispheres, focus bowls.

2.2.1. Surface-Bonded PZTs

SHM applications primarily depend on using surface-bonded PZT sensors. These transducers are adhered to a structural element's surface and can be used for guided wave monitoring, electromechanical impedance measurements, vibration sensing, and localized damage detection. Their convenient installation allows them to be used on metallic, composite, and reachable reinforced concrete structures [52].

2.2.2. Embedded PZTs

Embedded PZT sensors, often referred to as smart aggregates in concrete applications, consist of PZT elements encapsulated within protective materials and cast inside the structure during construction. They are particularly useful for the long-term internal monitoring of concrete members, slabs, foundations, and bridge components where external access is limited. Smart aggregates have been widely applied for crack detection, impact monitoring, and health assessment of concrete infrastructure [53].

2.3. Packaged or Reusable PZT Probes

PZT probes, whether packaged or reusable, utilize protective housing or detachable fixtures to allow temporary inspection, laboratory testing, and use in harsh environments where direct bonding is not appropriate. Many configurations are used for ultrasonic testing or repetitive measurements [54]. Surface-mounted patches are commonly used for retrofit applications and externally accessible structures, disk sensors are suited for compact or near-omnidirectional sensing requirements, and intelligent aggregates are typically employed for long-term embedded monitoring in concrete systems. The choice of PZT geometry and installation method influences the wave propagation characteristics, signal quality, and data consistency, which in turn affect feature selection, model transferability, and the robustness of AI-based SHM algorithms.

2.4. Actuator–Sensor Configurations

PZT elements can be configured as individual actuators and sensors or organized into sensor networks depending on the objectives of the monitoring strategy. Common interrogation schemes include pitch–catch and pulse–echo configurations.

2.4.1. Pitch–Catch Configuration

In the pitch–catch configuration, a PZT transducer is used as an actuator to generate diagnostic waves, while one or more spatially separated PZT sensors act as receivers to record the response after wave propagation through the structure (Figure 6a). Damage located along the wave path may alter signal amplitude, arrival time, phase, or frequency content due to scattering, attenuation, and mode conversion [11]. In AI-based SHM, these transmitted-wave features are commonly used as inputs for damage detection and classification models.

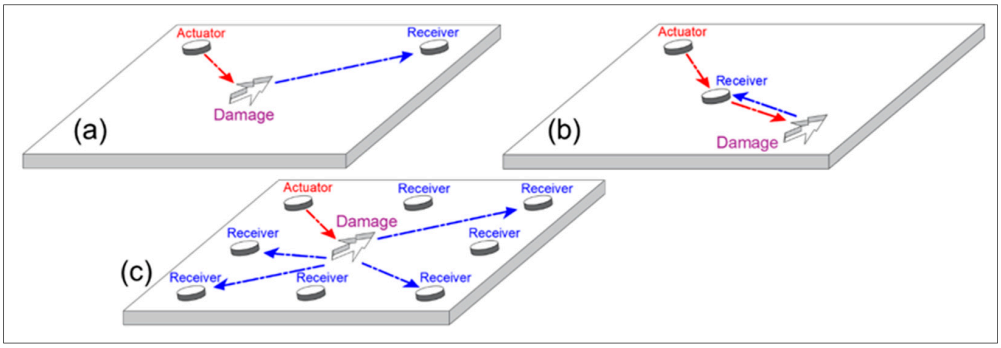

Figure 6. Sensor configurations: (**a**) pitch–catch, (**b**) pulse–echo, and (**c**) sensor network.

2.4.2. Pulse–Echo Configuration

In the pulse–echo configuration, a single PZT transducer or co-located transducer pair is used to transmit a wave pulse and receive reflections from boundaries, interfaces, or damage features [11] (Figure 6b). These reflections can be analyzed in terms of their arrival times and amplitudes to estimate the presence and location of defects. Additionally, the reflected-wave information obtained from pulse–echo measurements can provide damage-sensitive features for ML models focused on localization and defect characterization. A pulse–echo configuration is particularly useful when access is limited to one side of the structure or when internal reflections are of interest.

2.4.3. Sensor Network

Deploying multiple PZT elements as a sensor network is a common strategy for monitoring large or complex structures, improving both spatial coverage and reliability. In these configurations, PZT transducers can function alternately as actuators and sensors, generating multiple interrogation paths across the monitored region (see Figure 6c). Additionally, by improving damage localization accuracy, such network configurations reduce reliance on any single sensor measurement and provide redundancy in the event of sensor failure. From an AI perspective, sensor networks generate multi-path and multi-sensor datasets that can improve model robustness and localization accuracy, although they also increase the data dimensionality and computational requirements.

As a result, distributed PZT networks are now widely used in applications such as bridges, aircraft panels, composite components and reinforced concrete structures, where there is a requirement for continuous multi-point monitoring [55,56].

2.5. Wave Propagation in Structures

Many PZT-based SHM methods rely on wave propagation as a primary source of information. In particular, active sensing and ultrasonic techniques employ a PZT transducer as an actuator to generate structural excitation. Once generated, the incident wave propagates through the structure and interacts with boundaries, joints, geometric discontinuities, and damage features, producing reflections, scattering, and mode conversions [57]. As a result, changes in the received wave response provide important information about the structural condition [11]. Under suitable structural and excitation conditions, such as finite thickness and appropriate excitation frequencies, mechanical waves propagate in the form of guided waves.

Guided waves are commonly classified into three mode families: symmetric (S), antisymmetric (A), and shear horizontal (SH) modes. Symmetric modes exhibit particle motion that is symmetric about the mid-plane and are predominantly extensional in nature. Antisymmetric modes involve out-of-plane particle motion with a stronger flexural (bending) character, making them particularly sensitive to surface and interfacial damage. In contrast, SH modes are characterized by in-plane shear particle motion perpendicular to the direction of wave propagation, often resulting in less complex wave behavior and offering advantages in certain applications [57]. In addition to the fundamental mode families, multiple lower- and higher-order modes may exist depending on structural configuration and excitation frequency. Generally, the three basic modes, S_0, A_0, and SH_0 are the lowest-frequency modes used in SHM due to their ability to propagate effectively over practical monitoring distances [58]. The selected wave mode influences the damage information contained within the measured signals and therefore affects the features learned by the ML and DL models.

Guided waves are inherently dispersive, meaning that their propagation velocity is frequency-dependent. As a result, different frequency components travel at different phase and group velocities, leading to waveform distortion over distance and complicating arrival time estimation and damage localization. In addition, identifying wave packet modes may not always be possible. Consequently, incorrect mode identification can lead to inaccurate arrival time estimation and reduce the ability to detect and localize structural defects. An example of a phase velocity dispersion curve for a concrete beam is shown in Figure 7. The figure illustrates that for every frequency (e.g., 270 kHz) selected, there exists a number of propagating modes at different phase velocities.

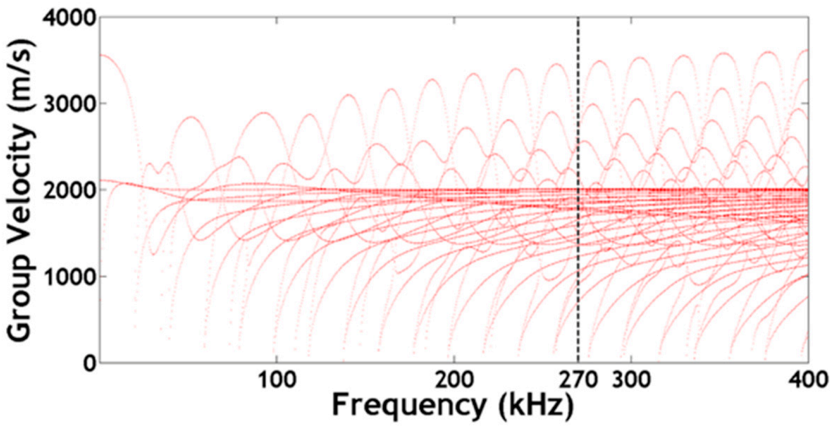

Figure 7. Phase velocity dispersion curve for a concrete beam.

Wave attenuation is another important factor influencing guided wave propagation. Attenuation arises from material damping, geometric spreading, scattering, mode conversion, and energy leakage into surrounding media. Signal dispersion as well as signal attenuation has the potential to degrade the quality of the signal and should also be given careful consideration when determining the frequency of excitation, spacing between sensors, and the methods used to process the signals in order to utilize PZT-based SHM technologies [59].

3. Signal Processing Methods

Raw signals acquired from PZT sensors are typically complex and influenced by noise, dispersion, and environmental effects, requiring systematic processing before meaningful interpretation. Effective extraction of damage-sensitive features therefore depends on appropriate signal transformation and analysis techniques. This section covers common signal processing approaches for guided wave data, including time, frequency, and time–frequency domain methods.

3.1. Time-Domain Analysis

One of the most common approaches in PZT-based SHM is time-domain analysis, which directly evaluates captured signals by examining waveform features such as arrival time, peak amplitude, duration, and shape. The simplest implementation involves comparing actuator–sensor signals with baseline data from an undamaged state. Deviations in the waveform are then used to identify damage such as cracks, debonding, corrosion, and delamination. Indicative features include waveform distortion, delayed arrivals, reflected components, and reduced transmitted energy. Time-of-flight (TOF) and time-of-arrival (TOA) are commonly used metrics in GW-based SHM, representing wave propagation and the detection times of wave packets. In practice, both are extracted from processed signals (e.g., envelope- or energy-based representations) and are influenced by dispersion, attenuation, and damage-induced scattering.

Signal modification is another commonly used damage-sensitive feature. Structural defects can scatter, absorb, or reflect wave energy, leading to reduced transmitted amplitude and increased reflected energy. Figure 8 illustrates wave modification due to debonding in a structural component. A clear difference is observed between the signal received by the sensor and that generated by the actuator, indicating wave modification potentially associated with structural damage. Since these indicators are based on amplitude variations, their implementation is relatively straightforward; however, they are sensitive to sensor coupling conditions, temperature fluctuations, and operational variability. Therefore, careful interpretation is required when using such features. To improve robustness, envelope detection is often applied to the time-domain signal [35]. In this method, the oscillatory waveform is transformed into a smooth envelope, highlighting the energy distribution and the main wave packets of the incident signal. This facilitates a more accurate identification of arrival times and tracking of wave packet peaks. Envelope extraction is commonly performed using the Hilbert transform or rectification-based approaches. It is particularly useful for noisy signals or cases involving multiple overlapping modes.

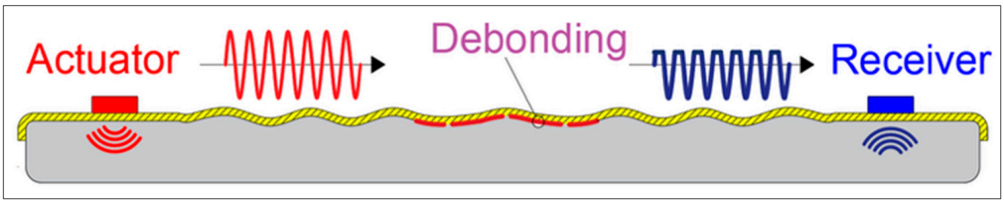

Figure 8. Modification of incident wave due to debonding.

3.2. Frequency-Domain Analysis

Frequency-domain analysis is widely used in GW-based SHM, particularly in nonlinear GW methods, where damage is typically identified through changes in the spectral content of the signal. In this approach, time-domain signals are converted into the frequency domain using the fast Fourier transform (FFT), which separates the signal into its frequency components.

This enables the detection of fundamental frequencies, harmonics, and sidebands that may not be clear in the time domain. In nonlinear GW analysis, damage such as cracks, delamination, or debonding can generate higher harmonics; for example, excitation at ω may produce components at 2ω or 3ω. The presence and growth of these components are commonly used as sensitive indicators of structural damage. The nonlinear GW response can be represented as a harmonic expansion in the time domain, where damage-induced nonlinearities generate higher-order harmonic components [60]:

$$x(t) = A_0 + A_1\cos(\omega t) + A_2\cos(2\omega t) + A_3\cos(3\omega t) + \cdots \quad (1)$$

where A_0 represents a constant (DC) component, A_1, A_2, . . . are the amplitudes of the fundamental and higher harmonic frequencies generated due to material or contact nonlinearity, and ω is the angular frequency. Nonlinear GW techniques are commonly divided into classical and nonclassical techniques [61]. The classical method focuses on wave nonlinearity arising from material nonlinearity (fatigue, corrosion, etc.), while the nonclassical nonlinear techniques rely on nonlinearity due to the interaction of defect interfaces (cracks, delamination, etc.) with the wave. This phenomenon is schematically shown in Figure 9.

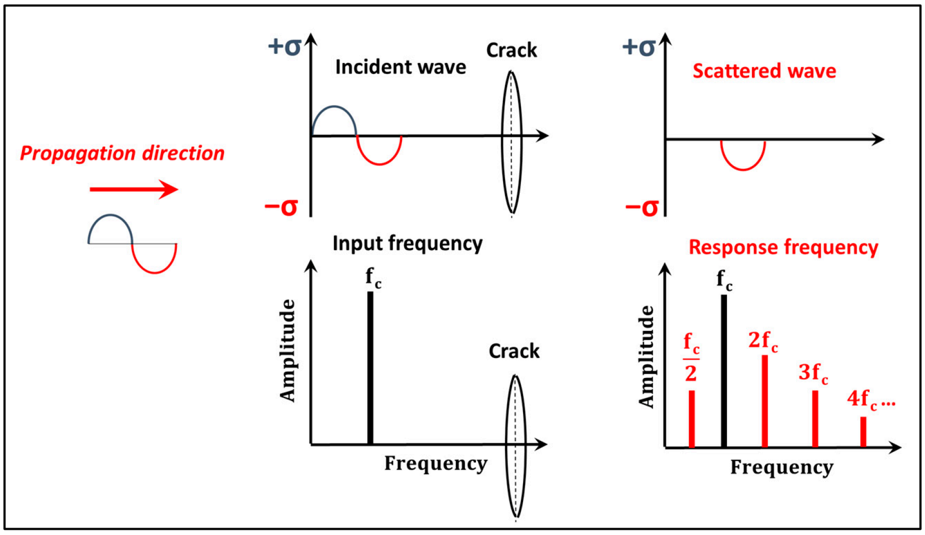

Figure 9. Higher harmonic generation due to non-classical nonlinearity (redrawn from [43]).

In addition to harmonic generation, frequency-domain analysis can be used to evaluate spectral energy, defined as the distribution of signal energy across frequency components obtained from the Fourier spectrum [35]. When waves interact with cracks, corrosion, delamination, or debonding, part of the signal energy may be attenuated, scattered, or redistributed to other frequency components. This results in measurable variations in the energy content of specific frequency bands within the spectrum. By comparing the spectral energy of intact and damaged states, changes associated with damage initiation, growth, and severity can be identified. Spectral energy analysis is also widely used as an effective damage indicator in SHM applications.

3.3. Time–Frequency Analysis

Time–frequency analysis is widely applied in SHM-based damage identification, where the accurate estimation of TOF and TOA is critical for reliable structural assessment. Damage-induced wave response signals are often non-stationary; hence, frequency-domain methods alone cannot capture the temporal arrival of signal components. Time–frequency analysis addresses this limitation by jointly representing signals in the time and frequency domains, enabling the improved localization of time-varying and nonlinear features in guided wave signals.

The continuous wavelet transform (CWT) is one of the most widely used time–frequency techniques in SHM applications. It decomposes a signal into scaled and shifted versions of a mother wavelet, enabling multi-resolution analysis in both the time and frequency domains. This representation allows for an accurate estimation of TOA, even in noisy environments, by providing a high temporal resolution of wave arrivals. CWT has been widely applied in SHM for detecting wave packet arrivals, characterizing dispersion in guided waves, and isolating damage-scattered signal components. Due to its strong time-localization capability, it is particularly effective for GW-based SHM in complex structural systems [43,44].

Figure 10 presents the CWT of signals acquired from a structural member containing a defect. The guided wave is generated by the actuator and propagates through the structure. Receiver 1 is positioned in a pulse–echo configuration, whereas receiver 2 is arranged in a pitch–catch configuration. Receiver 1 captures damage-related information through waves reflected from the defect, while receiver 2 receives defect information through scattered waves transmitted across the damaged region. As shown, the CWT of both received signals identifies the signal spectrum, providing both frequency content and time-of-arrival information. The actuator response exhibits a concentrated CWT contour around the incident excitation frequency *f*. In contrast, the CWT results of receivers 1 and 2 show two dominant frequency components: the fundamental frequency *f*, corresponding to the incident wave, and the second harmonic component 2*f*, generated due to the presence of damage-induced nonlinearities. Thus, CWT is capable of simultaneously revealing the frequency components of the signal and the arrival time of each component, making it an effective tool for structural damage detection and localization [62].

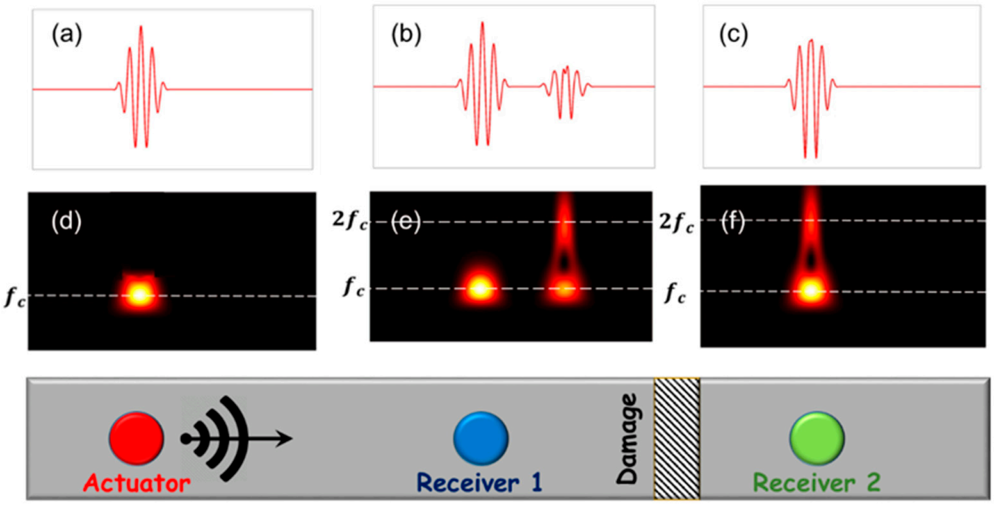

Figure 10. Time domain data at (**a**) actuator, (**b**) receiver 1 (pulse–echo), (**c**) receiver 2 (pitch–catch) and CWT at (**d**) actuator, (**e**) receiver 1 (pulse–echo), (**f**) receiver 2 (pitch–catch) [44].

4. Linear and Nonlinear Guided Waves SHM Techniques

The two main classifications of GW-based NDT methods include linear approaches (using conventional wave measurements: amplitude attenuation, velocity/phase/reflectance conversion). Conversely, the use of nonlinear approaches to detect structural defects is based on nonlinear phenomena resulting from the presence of damage (higher harmonics, subharmonics, superharmonics, sidebands). In order for linear techniques to provide reliable interpretations, they often need either data from the pristine state of a structure or pre-existing baseline measurement [61]. Thus, their sensitivity relies upon the difference in material/structural conditions associated with structural defects. In comparison, nonlinear techniques can often detect damage without requiring a direct baseline measurement, depending on the implementation and operating conditions as they assess changes associated with the excitation waveform. These include shifts in frequency content and the emergence of higher-order harmonics. This makes nonlinear methods baseline-independent in many applications. This characteristic is considered a primary benefit of nonlinear methodologies as a means of detecting structural defects. Another limitation of linear techniques to detect defects is that environmental fluctuations (e.g., temperature variance, load conditions, humidity, boundary conditions) can introduce variations in the measurement (e.g., amplitude/velocity) and create erroneous defect indications [63]. Conversely, the focus of nonlinear methods on newly developed frequency components if damage exists provides a situation where the effects of environmental fluctuations may have a reduced influence on the detection process in some cases, although they can still affect nonlinear measurements [64].

On the other hand, nonlinear methods can be more challenging to implement, as the amplitudes of nonlinear components are typically much smaller than the fundamental response and are therefore highly sensitive to noise, sensor limitations, and signal processing errors, which can reduce detection accuracy and increase experimental complexity [65].

Nevertheless, the transition from linear to nonlinear GW techniques is motivated by their enhanced sensitivity to early-stage and small-scale defects that may not be detectable using conventional linear approaches. However, nonlinear GW responses remain influenced by practical factors such as sensor coupling conditions, excitation level, boundary conditions, and signal processing artifacts, which can affect measurement reliability in field applications. Table 3 provides a comparison of linear and nonlinear GW techniques.

Table 3. Comparison of linear and nonlinear GW techniques.

Technique	Parameters Used	Advantages	Disadvantages
Linear GW	• *Amplitude* • *Attenuation* • *Wave Velocity* • *Phase Shift* • *Reflection* • *Mode Conversion* • *Scattering* • *Time-Of-Flight Variations*	• *Mature methodology* • *Simple excitation* • *Easy measurement* • *Fast processing* • *Long-range inspection* • *Multi-material applicability* • *Low cost* • *Industry accepted*	• *Baseline often required* • *Low early sensitivity* • *Environmental sensitivity* • *Limited microcrack detection* • *Mode complexity issues* • *Signal attenuation losses* • *Interpretation can vary* • *Damage quantification difficult* • *Boundary effect sensitive*
Nonlinear GW	• *Higher Harmonic* • *Subharmonics* • *Superharmonics* • *Sidebands* • *Modulation Effects*	• *Baseline-free* • *High sensitivity* • *Early defect detection* • *Microcrack detection* • *Generally less environmental influence*	• *Weak signal amplitude* • *Noise sensitive* • *Weak nonlinear signals* • *Advanced processing needed* • *Calibration often required* • *Interpretation more difficult* • *Limited standardization*

5. Machine Learning in PZT-Based Guided Waves SHM

The signal processing and guided wave techniques discussed in the previous sections provide the foundation for extracting damage-sensitive information from measured responses. However, the large volume of data generated by modern SHM systems and the complexity of damage-related patterns often make manual interpretation challenging. Consequently, ML is used as a tool for automating structural condition assessment and supporting damage identification. This section reviews the principal ML approaches applied to GW-based SHM, including both classical ML algorithms, hybrid, and modern DL frameworks.

5.1. Feature Extraction

Feature extraction plays a critical role in SHM, as raw sensor signals are typically high-dimensional, complex, and noisy, making direct interpretation challenging. Its objective is to transform coarse measurements into a compact set of representative features that are sensitive to structural damage. This process also reduces the influence of irrelevant information, noise, and operational or environmental effects that may mask damage-related signatures. Consequently, feature extraction is essential for reliable damage detection, localization, and classification. This is particularly important in large-scale SHM systems, where numerous sensors generate continuous streams of high-volume data [66]. In GW-based SHM applications, such features are commonly classified into time-domain, frequency-domain, and time–frequency-domain features. Time-domain features include a variety of statistical quantities such as root mean square (RMS), peak value, mean, variance, and kurtosis, which may be useful for indicating a change in amplitude behavior due to damage. Frequency-domain features such as spectral energy, dominant frequency, and variations in bandwidth are useful in indicating that a change in content is taking place within the signal due to a reduction in stiffness or due to a discontinuity.

Time–frequency features, for example, those obtained from a wavelet analysis, have localized features in both the time domain and frequency domain and are particularly suited to the application of non-stationary GW signals. These types of features are often used as inputs for statistical pattern recognition and ML automation of decision-making [67]. Careful feature selection is essential in nonlinear GW-based SHM, as weak higher-harmonic components associated with material nonlinearity may be misinterpreted as noise-induced spectral artifacts. Due to their low amplitudes, inappropriate feature selection can result in misinterpretation and false damage indications. The extracted features are often combined into damage indices (DIs), which are quantitative metrics used to represent the deviation of a monitored structure from its reference or healthy condition. Higher DI values generally indicate a greater likelihood or severity of damage, although the specific definition depends on the selected feature and monitoring methodology.

5.2. Classical Machine Learning Models in SHM

In SHM, including GW-based approaches, ML models are widely used to detect the presence of damage and estimate its location based on features extracted from signals. In most cases, raw GW signals are first processed in the time, frequency, or time–frequency domains to obtain representative features such as amplitude, energy, statistical moments, and wavelet coefficients. These features are then used as inputs to ML models, which are typically formulated as either classification tasks (damage present or absent) or regression tasks (estimating damage location or severity) [68].

5.2.1. Support Vector Machine (SVM)

Support vector machine (SVM) is one of the most widely used classifiers in SHM. In GW-based SHM, SVM performs effectively because extracted features such as TOF shifts, amplitude, spectral energy, and wavelet coefficients often exhibit clear separation between damaged and undamaged conditions. The method constructs an optimal hyperplane that maximizes the margin between classes, while kernel functions enable it to capture the nonlinear characteristics of GW propagation in complex structures. The general decision function of SVM is [68]:

$$f(x) = sign(\mathbf{w}^T\mathbf{x} + \mathrm{b}) \tag{2}$$

where $\mathbf{x}$ is the feature vector, $\mathbf{w}$ is the weight vector, and b is the bias term.

SVM is particularly effective in GW-based SHM applications involving small experimental datasets, which are common in laboratory-scale damage detection studies. However, its performance depends strongly on kernel selection and hyperparameter tuning. In addition, its scalability becomes limited as dataset size and feature dimensionality increase, making it less suitable for large-scale monitoring compared with deep learning approaches.

5.2.2. Artificial Neural Networks (ANNs)

Due to their ability to model complex nonlinear relationships between input features and structural condition, ANNs have been widely applied in modern SHM. An ANN consists of interconnected layers of neurons that learn patterns in data through a training process. A typical architecture includes an input layer, one or more hidden layers, and an output layer. In GW-based SHM, the input layer receives features extracted from processed signals, such as time-of-flight, amplitude, root mean square (RMS), spectral energy, wavelet coefficients, and higher harmonic components.

The hidden layers of the ANN will learn the correlations between the input features of the signal and the corresponding structural condition, and the output layer will give the final prediction for the ANN. ANNs are frequently used in SHM to perform classifications (such as detecting damage) and regressions (like estimating the location of damage based on the characteristics of the waves). The performance of ANNs improves as the quantity of data available to the ANN increases [69]. The output of a neuron can be expressed as [70]:

$$y = \phi(\mathbf{w}^T\mathbf{x} + b) \tag{3}$$

where x is the input feature vector, w is the weight vector, b is the bias term, and $\phi(\cdot)$ is the activation function (e.g., sigmoid, ReLU, or tanh). The ANN architecture is schematically shown in Figure 11.

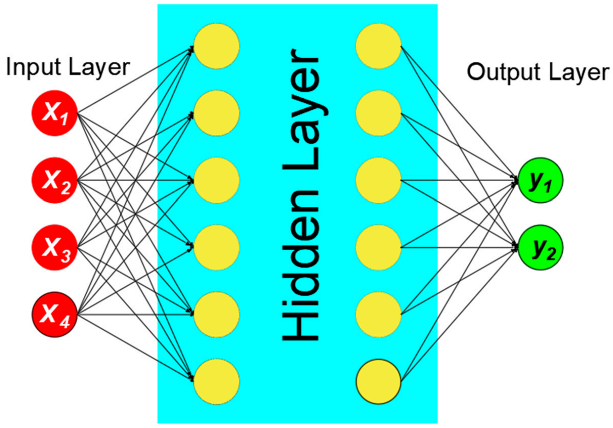

Figure 11. Schematic diagram of the ANN architecture.

Although ANNs are capable of modeling complex nonlinear relationships between GW features and structural conditions, their performance is strongly dependent on the quantity and quality of available training data. Overfitting can occur when training datasets are limited, which is frequently the case in SHM applications. In addition, ANN predictions are often difficult to interpret, limiting their acceptance in safety-critical infrastructure monitoring.

5.2.3. K-Nearest Neighbors (KNN)

KNN is an effective and straightforward method to classify new samples based on the labels of the K-nearest neighbors of that sample in a feature space. In GW-based SHM, the feature space is typically created from the extracted features of GW characteristics such as: TOF shifts, energy of the wave packet, spectral features, or descriptors based on wavelets. The classification of a new measurement is performed by comparing its GW feature vector with baseline vectors. The class label is assigned based on the nearest neighbors. If the feature vector is closer to the damaged baseline, it is classified as damaged. Owing to this intuitive decision mechanism, K-nearest neighbors (KNN) is particularly suitable for GW-based damage classification when feature distributions are well-separated [71]. KNN is also an effective classifier when the extracted features maintain damage sensitive patterns and the dataset is structured well. In KNN, the classification of a new sample x is based on the majority vote for K training examples that are nearest to x:

$$f(x) = \mathrm{mode}(y_i \; for \; i \in \mathrm{N}_k(\mathbf{x})) \tag{4}$$

where $\mathrm{N}_k(\mathbf{x})$ denotes the set of K nearest neighbors of $\mathbf{x}$ in the feature space, and y_i represents their corresponding class labels. The distance between samples is typically computed using Euclidean distance:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2} \tag{5}$$

In GW, the feature vector $\mathbf{x} = [x_1,\ x_2, \ldots, x_n]$ represents extracted guided wave characteristics from the measured signals. Typically, each component corresponds to a damage-sensitive feature such as TOF shifts, signal amplitude, RMS value, wave packet energy, spectral peaks from FFT analysis, or wavelet-based coefficients. The training samples $\mathbf{x_i}$ are feature vectors obtained from previously recorded healthy and damaged states of the structure, while y_i denotes their associated class labels (e.g., healthy or damaged). The distance $d(x, x_i)$ quantifies similarity between a new measurement and stored reference states in the feature space.

Despite its simplicity, KNN becomes computationally inefficient for large datasets because all training samples must be considered during prediction. The method is also highly sensitive to feature scaling, noise, and class imbalance. Consequently, KNN is generally more suitable for proof-of-concept studies and relatively simple damage-classification problems than for large-scale real-time SHM deployment.

5.2.4. Random Forest (RF)

Random forest (RF) is an ensemble learning method based on multiple decision trees. It is widely used in GW-based SHM due to the presence of noise, boundary reflections, and environmental variations, which can introduce instability in single-model predictions. Each tree is trained using a randomly selected subset of GW-derived features such as TOF deviations, amplitude attenuation, spectral energy distribution, and wavelet descriptors [72]. The final output is obtained through majority voting (classification) or averaging (regression), improving generalization across varying signal conditions. This ensemble strategy reduces overfitting compared with individual decision trees and makes RF well-suited for GW data analysis, where variability in wave propagation can affect damage detection and localization reliability [73]. Despite these advantages, RF has limited interpretability because decisions are aggregated across multiple trees. In addition, model complexity and memory requirements increase with the number of trees, which can be a limitation in large-scale SHM applications.

Overall, each algorithm has its own areas of strengths and limitations depending on the monitoring objective, data characteristics, and computational requirements. Table 4 presents a comparison of discussed ML algorithms in terms of typical applications, advantages, and limitations.

Table 4. Comparison of ML algorithms for GW.

ML Algorithm	GW Applications	Advantages	Limitations
Support Vector Machine (SVM)	• *Damage detection* • *Damage classification* • *Condition assessment*	• *High accuracy* • *Small datasets* • *Good generalization* • *Nonlinear kernels*	• *Parameter tuning* • *Low interpretability* • *High computation*
Artificial Neural Networks (ANNs)	• *Damage detection* • *Damage localization* • *Damage quantification* • *Condition classification*	• *Nonlinear learning* • *Regression capable* • *High adaptability*	• *Large datasets* • *Overfitting risk* • *Black box* • *Slow training*
K-Nearest Neighbors (KNN)	• *Damage detection* • *Damage classification* • *Basic localization*	• *Simple implementation* • *No training* • *Intuitive method* • *Good separation*	• *Noise sensitive* • *Slow prediction* • *K selection*
Random Forest (RF)	• *Damage detection* • *Damage localization* • *Damage quantification* • *Condition classification*	• *Noise robust* • *Overfitting resistant* • *Mixed features* • *Feature ranking*	• *High memory* • *Low interpretability* • *Parameter tuning* • *Slower prediction*

5.3. Deep Learning (DL)

Despite the success of ML models such as KNN and random forest in GW-based SHM, their performance strongly depends on the quality of manually engineered features and their suitability for the target application. However, in many SHM scenarios, GW signals are affected by complex propagation behavior, nonlinearity, noise, mode variations, and environmental factors, which complicate feature extraction and limit feature robustness. To address these limitations, deep learning (DL) approaches have been widely developed to enable automatic feature extraction directly from raw or minimally processed GW data [74]. Unlike classical ML methods that rely on handcrafted features, DL models learn hierarchical representations directly from signals. However, their effectiveness in GW-based SHM depends strongly on data availability, excitation repeatability, and environmental consistency. In many practical cases, DL models do not necessarily outperform well-tuned ML approaches when datasets are limited or when damage-related signatures are weak relative to noise and operational variability. Therefore, the suitability of a DL architecture should be evaluated not only in terms of accuracy, but also in terms of data requirements, generalization capability, and robustness to domain shift [75,76]. The following sections will assess the performance of common DL techniques when using GW data.

5.3.1. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) can learn patterns from image-like representations, making them highly effective for GW-based SHM. Guided wave signals are often transformed into time–frequency representations such as spectrograms or wavelet scalograms, which preserve both temporal and frequency information related to wave propagation. A typical CNN architecture consists of convolutional layers, activation functions, pooling layers, fully connected layers, and an output layer used for damage classification or localization.

The convolution operation can be expressed as [77,78]:

$$y(i,j) = \sum_{m}\sum_{n} x(i-m, j-n)k(m,n) + b \quad (6)$$

where x is the GW input image (e.g., spectrogram or scalogram), k is the learnable filter used to identify damage-sensitive patterns, y is the extracted feature map, i,j denote spatial positions in the image, m,n are filter indices, and b is the bias term. However, in most DL implementations, CNN layers compute cross-correlation instead of strict convolution, expressed as:

$$y(i,j) = \sum_{m}\sum_{n} x(i+m, j+n)k(m,n) + b \quad (7)$$

where kernel flipping is not applied. This formulation is widely used in practice while still referred to as convolution in the literature. This framework enables the network to automatically extract damage-sensitive features such as reflections, scattering, and energy redistribution from GW signals without manual feature engineering. Figure 12 shows a schematic diagram of the CNN architecture.

Despite their strong performance in GW-based SHM when signals are converted into time–frequency images, CNNs are highly dependent on the quality and consistency of these representations. Variations in excitation signals, sensor coupling, or boundary conditions may alter spectrogram patterns, which can reduce the generalization performance across different structures. In addition, CNNs require relatively large labeled datasets to avoid overfitting, which is often not feasible in experimental SHM studies. As a result, CNN-based approaches are most suitable for controlled laboratory environments or when transfer learning strategies are employed to compensate for limited GW data.

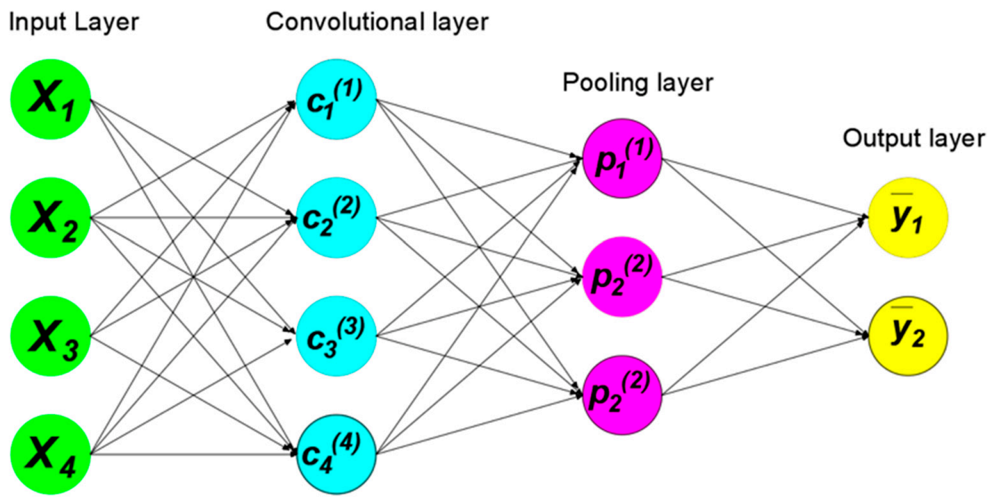

Figure 12. Schematic diagram of the CNN architecture (redrawn from [77]).

5.3.2. Long Short-Term Memory (LSTM)

LSTM networks are used for modeling sequential guided wave signals in SHM. Unlike CNNs, which focus on image-like representations, LSTMs directly process time-series data and capture how waveforms evolve over time. This is important in GW analysis, where damage information is embedded in time-dependent features such as wave arrivals, reflections, and scattering. The model operates on an input sequence x_t, representing the guided wave signal at time step t, while h_{t-1} denotes the previous hidden state (short-term memory) and C_{t-1} represents the previous cell state (long-term memory of wave propagation).

The LSTM uses a gated mechanism controlled by learnable parameters W_f, W_i, W_c, W_o (weight matrices) and b_f, b_i, b_c, b_o (bias terms). The forget gate f_t determines which past information from C_{t-1} is retained, while the input gate i_t controls the incorporation of new information. The candidate state $\tilde{C}_t$ represents newly extracted features from the current GW input. The cell state C_t integrates both past and new information, and the output gate o_t regulates what information is passed to the hidden state h_t, which serves as the final feature representation for damage detection or localization (Figure 13). The governing equations are [79,80]:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{8}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{9}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{10}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{11}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{12}$$

$$h_t = o_t \odot \tanh(C_t) \tag{13}$$

LSTM networks are particularly sensitive to sequence length and signal consistency when used in GW-based SHM. While they are capable of capturing wave propagation dynamics, their performance may be affected when time-series signals are contaminated by noise, missing reflections, or inconsistent wave arrivals caused by environmental variability. Moreover, long sequence training can lead to gradient instability and increased computational cost, making LSTMs less practical for high-channel dense SHM systems unless dimensionality reduction or hybrid feature extraction is applied.

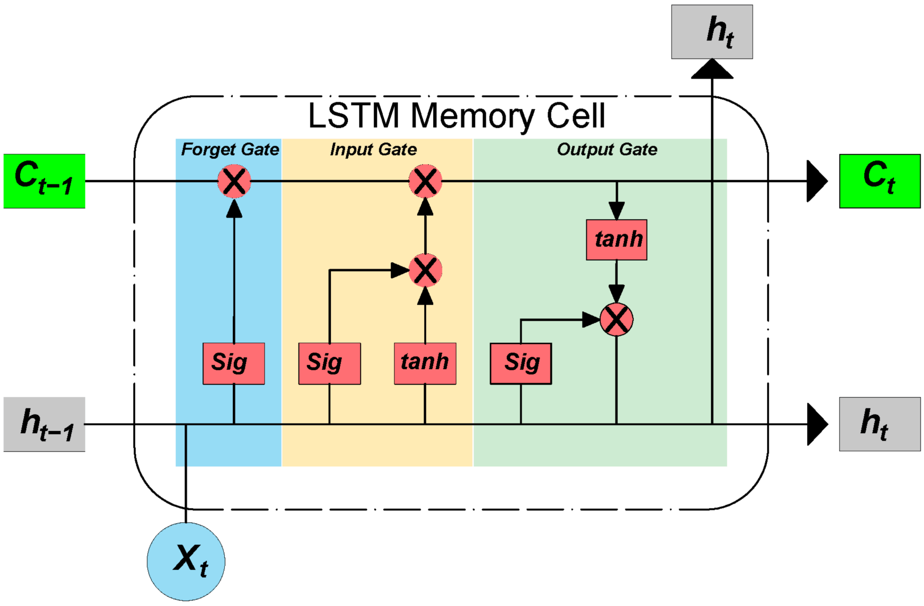

Figure 13. Schematic diagram of an LSTM network (redrawn from [81]).

5.3.3. Autoencoders

Autoencoders are widely used in GW-based SHM for unsupervised anomaly detection. They are trained using only intact GW signals to learn a compressed latent representation of the normal structural response and to reconstruct the input signal. In GW applications, the input x may consist of raw signals or extracted features containing wave propagation information such as reflections, attenuation, mode conversion, and dispersion. The encoder maps the input into a latent feature vector z, while the decoder reconstructs the signal as $\hat{x}$. The encoding and decoding processes are commonly expressed as [77,82,83]:

$$z = f(W_e x + b_e) \tag{14}$$

$$\hat{x} = g(W_d z + b_d) \tag{15}$$

where W_e and W_d are the encoder and decoder weight matrices, b_e and b_d are bias terms, and $f(\cdot)$ and $g(\cdot)$ denote activation functions. The network is trained by minimizing the reconstruction loss:

$$L = \|x - \hat{x}\| \tag{16}$$

The model learns the normal wave propagation patterns of a healthy structure when trained on undamaged GW signals. When applied to damaged conditions, such as cracks, debonding, or delamination, the reconstruction error increases significantly compared with the healthy baseline. This reconstruction error can therefore be used as a damage indicator, where higher values suggest a greater likelihood of structural damage. Accordingly, autoencoders are well-suited for weakly supervised GW-based SHM applications in which labeled damage data are limited or unavailable, although their performance may still be affected by environmental and operational variability.

Despite their effectiveness for baseline-free anomaly detection in GW-based SHM, autoencoders are strongly influenced by the definition of “healthy-state variability”. In practical applications, environmental and operational effects such as temperature changes, loading conditions, and boundary variations can increase reconstruction error even in undamaged states, leading to false alarms. Conversely, subtle damage that does not significantly alter the reconstructed signal may remain undetected. Therefore, appropriate threshold selection and domain adaptation strategies remain critical challenges for reliable field deployment.

As discussed, CNNs, LSTMs, and autoencoders are all widely used in GW-based SHM. However, their suitability depends on the nature of the available data and monitoring objective. CNNs are generally preferred when guided wave signals are transformed into time–frequency images because they can effectively identify spatial damage patterns. LSTMs are more suitable when temporal dependencies within waveforms contain important damage information. Autoencoders are particularly attractive when labeled damage data are unavailable, as they can learn normal structural behavior using only healthy-state data. However, CNNs and LSTMs typically require larger labeled datasets, whereas autoencoders may suffer from false alarms caused by environmental and operational variability. Consequently, no single DL architecture is universally optimal for all GW-based SHM applications.

Table 5 compares common DL algorithms used in GW-based SHM terms of their applications, advantages, and limitations.

Table 5. Comparison of DL algorithms for GW.

Algorithm	Application	Advantages/Strengths	Limitations
CNN	• *Damage detection* • *Damage localization* • *Damage classification*	• *Auto features* • *High accuracy* • *Spatial learning* • *Robustness*	• *Data demand* • *High cost* • *Tuning needed* • *No memory*
LSTM	• *Damage detection* • *Damage localization* • *Damage prediction* • *Condition monitoring*	• *Temporal learning* • *Sequence modeling* • *Noise tolerant* • *Memory retention*	• *Slow training* • *High cost* • *Long sequences* • *Gradient issues*
Autoencoder	• *Damage detection* • *Anomaly detection*	• *Unsupervised learning* • *Healthy only* • *Label free* • *Good screening* • *Baseline free*	• *Threshold tuning* • *False alarms* • *Weak localization* • *Mild reconstruction*

5.4. Existing Challenges

Although ML and DL have demonstrated significant potential for improving GW-based SHM, several challenges continue to limit their reliability and large-scale deployment. Many of these challenges have been discussed throughout the preceding sections in relation to wave propagation, signal processing, sensing systems, and learning algorithms. For clarity, they are synthesized here into five broad categories: (1) data-related, (2) physics-related, (3) sensor-related, (4) algorithmic, and (5) deployment-related challenges. In this section, these challenges will be discussed.

5.4.1. Data-Related Challenges

One of the primary challenges in AI-based GW SHM is the limited availability of labeled damage datasets. Acquiring GW data from structures with known damage states is costly and often requires controlled experiments, resulting in relatively small datasets compared with other AI domains. Consequently, ML and DL models may suffer from overfitting and reduced robustness when applied to unseen structures. Data augmentation, transfer learning, synthetic data generation, and physics-based simulations have therefore become important approaches for improving model performance under limited-data conditions [84].

5.4.2. Physics-Related Challenges

The complex nature of guided wave propagation presents significant challenges for AI models. Dispersion, attenuation, mode conversion, and boundary reflections can alter signal characteristics and complicate feature extraction. In addition, environmental and operational variability, such as temperature changes and varying loading conditions, may introduce signal variations that resemble damage-induced responses. To address these issues, physics-informed learning and advanced signal-processing techniques are increasingly being explored to improve robustness against these effects [85,86].

5.4.3. Sensor-Related Challenges

Reliable AI predictions depend on the quality and stability of the measured GW signals. In long-term monitoring applications, PZT transducers may experience degradation, debonding, coupling variations, or calibration drift, which can influence signal consistency and detection accuracy. Sensor placement and network design also affect monitoring coverage and localization capability. Sensor redundancy, periodic calibration, and sensor-health assessment strategies are commonly used to mitigate these issues [87,88].

5.4.4. Algorithmic Challenges

Although ML and DL algorithms have demonstrated promising results for damage detection and localization, poor generalization remains a major challenge. Models trained under specific laboratory conditions may not perform reliably when applied to different structures, excitation frequencies, or environmental conditions. Furthermore, DL models often lack interpretability and may generate false alarms when exposed to previously unseen data. Domain adaptation, explainable AI, and hybrid physics-guided learning frameworks are emerging solutions to improve model reliability and trustworthiness [89,90].

5.4.5. Deployment Challenges

Translating ML and DL-enabled GW SHM from laboratory studies to field implementation remains challenging. Large-scale deployment requires the consideration of power supply, data acquisition, communication infrastructure, sensor maintenance, and long-term system reliability. In addition, the cost of installing and maintaining dense sensor networks must be justified by measurable benefits in inspection and maintenance planning [91]. Future systems should therefore focus on scalable architectures and integration with infrastructure asset-management frameworks.

5.5. Hybrid Methods

Traditional ML and DL approaches each exhibit limitations when applied independently to GW-based SHM. Consequently, there is growing interest in hybrid frameworks that combine complementary techniques to improve the robustness, accuracy, and reliability of damage detection and localization in GW-based SHM systems [92].

Hybrid frameworks integrate signal processing, ML, DL, and/or physics-based knowledge to exploit the strengths of each approach while mitigating their individual limitations. In practical SHM applications, GW signals are often affected by noise, dispersion, environmental variability, and boundary reflections, which can reduce the reliability of purely data-driven models [93]. By incorporating signal processing techniques such as filtering, denoising, normalization, and time–frequency transformations, damage-sensitive information can be enhanced before being supplied to learning algorithms. This improves the quality and interpretability of the input data, enabling more stable model training, improved generalization, and enhanced damage assessment performance [94]. Furthermore, hybrid approaches can reduce the dependence on extensive labeled datasets and improve robustness under varying operational and environmental conditions, making them more suitable for real-world engineering applications. Hybrid approaches in GW-based SHM can be broadly grouped into: (i) signal processing–ML pipelines, (ii) PIML, (iii) physics-guided machine learning (PGML), and (iv) digital twin-assisted learning (DT) frameworks. These approaches are briefly discussed in the following sections. In this section, we briefly discuss these approaches.

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5.5.1. Signal Processing + ML Pipeline

An SHM hybrid framework based on GW principles typically follows a sequential pipeline starting from the acquisition of raw data via sensors through automated data processing to achieve the goal of damage identification. In the first stage, the initial step is to excite a structural component with a GW transducer (i.e., piezoelectric) and capture the GWs returned from the component. As a result, the data captured contain information regarding the propagation of the GWs, the nature and modality of reflections/scattering of the GWs, the characterization of GWs including attenuation, etc., along with the potential existence of some form of damage interaction. However, the responses captured will likely contain many undesirable and/or noisy responses. In the second stage of pipeline processing, the captured responses are subjected to preprocessing operations in order to clean up the dataset through the application of some type of filtering technique. Commonly used filtering techniques include: bandpass filter; wavelet denoising; normalization; baseline removal; and windowing [95]. The goal of the filtering operations is to suppress the noise; isolate the desired frequency ranges of the GW; and enhance the visual representation of damage sensitive features of the GWs. The quality of the raw data (or preprocessed data) significantly impacts the overall performance of the model, thus impacting the data learning process when creating the model, so effective preprocessing of the data is critical. The third stage of processing, feature extraction, involves identifying the relevant descriptors of the preprocessed features via the time-domain, frequency-domain, and/or time–frequency domain methods. Commonly used descriptors for feature extraction include peak amplitude, root mean square amplitude, signal energy, time of flight, dominant frequency, spectral entropy, and wavelet coefficients. When incorporated into the ML model, these characteristic descriptors simplify the data representation of structural conditions into a compact form that can readily facilitate the learning process [96].

Lastly, these extracted features then go into any ML or DL algorithm (for example, SVM, random forest, KNN, CNN or LSTM). The trained model can identify whether a structure is healthy or damaged, determine what type of damage has occurred, estimate how severe that damage may be, or pinpoint the location of defects. The hybrid pipeline improves the SHM system reliability by allowing very detailed interpretations of GW data. As depicted in Figure 14, the GW-based SHM hybrid framework follows an extraction and processing pipeline through acquisition and processing of the signals, and finally goes to the ML/DL algorithm to provide output on detecting, localizing and quantifying, or identifying the defect [90,97].

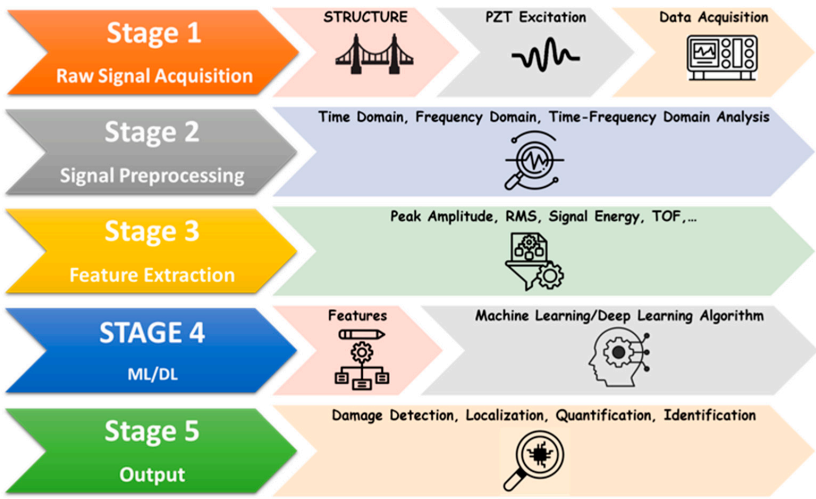

Figure 14. Typical GW-based SHM hybrid framework combining signal processing and ML for damage assessment.

5.5.2. Physics-Informed Machine Learning (PIML)

Physics-informed machine learning (PIML) has emerged as a promising framework for GW-based SHM by explicitly incorporating wave propagation physics into data-driven models. In contrast to purely data-driven approaches, which learn patterns solely from training data, physics-informed methods integrate prior knowledge of wave behavior, dispersion characteristics, and boundary conditions directly into the learning process. This ensures that the resulting models remain consistent with the fundamental physics of guided waves while retaining the flexibility of machine learning techniques.

PIML can reduce physically inconsistent predictions and improve performance in data-scarce SHM applications. Physics information is typically incorporated through constraints in the loss function, regularization terms, or hybrid model architectures that enforce consistency with wave propagation principles. By ensuring that learned representations are both statistically and physically meaningful, key wave phenomena associated with damage such as reflection, scattering, and mode conversion can be effectively captured. This improves model robustness to noise and environmental variability, which are among the main challenges in practical structural monitoring [98].

In addition, incorporating physical laws into the learning process enhances interpretability, as model outputs can be directly related to wave behavior rather than purely abstract feature representations. This improves confidence in model predictions for engineering decision-making.

5.5.3. Physics-Guided Machine Learning (PGML)

Physics-guided machine learning (PGML) represents a class of hybrid approaches in GW-based SHM where prior knowledge of wave propagation physics is incorporated into classical ML models through feature design and constraint-based learning. Similar to PIGW, PGML does not rely solely on statistical patterns extracted from data but embeds physical knowledge of guided wave behavior into the feature space [99]. In GW-based applications, this includes physics-informed damage-sensitive features such as TOF variations, wave attenuation trends, dispersion characteristics, and energy decay behavior. These features are derived from established wave propagation principles and structural response mechanisms, ensuring physically consistent input representations rather than purely empirical descriptors.

By constraining the feature space using physical principles, PGML may improve robustness in small-sample scenarios, which are common in laboratory-based SHM studies. It also can reduce overfitting to noise and experimental artifacts, a key limitation of conventional ML when applied to raw or weakly structured GW data. PGML is typically implemented using classical algorithms such as SVM, random forest, or KNN, where physically informed features replace generic statistical descriptors. Overall, PGML provides a practical balance between interpretability and predictive performance, making it suitable for GW-based damage detection and localization under limited data availability and controlled experimental conditions.

5.5.4. Digital Twin-Assisted Learning

Digital twin-assisted learning in GW-based SHM integrates physics-based numerical models with data-driven algorithms to enable bidirectional interaction between the physical structure and its virtual counterpart. The digital twin is typically constructed using finite element or semi-analytical wave propagation models capable of simulating GW dispersion, scattering, and mode conversion under varying damage states. Within hybrid GW frameworks, digital twins serve two primary roles: (i) data augmentation, where simulated GW responses under different damage scenarios are used to expand limited experimental datasets, and (ii) model calibration, where discrepancies between simulated and measured signals are minimized through parameter updating strategies. This enables improved representation of wave–damage interaction mechanisms under sparse labeling conditions [100,101].

From a learning perspective, digital twin outputs (e.g., simulated wavefields, time-of-flight shifts, or reflection coefficients) are fused with experimental measurements to train machine learning or deep learning models with enhanced generalization capability. Recent approaches also employ iterative updating schemes, where the digital twin is continuously corrected using incoming sensor data to track evolving structural conditions [102]. Despite its advantages in improving data efficiency and physical consistency, digital twin-based GW frameworks remain computationally expensive and strongly dependent on accurate physics modeling and boundary condition representation, which limits scalability in large civil infrastructure systems.

5.6. Emerging AI Trends in GW-Based SHM

Recent developments in GW-based SHM are extending beyond conventional ML and DL models. Current research is increasingly focused on more advanced learning paradigms aimed at improving generalization, reducing data dependency, and enabling robust field deployment in GW-based SHM applications. In this section, some of them are briefly discussed.

Self-supervised and contrastive learning methods are being explored to exploit large volumes of unlabeled GW data, which is particularly important given the limited availability of labeled damage datasets in GW-based SHM [90]. However, their applications in GW-based SHM remain limited. Domain adaptation and transfer learning techniques are also gaining attention to address variability caused by environmental and operational conditions, which often limits the performance of models trained under controlled laboratory GW experiments. Graph neural networks (GNNs) are emerging as a natural choice for modeling PZT sensor networks in GW-based SHM, where spatial relationships between sensors can be explicitly represented as graph structures [103,104]. In parallel, transformer-based architectures are being investigated for capturing long-range temporal dependencies in GW signals using attention mechanisms. Probabilistic and Bayesian learning frameworks are increasingly used to quantify uncertainty in GW-based damage predictions, which is critical for safety-critical infrastructure monitoring [105,106]. Active learning strategies are also being developed to reduce labeling costs by selecting the most informative GW samples for model training [107].

In addition, multimodal data fusion approaches combining GW data with vibration, acoustic emission, or environmental monitoring data are being studied to improve robustness [108]. Finally, edge-based and real-time deployment of AI models is becoming an important research direction for enabling in situ GW-based SHM with limited computational resources. These emerging approaches collectively aim to overcome the main limitations of conventional data-driven methods in GW-based SHM, particularly in terms of data scarcity, domain shift, and a lack of uncertainty quantification in real-world applications.

A summary of the AI-based methodologies for GW-based SHM discussed in this study is provided in Figure 15, which highlights the relationships between classical machine learning, deep learning, hybrid frameworks, and emerging AI approaches.

5.7. Comparative Analysis of AI-Based Approaches

This section provides a comparative overview of ML, DL, hybrid, and emerging AI approaches for GW-based SHM. The comparison focuses on key aspects including feature representation, data requirements, interpretability, robustness, and practical deployment considerations

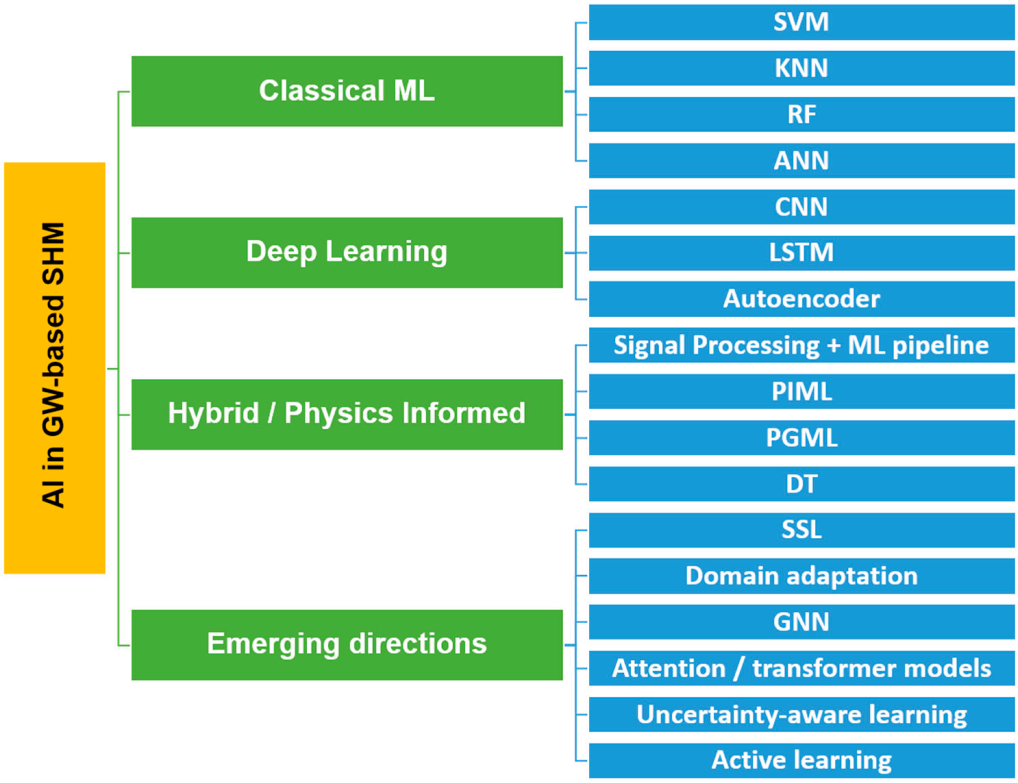

Figure 15. Summary of the AI-based methodologies for the GW-based SHM discussed in this study.

Classical ML methods such as SVM, KNN, random forest, and ANN rely heavily on manually engineered features extracted from GW signals in the time, frequency, or time–frequency domains. These approaches are generally effective when the damage-sensitive features are well-defined and the dataset size is limited. They offer relatively low computational cost and better interpretability compared to more complex models. However, their performance is dependent on the quality of feature engineering and prior domain knowledge, which may limit their ability to capture complex nonlinear wave–damage interactions in heterogeneous or evolving structural conditions. In contrast, DL-based approaches such as CNNs, LSTMs, and autoencoders could reduce the reliance on manual feature extraction by learning hierarchical representations directly from raw or minimally processed GW signals. This enables more powerful modeling of nonlinear relationships, spatial patterns, and temporal dependencies associated with wave propagation and damage scattering. Nevertheless, DL models typically require large labeled datasets, significant computational resources, and careful hyperparameter tuning. Their performance may also degrade under domain shift conditions caused by changes in environmental or operational factors.

In GW-based SHM, hybrid pipelines often combine preprocessing steps such as filtering, denoising, normalization, and time–frequency transformation with ML or DL models to enhance the quality of input features. Physics-informed machine learning (PIML) further incorporates governing physical principles of wave propagation into the learning process through constraints or physics-based loss functions. These strategies improve robustness, reduce data dependency, and enhance generalization performance, particularly in realistic monitoring environments where noise, dispersion, and boundary reflections are unavoidable.

Emerging AI paradigms such as self-supervised and contrastive learning methods enable the exploitation of large-scale unlabeled GW datasets, reducing the dependence on costly labeled damage data. Transfer learning and domain adaptation techniques address variability across different structures and environmental conditions, improving model transferability. GNNs provide a natural representation of PZT sensor networks by explicitly modeling spatial relationships between sensors, while transformer-based architectures improve the capture of long-range temporal dependencies in GW signals. In addition, probabilistic and Bayesian learning frameworks enable uncertainty quantification, which is critical for safety-critical SHM applications. Active learning and multimodal data fusion further enhance efficiency and robustness by optimizing data selection and integrating complementary sensing modalities.

Overall, no single AI paradigm is universally optimal for GW-based SHM applications. ML approaches remain suitable for small datasets with well-defined features, DL approaches are more effective for large-scale data-driven learning, while hybrid and emerging AI methods offer improved robustness, generalization, and adaptability under real-world conditions. The selection of an appropriate method therefore depends on data availability, computational resources, and the specific monitoring objectives. Table 6 summarizes the main characteristics, advantages, and limitations of each category.

Table 6. Comparison of AI approaches in GW-based SHM.

Category	Methods	Input Features	Strengths	Limitations
ML	• *SVM* • *KNN* • *RF* • *ANN*	• *Hand-crafted features (time, frequency, time–frequency, statistical, physics-based indicators)*	• *Efficient with limited data* • *Low computational cost* • *Interpretable*	• *Strong dependence on feature engineering* • *Reduced robustness under environmental variability* • *Limited generalization to complex structures and material heterogeneity*
DL	• *CNN* • *LSTM* • *Autoencoder* • *CNN–LSTM*	• *Raw or minimally processed GW signals* • *Time–frequency representations*	• *Automatic feature learning* • *Strong nonlinear modeling capability* • *Improved performance in complex damage scenarios*	• *High data requirement* • *Increased computational cost* • *Limited interpretability* • *Sensitivity to domain shift and in-service variability*
Hybrid Methods	• *Signal Processing + ML/DL* • *PIML* • *PGML*	• *Preprocessed GW signals* • *Filtering* • *Denoising* • *Normalization* • *Time–frequency transformation* • *Physics-constrained inputs*	• *Improved robustness* • *Reduced data dependency* • *Better generalization* • *Enhanced feature quality* • *Integration of domain knowledge* • *Physics-based constraints*	• *Increased methodological complexity* • *Higher implementation effort* • *Limited standardization* • *Requires careful pipeline design*
Emerging AI Approaches	• *Self-Supervised Learning* • *Contrastive Learning* • *Transfer Learning* • *Domain Adaptation* • *GNNs* • *Transformers* • *Bayesian Learning* • *Active Learning* • *Multimodal Fusion*	• *Large-scale unlabeled GW datasets* • *Sensor network data* • *Multimodal inputs* • *Vibration data* • *Acoustic emission data* • *Environmental monitoring data*	• *Reduces labeling requirements* • *Improved transferability across structures* • *Uncertainty quantification* • *Scalable learning* • *Better utilization of sensor networks*	• *Limited validation in real GW-SHM systems* • *High computational demand* • *Lack of benchmark datasets* • *Increased implementation complexity*

5.8. Selection of AI Models for GW-Based SHM

The selection of an AI model for GW-based SHM should be guided by data availability, monitoring objectives, computational resources, and operational constraints. This section focuses on the practical suitability of different AI categories rather than detailed algorithmic descriptions. Classical machine learning methods such as SVM, random forest, and KNN are most effective when datasets are limited and damage-sensitive features can be reliably engineered from guided wave signals. They perform well in controlled environments with relatively well-separated feature distributions between healthy and damaged states. However, their performance degrades under strong nonlinear wave propagation effects, noisy measurements, or significant environmental variability, where feature extraction becomes unreliable.

Deep learning approaches are more suitable when large-scale GW datasets are available and when damage–signal relationships are highly nonlinear. CNNs are effective for time–frequency representations such as spectrograms and wavelet scalograms, while LSTMs capture temporal dependencies in wave propagation signals. Autoencoders are useful in scenarios with only healthy-state data for unsupervised anomaly detection. Nevertheless, DL methods are limited by high data requirements, computational cost, sensitivity to domain shift, and reduced interpretability.

Hybrid approaches are particularly effective in practical SHM environments where GW signals are affected by noise, dispersion, and environmental variability. Integrating signal processing techniques with ML or DL improves feature quality and robustness, while physics-informed machine learning enhances consistency with wave propagation principles. However, their performance may be constrained by system complexity, uncertainty in physical modeling, and lack of standardization.

Emerging AI approaches target large-scale and field-deployed SHM systems, addressing challenges of data scarcity, domain shift, and uncertainty quantification. Methods such as transfer learning, domain adaptation, graph neural networks, transformers, and probabilistic learning improve generalization and scalability. However, these methods remain computationally demanding and are still limited by relatively low maturity and lack of standardized deployment in GW-based SHM. Table 7 presents guidelines for selecting AI models in GW-based SHM.

Table 7. Guidelines for selecting ai models in GW-based SHM.

Method	Best Application	Data Req.	Interpretability	Comp. Cost	Major Limitation
SVM	• *Damage classification*	• *Low*	• *Medium*	• *Low–Medium*	• *Kernel selection, scalability*
KNN	• *Simple classification*	• *Low*	• *High*	• *Low training* • *High inference*	• *Noise sensitivity*
RF	• *Detection and localization*	• *Low–Medium*	• *Medium*	• *Medium*	• *Limited interpretability*
ANN	• *Nonlinear damage assessment*	• *Medium*	• *Low*	• *Medium*	• *Overfitting*
CNN	• *Complex pattern recognition from GW images/scalograms*	• *High*	• *Low*	• *High*	• *Requires large labeled datasets*
LSTM	• *Sequential/time-series GW analysis*	• *High*	• *Low*	• *High*	• *Long training time*
Autoencoder	• *Unsupervised anomaly detection*	• *Medium*	• *Low*	• *Medium–High*	• *False alarms and threshold selection*
Hybrid Methods	• *Robust field deployment* • *Physics-informed SHM* • *Multiscale feature learning*	• *Medium*	• *Medium–High*	• *High*	• *High implementation complexity* • *Lack of standardization*
Emerging AI	• *Large scale monitoring* • *Domain adaptation* • *Multimodal SHM* • *Uncertainty quantification*	• *High*	• *Medium*	• *Very High*	• *Limited real-world validation* • *High computational demand*

As shown in Table 7, no single AI model is universally optimal for all GW-based SHM applications due to differences in data availability, monitoring scale, and operational constraints. Classical ML approaches remain effective for small datasets and scenarios where interpretability and engineered feature reliability are important, whereas deep learning approaches are more suitable for large-scale monitoring problems where sufficient data are available to capture complex wave–damage relationships. Hybrid and emerging AI approaches further extend these capabilities by improving robustness, generalization, and uncertainty handling in real-world deployment conditions. Therefore, AI model selection should be guided by data availability, computational resources, monitoring objectives, and practical deployment requirements.

6. Applications in Civil Engineering Structures

GW-based AI methods have proven effective on various types of structures according to recent studies. Researchers have tested different categories of GW-based AI methods, including classical ML, DL, hybrid frameworks, and emerging AI approaches, on both laboratory-scale specimens and real engineering components to classify conditions, locate damage, and assess structural performance. Examples of the use of GW-based AI methods include composite materials, metallic members, concrete structures, strengthened systems, and full-scale infrastructure. The next sections describe the categories of structural systems where GW-based AI has been applied and evaluated.

6.1. Metallic Structures

Metallic structures have been extensively studied in GW-based SHM because of their widespread use in bridges, pipelines, storage tanks, offshore platforms, and transportation systems. Compared with composite materials, metals are generally more homogeneous and isotropic, resulting in more predictable wave propagation and making them well-suited for data-driven monitoring approaches. However, defects such as fatigue cracks, corrosion pitting, weld discontinuities, and wall-thickness reduction can alter GW responses, requiring reliable methods for signal interpretation. AI has increasingly been adopted to automate damage assessment in metallic structures. Features extracted from GW signals, including TOF variations, attenuation levels, frequency-domain characteristics, and reflected-wave responses, are commonly used to train ML classifiers such as SVM, KNN, and random forest for distinguishing between healthy and damaged conditions. Significant progress has been reported in the detection of crack and corrosion damage using both ML and DL approaches, particularly when multiple sensing paths are available [109–113]. More recently, CNN-based models have demonstrated strong capability in identifying damage-related patterns directly from raw GW signals or time–frequency representations, while LSTM networks have shown promise for continuous monitoring applications involving sequential GW measurements.

Although hybrid and physics-informed approaches have also been investigated for metallic SHM in civil engineering systems, most studies remain limited to laboratory-scale or controlled experimental environments. Emerging AI techniques, including transfer learning and domain adaptation, are being explored to improve model transferability across different structural geometries, material types, and sensor configurations. However, widespread deployment in real-world civil engineering applications remains limited by the lack of large-scale validation datasets and the challenges associated with environmental and operational variability. A summary of the ML, DL, hybrid/physics-informed and emerging AI studies performed on GW and metallic structures is shown in Tables 8–10, respectively.

Table 8. Summary of ML applications in metallic structures using GW.

Ref.	Structure	Method	Input Features	Task
[114]	Steel Frame Structure	SVM	System Parameters (Mass, Damping, Stiffness) + Dynamic Load (Sine Wave Excitation) + Initial Conditions	Dynamic Response Analysis (Displacement, Velocity, Acceleration Prediction)
[115]	Steel Beam	SVM	Statistical Features of Wavelet Packets	Damage Detection & Severity Estimation
[116]	Aluminum Plate & Glass-Fiber Resin Epoxy Composite Plate	ANN	Sum of Squares of Differences (SSDs) of Frequency Spectrums (SuRE Method)	Load Location Classification (Load Monitoring on Plates)
[117]	Aluminum Plate and T-Joint	KNN + SVM	Time-Domain, Frequency-Domain, and Wavelet Transform Features	Sharp Defect Depth Prediction (Pitting Corrosion Characterization)
[118]	Aluminum Rectangular Profile/Aluminum Plate/Composite Plate (Carbon Fiber)	k-NN (Fine, Medium, Coarse, Cosine, Cubic, Weighted) + PCA	PCA Scores (Principal Components Projections)	Damage Detection & Classification
[119]	Aluminum Plate	Random Forest + SVM	Physics-Informed Features (RMS, Peak Measures, Envelope Statistics, Band-Limited Energies, Spectral Peak, Inter-Channel Correlation, Second Harmonic Index)	Damage Severity Classification
[120]	Aluminum Alloys	Random Forest + KNN	Stress Intensity Factor Range, Maximum Stress Level, Stress Ratio	Short Fatigue Crack Growth Rate Prediction

Table 9. Summary of DL applications in metallic structures using GW.

Ref.	Structure	Method	Input Features	Task
[121]	Stainless Steel Test Bars	CNN + LSTM	2D Time-Frequency Images (STFT & CWT) For CNN; Raw Signal Data For LSTM	Load Detection & Fabrication Classification (Anomaly Detection)
[122]	Thin Aluminum Plate	CNN	Lamb Wave Data Converted Images	Crack Damage Detection
[123]	45CrNiMoVA Steel Torsion Shafts	PGCNN (Physics-Guided CNN)	Nonlinear Rayleigh Wave Signals (Damage Indicator/Relative Nonlinear Coefficient)	Microcrack Quantification (Length & Width Prediction/Decoupling)
[124]	Aluminum Panel	LSTM	Wavelet Time Scattering Features	Damage Classification (Region & Size)
[125]	Double-Layer Plate (Aluminum Substrate with Stainless-Steel Coating Layer)	LSTM + CNN	Guided Wave Pulse–Echo & Pitch–Catch Signals (With Gaussian Noise Added)	Disbond Localization & Sizing
[98]	Riveted Metallic Aluminum Panels	Stacked Autoencoders	AE Waveforms	AE Source Localization & Characterization (Single-Sensor)
[86]	Aluminum Plate	Denoising Autoencoders	GW Signals	Temperature Compensation & Baseline Signal Selection

Table 10. Summary of the hybrid, physics-informed, and emerging AI applications in metallic structures using GW.

Ref.	Structure	Method	Input Features	Task
[126]	Large-Scale Steel Tube	Physics-Informed Deep Filtering (DL + Simulation-Based Training)	Simulated GW Signals + Experimental Ultrasonic GW Signals	Signal Enhancement & Incipient Defect Detection in Noisy Conditions
[127]	Metallic component (steel structure using SH wave EMAT-based GW)	Physics-Informed Deep Neural Network (GuwNet)	High-Frequency High-Order Shear Horizontal GW Signals Acquired via EMAT	Microcrack Detection & Quantitative Estimation (Length, Depth, Orientation)
[128]	Metallic Component	Surrogate-Based Neural Network + Monte Carlo Bayesian Optimization	Finite Element Simulation Data of Acoustic Wave Propagation (Stress Field, Excitation Width, Propagation Time)	Defect Depth & Width Estimation
[129]	Aluminum Plate with Circular Defect	Physics-Based GW Scattering Model + Inverse Bayesian Framework	GW Reflection & Transmission Coefficients from Experimental & Semi-Analytical Models	Damage Identification & Estimation of Defect Geometry (Size and Type)
[130]	Aluminum Plates	Distribution Adaptation Deep Transfer Learning Using Joint Distribution Alignment with CNN–LSTM Network	GW Signals Processed Across Different Structures with Differing Dispersion & Sensor Configurations	Damage Detection & Imaging
[131]	Aluminum Alloy Plates under Varying Vibration Conditions (Aerospace Structural Components)	Domain-Separated Capsule Network (DS-CapsNet) with Attention Mechanism, Dynamic Adversarial Alignment, & Multi-Head Self-Attention	GW signals	Damage Detection & Classification under Vibration-Induced Domain Shift

6.2. Composite Structures

Composite structures represent an important application area for GW-based AI approaches because of their widespread use in aerospace, marine, and energy systems. They are particularly susceptible to internal damage mechanisms such as delamination, matrix cracking, and impact-induced defects, many of which are difficult to detect using conventional inspection methods because of the layered and anisotropic nature of composite materials. Guided waves provide an effective means of interrogating these structures; however, their anisotropic and heterogeneous characteristics result in complex propagation behavior that is considerably more difficult to interpret than in metallic materials. Variations in material interfaces, fiber orientations, and laminate layups can significantly influence wave speed, attenuation, energy distribution, and mode behavior. Furthermore, these effects are often direction-dependent, making GW signal interpretation and damage characterization particularly challenging.

Supervised ML techniques have been employed for classifying damage in composite laminates using GW and their corresponding features. For example, SVMs have been successfully used to distinguish between healthy and damaged laminates based on features such as TOF variations, amplitude changes, and energy-based indicators [111]. ANNs have also been employed to model nonlinear relationships between GW features and damage severity or location, demonstrating strong adaptability to complex signal patterns.

In recent years, DL methods have gained increasing attention for the health monitoring of composite structures. For instance, CNNs have been applied to time–frequency representations such as spectrograms and wavelet scalograms, enabling automatic feature extraction without manual feature engineering and improving damage-sensitive pattern recognition [132]. Concurrently, autoencoder-based methods have been investigated for anomaly detection in composite structures, providing a baseline-free alternative for identifying deviations from healthy structural conditions. More recently, hybrid frameworks combining multiple AI architectures have been explored. For instance, CNN–LSTM-based models have been used to integrate the spatial feature extraction capability of CNNs with the temporal sequence-learning capability of LSTMs, thereby improving damage detection and characterization performance [133]. PIML and PGML strategies have also been investigated by incorporating prior knowledge of GW propagation into the learning process, enhancing model robustness and reducing data requirements. In addition, emerging approaches such as graph neural networks and transfer learning methods have shown promise for addressing complex structural geometries, noisy environments, and limited labeled datasets by exploiting spatial relationships between sensing locations and transferring knowledge from simulated or previously trained models. However, despite these advances, the application of hybrid, physics-informed, and emerging methods in GW-based composite SHM remains relatively limited compared to conventional ML and DL approaches.

These studies demonstrate that the integration of GW technology and AI can enhance autonomous NDT in composite materials. Nonetheless, challenges remain regarding data availability, generalization across different laminate layups and boundary conditions, and robustness under varying environmental conditions, which further limit reliable field-scale deployment. Tables 11–13 provide a summary of the use of ML, DL, hybrid/physics-informed and emerging AI approaches in composite materials via GW-based SHM.

Table 11. Summary of ML applications in composite structures using GW.

Ref.	Structure	Method	Input Features	Task
[134]	GFRP Laminates	SVM	Wavelet packet energy	Damage Detection
[111]	GFRP Laminates	SVM	Multi-feature extraction	Damage Localization & Quantification
[135]	Composite Laminate	SVM + Random Forest	Stress wave factors	Damage Localization
[136]	Aluminum Plate (Isotropic) & CFRP Composite Panel	ANN (Feed- Forward Neural Network, Levenberg–Marquardt Training)	Damage Indices (DIs) from S0 Mode Guided Wave Signals	Damage Detection & Localization (Coordinates Prediction)
[137]	Composite Wind Turbine Blades	KNN	Yule–Walker AR coefficients	Damage Detection & Diagnosis
[138]	CFRP Composite Panel	KNN + SVM	TOF	Damage Localization & Quantification
[109]	Multilayered Composite Plate	KNN	Dispersion Curve	Material Property Characterization
[139]	Composite Structures	Random Forest	CCD + RMSD	Damage Identification
[140]	Composite Wind Turbine Blades (GFRC)	Random Forest	A0/S0 Mode Group Velocities & Amplitudes	Damage Detection & Sensitivity

Table 12. Summary of DL applications in composite structures using GW.

Ref.	Structure	Method	Input Features	Task
[141]	CFRP Composite Plate	CNN	Wavefield Images/Wavenumber Spectrum Images	Delamination Depth Classification
[132]	Stiffened Skin-To-Stringer Composite Aircraft Panel	CNN	Ultrasonic Guided Wave Features (Automatically Selected by CNN)	Damage Imaging & Localization
[142]	CFRP Composite Laminates	BO-CNN-BiLSTM	Ultrasonic Guided Wave Features	Fatigue Life Prediction
[112]	Composite Laminates	LSTM	Incomplete Guided Wave Measurements	Full Wavefield Prediction & Damage Visualization
[133]	CFRP Adhesive Joints (Quasi-Isotropic CFRP Plates Bonded with Adhesive Layer)	Fully Connected Autoencoder + Transformer Autoencoder + CNN-LSTM Autoencoder	Ultrasonic Guided Wave Signals	Disbond Detection, Localization & Sizing (Unsupervised Anomaly Detection)
[143]	CFRP Composite Plate	Autoencoder	TOF of Scattered Signals	Damage Localization & Temperature Compensation
[63]	CFRP Composite Plate	Autoencoder	Ultrasonic Guided Wave Signals	Temperature Compensation & Signal Reconstruction

Table 13. Summary of hybrid, physics-informed, and emerging AI applications in composite structures using GW.

Ref.	Structure	Method	Input Features	Task
[144]	CFRP Composite Structure	Multilayer Coupled Attention Graph Neural Network (MCAGN)	GW Signals with Sensor Coordinate Embedding & Fused Feature Representations	Damage Detection & Classification under Limited & Noisy Training Data
[145]	CFRP Composite Coupons with Notch	Feature Alignment Neural Network (FANN) with Domain Adaptation & Adaptive Batch Normalization	GW Signals Collected under Varying Boundary Conditions	Damage State Classification & Transfer Learning across Different Structural Conditions
[146]	Air-Conditioning Condenser Tubes	Unsupervised Multi-Source Adaptation Adversarial Network (UMAAN) with Shared Feature Extractor & Adaptive Loss Weighting	Time–Frequency Representations of Laser-Excited GW Signals under Different Incident Angles	Damage Detection & Classification under Multi-Source Domain Shift Conditions
[147]	CFRP Composite Structures	Deep Transfer Learning with Domain Adversarial Training & Physics-Based Simulation Data Fusion	Monitoring Data Generated from Numerical Physical Models & Experimental Measurements under Varying Damage Conditions	Damage Detection & Generalization from Simulation Domain to Experimental Domain

6.3. Concrete Structures

Concrete structures are also commonly studied in GW-based SHM due to their extensive use in buildings, bridges, tunnels, and other civil infrastructure systems. The early detection of cracks, voids, delaminations, and deterioration of reinforcing steel is important for ensuring structural safety and extending the service life of concrete structures. Compared to metallic and composite structures, GW propagation in concrete is more complex due to its larger thickness, higher mass, and highly heterogeneous material composition. The presence of coarse aggregates increases wave scattering and attenuation, particularly at higher frequencies, reducing signal clarity and limiting the effective monitoring range. In most practical cases, concrete structural members are not plain but reinforced with steel bars, prestressing tendons, or other embedded components. These inclusions introduce additional scattering, reflection, mode conversion, and multi-path propagation effects as guided waves propagate through both the concrete matrix and embedded reinforcement, complicating damage identification.

Additionally, numerical modeling of concrete structures is challenging because concrete is a highly variable medium composed of cement paste, fine aggregates, and coarse aggregates. As a result, GW simulations using finite element models are computationally intensive. Strengthening and rehabilitation techniques such as FRP retrofitting, steel plate bonding, and jacketing are commonly used to enhance the load-carrying capacity and extend the service life of concrete structural members. In such cases, the performance of the retrofitted system depends on the integrity of the bond interface between the original concrete and the strengthening layer. Long-term degradation of these interfaces due to moisture ingress, thermal effects, shrinkage, and cyclic loading can further complicate reliable monitoring throughout the service life of the structure. In addition, sensor installation presents practical challenges, as embedded sensors may be difficult to maintain or replace, while surface-mounted sensors are susceptible to coupling degradation and environmental exposure.

ML and DL approaches have therefore become increasingly popular for analyzing complex GW responses from concrete and retrofitted structures. In classical ML approaches (e.g., SVM, KNN, and RF), extracted features are used for crack detection, condition classification, and debonding assessment. DL methods, particularly CNN and recurrent architectures such as LSTM and BiGRU, have been explored for automated feature learning and improved damage localization using raw or transformed GW signals. Autoencoder-based models are also widely used for unsupervised anomaly detection in concrete structures, especially when labeled damage data are limited.

Hybrid, physics-informed, and emerging AI methods have further been investigated to address more complex monitoring scenarios in concrete structures. These include domain adaptation and adversarial learning frameworks for improving cross-condition generalization, Bayesian updating strategies for incorporating GW-based damage indices into model updating, and graph-based or transfer learning approaches for handling sparse sensor configurations and cross-structure knowledge transfer. However, despite these developments, the overall number of studies in this category remains limited compared to conventional ML and DL approaches.

Furthermore, most published studies have been conducted on laboratory-scale specimens under controlled conditions, whereas full-scale concrete infrastructure involves longer propagation distances, more complex geometries, diverse reinforcement layouts, restricted inspection access, and higher environmental variability, all of which significantly influence guided wave propagation and AI model performance. These factors, combined with material heterogeneity, aggregate-induced scattering, reinforcement effects, strong attenuation, and practical sensor deployment constraints, make GW-based SHM in concrete particularly challenging. Consequently, issues related to data availability, robustness, and transferability across different structural configurations remain major barriers to large-scale field implementation.

Tables 14–16 present summaries of the ML, DL, hybrid/physics-informed and emerging AI approaches in concrete structures using GW-based SHM respectively. As can be seen from Tables 14–16, the number of studies are limited compared to metallic and composite structures.

Table 14. Summary of ML applications in concrete structures using GW.

Ref.	Structure	Method	Input Features	Task
[148]	Foundation Piles and Utility Poles (Timber & Concrete)	SVM (with Different Kernel Functions) + PCA	FFT Signals	Damage Classification (Condition Assessment)
[149]	Concrete Slabs	SVM + ANN	P-Wave, S-Wave, and R-Wave Velocities	Concrete Compressive Strength Prediction
[150]	Concrete Deck Slab with GFRP Reinforcement	ANN (Shallow Neural Network with One Hidden Layer)	Centers of Gravity of Absolute Cross-Correlation Vectors (From Elastic Wave Signals via PZT Sensors) and Loading Condition	Crack Detection & Structural Condition Monitoring (Alarm State Classification)
[69]	Reinforced Concrete Bridges	ANN	Wave Amplitude	Digital Twin for SHM (Bending Moment & Deflection Prediction, Baseline Strain Generation)
[151]	Underwater Concrete Specimens	SVM + Intelligent Algorithm (Physics-Embedded)	Sand–Aggregate Ratio, Water–Cement Ratio, Aggregate Diameter, P-Wave Velocity, Rayleigh Wave Velocity	Compressive Strength Evaluation
[152]	Basalt-FRP Reinforced Concrete Slabs (Bridge Decks)	K-NN (Supervised) + K-Means Clustering (Unsupervised) + SHAP Analysis	AE Features (Counts, Energy, Absolute Energy, Rise Time, Initiation Frequency, Peak Frequency, Frequency Centroid, Amplitude, Duration)	Damage Progression Monitoring (Tensile/Shear Crack Classification & Crack Width Prediction)
[153]	FRP Concrete Slabs (Fiber-Reinforced Polymer Concrete Blocks)	KNN + Lasso Regression	Compressive Strength, Fiber Volume Percentage, Slab Thickness, Reinforcement Ratio, Shear Span-To-Depth Ratio, Area, Dimensions, Density, Elastic Modulus	Punching Shear Performance Prediction (Structural Integrity Assessment)

Table 14. *Cont.*

Ref.	Structure	Method	Input Features	Task
[154]	FRP-to-Concrete Bond Joints	PSO–Random Forest (Particle Swarm Optimization + Random Forest)	Concrete Compressive Strength, Concrete Tensile Strength, Concrete Width, Maximum Aggregate Size, FRP Tensile Strength, FRP Thickness, FRP Elastic Modulus, Adhesive Tensile Strength, FRP Bond Length, FRP Bond Width	Bond Strength Prediction
[155]	FRP-Confined Concrete (Circular Specimens)	Random Forest + ANNMLP + ANNRBF	Concrete Diameter, Total FRP Thickness, Unconfined Concrete Strength, Hoop Rupture Strain of FRP, Elastic Modulus of Fiber, Tensile Strength of Fiber, Confinement Stiffness Ratio, Lateral Confining Pressure Ratio, Strain Ratio	Ultimate Condition Prediction (Strength Ratio & Strain Ratio
[156]	Reinforced Concrete Utility Poles (with Internal Steel Wires)	Random Forest + ISOMAP	Hall Effect Values	Structural Safety Inspection (Damage Classification: Safe vs. Crack/Broken Steel Wires)

Table 15. Summary of DL applications in concrete structures using GW.

Ref.	Structure	Method	Input Features	Task
[157]	Concrete (Plain Concrete with Hole Defects)	Multilevel CNN + Array Ultrasonic Testing (AUT)	Ultrasonic Echo Signals (One-Dimensional Time-Domain Signals)	Defect Localization
[158]	Concrete Beams (Lining Concrete under Bending Loads & Freeze–Thaw Cycling)	BiGRU + 2D CNN + Feature Fusion	Conductance Signals (EMI) + CWT Time-Frequency Spectra of Stress Wave Signals (WP)	Cyclic Freeze–Thaw Damage Monitoring & Classification (Damage Phase Classification)
[159]	Concrete-Filled Steel Tube (CFST) Arch Bridge Specimens	BO-LSTM + Random Forest (Bayesian Optimization + Long Short-Term Memory) + Random Forest + GBDT + XGBoost	Ultrasonic Amplitude & Pulse Wave Velocity	Debonding Defect Classification (Void/Debonding Detection in CFST)
[160]	Geopolymer Concrete Specimens	Deep Fully Connected Autoencoder + Isolation Forest	Ultrasonic Response Signals (Time-Domain: MSE & Reconstructed-to-Original Signal Ratio; Frequency-Domain: Fundamental Amplitude Ratio)	Distributed Damage Detection (Anomaly Detection—Damaged vs. Intact Classification)
[161]	Concrete (Reinforced Concrete Structures with Honeycomb Defects	U-AE (U-Net Autoencoder)	Impact Echo B-Scan Images (Frequency Spectra)	Anomaly Detection (Honeycomb Defect Classification—Sound vs. Defective)

Table 16. Summary of Hybrid, Physics-Informed, and Emerging AI applications in concrete structures using GW.

Ref.	Structure	Method	Input Features	Task
[162]	Reinforced Concrete Structures	Discriminative Wavelet Adversarial Adaptation Network (DWAAN) with CNN-Based Feature Extraction & Domain Adaptation	GW Signals Transformed Using CWT	Interfacial Debonding Detection under Cross-Scene Conditions
[163]	Reinforced Concrete Structures	GW Integrated with Bayesian Updating Strategy	GW Attenuation-Based Damage Index (DI) & Sparse Field Monitoring Data	Corrosion Quantification & Model Updating for Field Structures

6.4. Real World/Full Scale Applications

While AI-based techniques for GW-based SHM have advanced significantly in laboratory settings, validated full-scale field deployments on operational civil, aerospace, and energy structures remain limited. Most existing studies are still conducted on laboratory specimens or controlled component-level systems. Challenges associated with real-world implementation include the difficulty of obtaining labeled damage data from civil infrastructure, variability induced by environmental and operational loading conditions, and long-term sensor reliability issues, all of which hinder large-scale deployment.

Despite these limitations, a small number of real-world implementations have demonstrated the potential of GW-based and AI-assisted SHM systems. For example, GW and ML-based approaches have been applied to full-scale wind turbine blade monitoring for damage detection under operational conditions. In pipeline systems, GW-based SHM techniques combined with data-driven analysis have been used to assess corrosion and defect evolution over long distances [164]. In bridge engineering, emerging studies have explored indirect monitoring strategies such as drive-by sensing and crowdsensing, where instrumented vehicles or mobile measurement platforms are used to infer structural response without permanent dense sensor installation [165]. These examples demonstrate the feasibility of field deployment but also highlight that most applications remain limited in duration, scale, or operational maturity.

7. Challenges

AI-based GW-based SHM has proven efficient and effective in research studies. However, when it comes to real-world applications, several practical limitations still restrict its widespread deployment. Thus, this section discusses the key technical and practical challenges affecting current implementations. It highlights how these issues impact model reliability, generalization, and long-term performance.

7.1. Environmental Effects

In GW-based SHM, environmental variables present a continuing challenge, especially for linear guided wave methods integrated with ML techniques. Temperature, humidity, and operational loading are all examples of variables that substantially affect the wave velocity, attenuation, and dispersion characteristics, thus producing similar signal variations, which, in many circumstances, exceed the signal differences introduced by structural damage. The most substantial variable impacting wave behavior is temperature increases. The effects on the material properties caused by thermal expansion and the ability of temperature to alter the characteristics of the material itself produce a change in the waveforms' phase and time-of-flight characteristics, which are commonly utilized to provide input to ML algorithms [24].

From a data-driven perspective, environmental variability introduces significant domain shifts and distribution mismatches between the training (laboratory) and deployment (field) conditions, which negatively affect the performance of supervised learning models. Humidity and temperature further influence wave characteristics by altering material properties and sensor–structure coupling, particularly in concrete and composite materials. As a result, classifiers developed under controlled laboratory conditions often exhibit poor generalization in real operating environments and may not produce reliable predictions without compensation strategies such as normalization, adaptive learning, or transfer learning.

Nonetheless, nonlinear GW methods exhibit improved robustness, as harmonic generation is more strongly correlated with damage mechanisms than with environmental fluctuations. This leads to more stable damage-sensitive features compared with conventional linear ML approaches. Consequently, nonlinear GW-based SHM could be more suitable for field deployment; however, challenges related to noise and signal interpretation remain significant obstacles to reliable implementation [166,167].

7.2. Sensor Issues

The mounting of PZT transducers to civil engineering or aviation structures can create another major technical limitation in GW-based SHM systems. Sensor debonding as a result of environmental exposure, cyclic loads and the aging of adhesive over extended periods could rapidly deteriorate the coupling efficiency between a PZT transducer and its corresponding structure. Therefore a decrease in coupling efficiency will result in a decrease in the quality of the measured signal. This is manifested as a decrease in signal-to-noise ratio, reduced amplitude, and distortion of the guided wave measurements with respect to the actual guided wave measurements. Sensor degradation (e.g., temperature variation, moisture ingress and electrical fatigue) can further negatively impact the long-term reliability and precision of long-term SHM datasets. The consequences of these types of sensor-induced signal change will have substantial implications for ML models frequently misclassifying sensor-induced changes in the measured signal as structural damage, resulting in false alarms or reduced classification accuracy.

In the context of data-driven SHM, sensor variability and performance extends the uncertainty that is added to predictions and is typically not explicitly accounted for in the training of the model. Therefore, models trained using SHM data captured in the laboratory often fail to generalize when applied to real-world applications and characteristics due to substantial performance differences between trained sensors and installed sensors. While recalibration and redundancy strategies are somewhat effective in mitigating the uncertainties related to sensor performance, sensor reliability and precision over extended SHM periods is still a significant challenge. Therefore, enhancing sensor durability and developing learning algorithms capable of accommodating sensor drift and degradation will remain necessary for the accurate implementation of GW-based, ML SHM systems outside the lab workstations, and into production environments [168].

7.3. Signal Noise & Boundary Reflections

Signal noise is a significant challenge in GW-based SHM, particularly in realistic structural environments where reflections arise from boundaries, welds, joints, and geometric discontinuities. In linear GW-based SHM, reflections and interference are critical challenges, as damage detection typically relies on changes in amplitude, phase, or time-of-flight, all of which can be distorted by multipath propagation and structural complexity. Consequently, the presence of noise and overlapping wave features can degrade the quality of input data used for ML model development, reducing the model's ability to accurately learn damage-related patterns [169–171].

Nonlinear GW approaches are less sensitive to measurement reflections due to the reliance on nonlinear GW parameters. Nonetheless, nonlinear signals are exposed to greater susceptibility to measurement noise by virtue of the fact that weakly nonlinear signal components may be masked or created by measurement noise, sensor instability, or signal processing artifacts. From a ML perspective, this creates label uncertainty and features contamination, both of which contribute to the probability of misclassification or poor stability in classification boundary [172]. As a result, robust pre-processing denoising approaches and feature engineering are necessary to provide reliable inputs from both linear and nonlinear GW signals to support the success of ML-based SHM systems [173].

7.4. Data Problems

The lack of existing datasets used in ML is one of the major challenges to using the techniques of GW-based SHM systems. There are no publicly accessible datasets that comply with a consistent standard for GW signals taken from actual engineering structures; rather, existing datasets are created in lab settings using model specimens, regulated boundary conditions, and artificial damage. Because of this inconsistency and complexity (as well as the presence of excessive noise) in real structures' responses, the ability of a trained model to generalize is limited [101,174].

The lack of standardization in ML datasets limits the reproducibility of individual studies and makes the direct comparison of model performance across different works difficult, as models are typically trained and evaluated on separate datasets. In addition, the scarcity of data from real-world structures often necessitates the use of synthetic or simulated data for supervised learning, which complicates the accurate representation of operational damage conditions. This reliance on simulated data introduces a significant gap between training and deployment domains. Therefore, to enable the effective application of ML in GW-based SHM, it is essential to develop strategies for dataset sharing, data augmentation, and transfer learning frameworks.

8. Future Directions

While there have been major improvements in ML for GW-based SHM, there are still many obstacles left to overcome before SHM can be fully developed and implemented on a large scale. The reasons for these challenges are due to a lack of available data; an increase in sensor failure rates; the impact of weather conditions on the results; and increasing levels of noise in signals, all of which can affect how reliable and generalizable a model is. As a result, there is growing interest among researchers who want to develop new adaptive, interpretable, and physics aware learning frameworks that will allow for more reliable performance under real-world conditions. In the next section, we discuss some of the anticipated future trends that will impact the next generation of SHM systems.

8.1. Transfer Learning

Transfer learning is a promising approach to address the limited availability of labeled data in GW-based SHM by reusing knowledge learned from one structure and applying it to another. In cross-structure learning, models trained on one type of structure, such as laboratory beams or composite panels, are adapted to different but related systems like pipelines, bridge elements, or stiffened plates. This reduces the need for extensive retraining and large-scale data collection in each new application. However, variations in geometry, material properties, and boundary conditions introduce significant domain shifts that can degrade performance. Therefore, effective domain adaptation techniques are essential to ensure reliable and robust model transfer across different structural configurations [175,176].

8.2. Explainable AI (XAI)

XAI is increasingly important in GW-based SHM to improve the transparency and interpretability of ML models. In many existing approaches, especially DL methods, damage detection decisions are made in a "black-box" manner, making it difficult to understand which signal features contribute to the final prediction. XAI techniques aim to address this limitation by revealing the relationship between guided wave features (such as TOF, frequency content, or nonlinear harmonics) and model outputs. This is particularly important in safety-critical civil and aerospace applications where engineering justification is required. By improving interpretability, XAI also increases user trust and helps validate whether the model is learning true damage-sensitive features or environmental/noise-induced artifacts [67,177].

Despite these developments, the application of XAI in GW-based SHM is still at an early stage of development and has not yet been fully established for complex structural systems subjected to varying operational and environmental conditions. Most existing studies focus on post hoc interpretation methods applied to trained deep learning models, which may not always guarantee consistent physical interpretability across different datasets or damage scenarios. Therefore, further research is needed to develop more robust and generalizable XAI frameworks that can reliably explain model decisions in terms of physically meaningful guided wave features, while maintaining high predictive performance under realistic conditions. In particular, future efforts should focus on integrating interpretability directly into the learning process rather than treating it as an auxiliary post-processing step.

8.3. PIML in GW-Based SHM

PIML incorporates constraints from elastodynamics, dispersion behavior, and wave–structure interactions, ensuring that predictions remain physically consistent. This helps reduce overfitting and improves generalization, particularly in data-limited scenarios. Embedding prior knowledge of wave velocity, boundary reflections, and mode characteristics further enables the model to distinguish damage-induced responses from environmental and noise effects. As a result, physics-informed models offer improved robustness and interpretability, making them more suitable for real-world SHM applications [28].

8.4. Baseline-Free SHM

Baseline-free SHM is increasingly shifting toward nonlinear GW methods, where damage is identified with a reduced reliance on baseline data. In particular, techniques such as frequency mixing and modulation-based nonlinear analysis exploit damage-induced nonlinear interactions in the material response. Compared to harmonic-based approaches, frequency mixing and modulation effects can provide more pronounced and stable damage indicators, making the detection of weak nonlinearities more reliable in practice. A key advantage of these nonlinear methods is that the influence of environmental variability and baseline uncertainty is reduced, since the focus is on interaction-generated spectral components rather than direct signal comparison. This also makes them more compatible with ML frameworks, where features derived from nonlinear spectral content can improve damage identification. However, challenges remain in accurately isolating true nonlinear effects from noise and ensuring consistent feature extraction under real operating conditions [60,178].

8.5. Future Digital Twin Evolution

When combined with ML frameworks, digital twins are expected to play an increasingly important role in enabling predictive maintenance and real-time defect detection in GW-based SHM through continuous model updating. Future developments are likely to focus on scalable and computationally efficient digital twin architectures that can support real-time deployment in large and complex civil infrastructure systems, including bridges, pipelines, and transportation networks [100,101].

Despite their potential, several challenges still limit large-scale implementation. These include high computational cost, difficulties in model calibration, and the need for the accurate representation of boundary conditions and wave propagation physics in complex structural environments. Addressing these limitations will be essential for transitioning digital twin-based GW monitoring systems from laboratory research to practical field-scale applications [102].

Figure 16 presents a schematic summary of future research directions in the ML-assisted GW-based SHM discussed in this section.

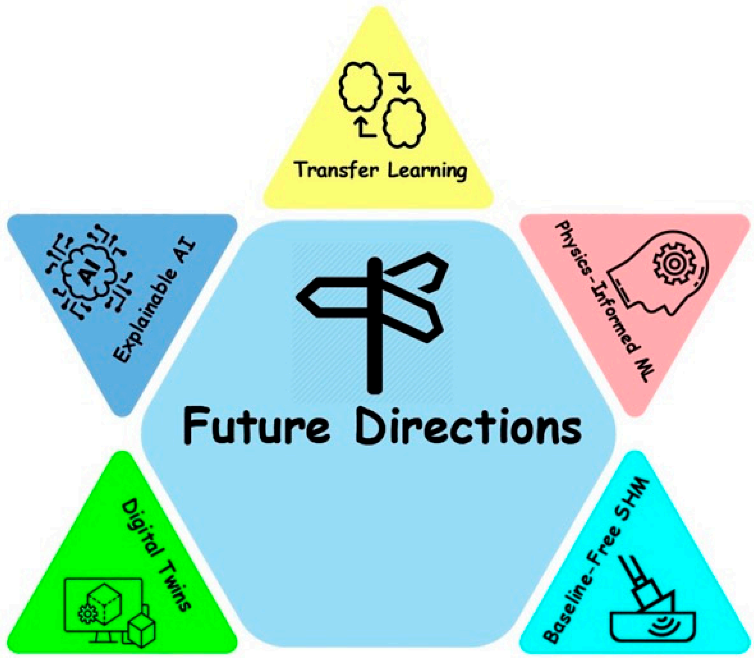

Figure 16. Schematic overview of future research directions in ML-assisted GW-based SHM.

9. Conclusions

ML has emerged as a strong tool for enhancing GW-based SHM by enabling automated damage detection, classification, localization, and prognosis from complex sensing data. This review highlighted the main stages of the workflow, including signal preprocessing, feature extraction, model development, and performance evaluation, together with recent advances in DL and hybrid frameworks. Compared with conventional approaches, ML offers improved capability for handling large datasets and extracting subtle damage-sensitive patterns that may be difficult to identify using manual analysis alone. However, several challenges still hinder practical deployment, including environmental variability, sensor degradation, signal noise, limited standardized datasets, and poor model generalization under real operating conditions. These issues are particularly important for full-scale structures, where robust long-term monitoring is required. Emerging directions such as transfer learning, explainable artificial intelligence, physics-informed ML, baseline-free nonlinear methods, and digital twins provide promising pathways to address current limitations. Overall, the successful integration of guided wave sensing, advanced signal processing, and intelligent learning algorithms has strong potential to transform next-generation SHM systems from laboratory demonstrations into reliable field-deployable technologies for safer and more sustainable infrastructure.

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