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A Comprehensive Review on Applications of Artificial Intelligence and Machine Learning Techniques in Structural Health Monitoring

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***Abstract*— Non-destructive testing (NDT) and structural health monitoring (SHM) play a critical role in ensuring the safety, durability, and lifecycle performance of concrete infrastructure. Recent advances in artificial intelligence (AI) and machine learning (ML) have significantly enhanced the capability of conventional NDT techniques by enabling automated damage detection, improved prediction accuracy, and data-driven decision support. This paper presents a comprehensive and systematic review of AI-based NDT and SHM approaches applied to concrete and reinforced concrete structures. Conventional NDT methods, including ultrasonic testing, acoustic emission, vibration-based monitoring, and vision-based inspection, are reviewed alongside state-of-the-art AI techniques such as artificial neural networks, ensemble learning, deep learning, and explainable AI. Particular emphasis is placed on hybrid and smart SHM systems that integrate multi-sensor data, nanomaterial-based sensing, Internet of Things (IoT) frameworks, and digital twin concepts. Comparative performance trends, key research gaps, and deployment challenges are critically analyzed. Based on the reviewed literature, a future research roadmap is proposed, highlighting physics-informed machine learning, explainable AI, federated learning, and digital twin–enabled predictive maintenance as enabling technologies for next-generation SHM.**

***Index Terms*—Non-destructive testing, structural health monitoring, artificial intelligence, machine learning, concrete, digital twins.**

I. INTRODUCTION

Concrete and reinforced concrete (RC) structures form the backbone of modern infrastructure, including buildings, bridges, dams, tunnels, and marine facilities. Over their service life, these structures are subjected to mechanical loading, environmental exposure, corrosion of reinforcement, sulfate and chloride attack, freeze–thaw cycles, and fatigue effects. These degradation mechanisms may lead to cracking, loss of stiffness, reduction in load-carrying capacity, and ultimately structural failure [1], [4]. Early detection and continuous monitoring of such damage are critical for ensuring structural safety and extending service life. Non-destructive testing (NDT) and structural health monitoring (SHM) techniques provide effective means to assess the in-situ condition of concrete structures without interrupting service or causing damage. Traditional NDT methods, while widely adopted, often rely on empirical correlations and expert interpretation, limiting their accuracy and scalability [2]. With advances in sensing technologies, data acquisition systems, and computational intelligence, artificial intelligence (AI) has emerged as a transformative approach for automating damage identification and improving prediction reliability.

Recent research, reviewed in this paper, demonstrates that AI-driven approaches can significantly enhance defect detection, damage classification, strength estimation, and durability prediction. Machine learning (ML), deep learning (DL), and explainable AI (XAI) techniques are increasingly integrated with ultrasonic testing, acoustic emission, vibration-based monitoring, and imaging methods [1]–[3]. This paper provides a comprehensive review of AI-based NDT and SHM of concrete structures, emphasizing methodological trends, performance comparison, and research gaps. This review paper aims to provide a comprehensive overview of AI-based NDT and SHM applications in concrete engineering. The objectives are to: (i) summarize conventional NDT and SHM techniques, (ii) review AI and ML models applied to NDT data, (iii) discuss hybrid and smart monitoring systems, and (iv) identify challenges and future research opportunities.

II. CONVENTIONAL NDT AND SHM TECHNIQUES

This section provides an expanded discussion of conventional NDT and SHM techniques commonly used for assessing concrete and reinforced concrete structures. These techniques form the foundation upon which AI-driven models are built.

- Ultrasonic Testing
- Acoustic Emission (AE)
- Vibration-Based Monitoring
- Imaging and Vision-Based Methods

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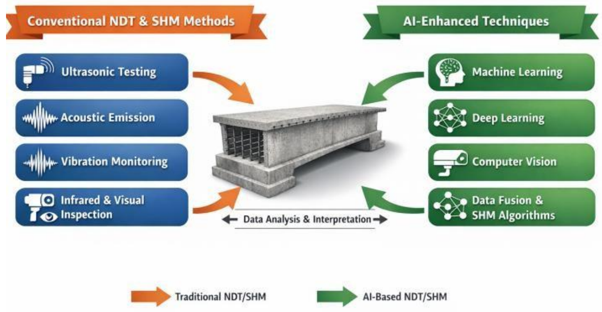

Fig. 1 Classification of conventional and AI-enhanced NDT and SHM techniques for concrete structures.

III. Artificial Intelligence Techniques in NDT and SHM

A. *Artificial Neural Networks (ANN)*

ANNs are extensively applied to model nonlinear relationships between NDT parameters and concrete properties. Studies across the reviewed literature report improved prediction accuracy for compressive strength and damage indices using ANN-based models [2]. Ensemble learning techniques such as Random Forest (RF), Gradient Boosting, and Extreme Gradient Boosting (XGBoost) combine multiple weak learners to improve robustness and generalization. XGBoost, in particular, has been reported to achieve superior performance for ultrasonic-based strength and durability prediction [2], [3]. Deep learning models, including CNNs and recurrent neural networks (RNNs), are increasingly applied to image-based crack detection and time-series SHM data. These models outperform traditional ML approaches when sufficient labeled data are available [1]. Explainable AI techniques such as SHAP (SHapley Additive exPlanations) enhance model transparency by identifying influential input parameters affecting predictions. XAI is particularly important for engineering applications where trust and interpretability are essential [3], [4].

IV. Hybrid and Smart SHM Systems

Hybrid and smart SHM systems represent the convergence of advanced sensing technologies, intelligent data acquisition, communication networks, and AI-driven analytics. Unlike conventional SHM approaches that rely on isolated sensors and offline analysis, hybrid SHM systems enable continuous, autonomous, and adaptive monitoring of concrete infrastructure.

- Sensor Technologies and Data Acquisition
- Internet of Things (IoT) and Wireless Sensor Networks
- AI-Driven Data Fusion and Decision-Making
- Digital Twins and Predictive Maintenance

A. *Advantages and Practical Challenges*

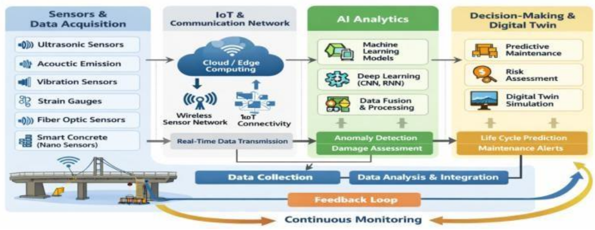

Fig. 2 Framework of an AI-enabled hybrid SHM system incorporating sensors, IoT, AI analytics, and decision-making modules.

Hybrid and smart SHM systems offer several advantages, including real-time monitoring, early damage detection, reduced reliance on manual inspections, and improved lifecycle management. However, challenges remain in terms of sensor durability, data management, cybersecurity, interoperability, and validation under field conditions. Addressing these issues is critical for large-scale implementation [1], [4].

B. *Comparative Review and Performance Analysis*

A consolidated summary of recent AI applications in NDT, SHM, and concrete engineering is presented in Table 1, highlighting the progression from traditional machine learning models to explainable, hybrid, and digital twin–enabled frameworks.

TABLE I: Summary of CNN applications in NDT & SHM

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No.	Author(s)	Year	Title	NDT / Application Area	Key Findings
1	Cha et al.	2018	Autonomous structural visual inspection using deep learning	Image-based NDT	CNN-based systems achieved high crack detection accuracy and reduced dependency on manual inspection, supporting scalable infrastructure monitoring.
2	Gopalakrishnan et al.	2019	Deep learning in structural health monitoring	Vision-based crack detection, SHM	Demonstrated that deep learning models significantly outperform traditional feature-based methods for crack detection and damage classification, enabling automated SHM.
3	Sun et al.	2022	Smart sensing concrete for structural health monitoring	Self-sensing concrete, smart SHM	Integration of nanomaterial-based sensors with AI enabled real-time monitoring of strain and microcracking.

4	Wang et al.	2023	Federated learning for infrastructure monitoring	Distributed SHM systems	Federated learning enabled collaborative model training across structures without centralized data sharing, addressing data privacy concerns.
5	Mohammed et al.	2025	A Comprehensive Review of Structural Health Monitoring in Reinforced Concrete	SHM, NDT, smart concrete	Integration of AI with NDT and nanomaterial-based sensors significantly improves damage detection accuracy and enables predictive maintenance in RC structures; sensor lifespan improved by ~30%.

TABLE II: SUMMARY OF ANN APPLICATIONS IN NDT & SHM

No.	Author(s)	Year	Title	NDT / Application Area	Key Findings
1	Mishra et al.	2020	Machine learning for ultrasonic evaluation of concrete	Ultrasonic pulse velocity (UPV) testing	Gradient-boosting models achieved higher prediction accuracy for compressive strength estimation compared to ANN and regression-based approaches.

2	Ye et al.	2021	AI-assisted digital twin framework for civil infrastructure	Digital twin–enabled SHM	AI-driven digital twins enabled continuous updating of structural condition and improved prediction of future damage evolution.
3	Sun et al.	2022	Smart sensing concrete for structural health monitoring	Self-sensing concrete, smart SHM	Integration of nanomaterial-based sensors with AI enabled real-time monitoring of strain and microcracking.
4	Öncü, Z.	2025	Estimation of Concrete Strength by Using Artificial Intelligence Methods	Ultrasonic NDT (P & S waves)	XGBoost achieved the highest prediction accuracy; RMSE reduced by 12% compared to RF, proving ML reliability for strength estimation of reinforced and plain concrete.
5	Mohammed et al.	2025	Hybrid SHM Systems Using Nanomaterials and AI	SHM, smart sensors	Nanomaterial-enhanced concrete combined with AI improves sensitivity to strain, crack initiation, and corrosion detection in RC infrastructure.

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6	Öncü, Z.	2025	AI-Based Ultrasonic Evaluation of Concrete Strength	Ultrasonic NDT	ML models successfully capture nonlinear relationships between wave velocity, curing conditions, and compressive strength.
7	RILEM TC 315-DCS	2025	Data-Driven Concrete Science: State of the Art	Concrete durability & NDT	Recommends open datasets, hybrid models, and explainable AI for next-generation NDT and SHM systems.

TABLE II: SUMMARY OF ENSEMBLE ML, XGBOOST AND RANDOM FOREST APPLICATIONS IN NDT & SHM

No.	Author(s)	Year	Title	NDT / Application Area	Key Findings
1	Pan et al.	2020	Acoustic emission signal analysis using machine learning	Acoustic emission (AE) monitoring	ML-based classification effectively distinguished between crack initiation and propagation stages in concrete structures.
2	Zhang et al.	2021	Explainable machine learning for concrete durability prediction	Durability assessment (sulfate attack, corrosion)	Explainable AI improved model transparency and identified key durability-influencing parameters such as mix composition and exposure conditions.

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3	Liu et al.	2022	Hybrid AI models for concrete durability assessment	Chemical and durability-oriented NDT	Hybrid and explainable AI models improved prediction reliability while addressing black-box limitations in durability studies.
4	Hilloulin et al.	2023	Interpretable Ensemble Machine Learning for Prediction of Expansion under Sulfate Attack	Durability, sulfate attack	XGBoost achieved R^2 = 0.933 (train) and 0.788 (test); SHAP revealed clinker composition and mix proportions as dominant parameters influencing expansion.
5	Hilloulin et al.	2023	ML-Based Prediction of Cementitious Material Degradation	Durability modeling	Demonstrated ML's capability to predict time-dependent expansion behavior and identify influential parameters governing degradation mechanisms.
6	Kumar et al.	2023	Physics-informed machine learning for NDT of concrete	Multi-modal NDT	Physics-informed ML improved generalization and reduced data dependency compared to purely data-driven models.

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7	Taffese et al. (RILEM TC 315-DCS)	2025	Machine Learning in Concrete Durability: Challenges and Pathways	Durability (carbonation, chloride, sulfate, corrosion)	Highlights dominance of lab-based datasets; ensemble and hybrid models outperform single ML models; emphasizes explainability and multi-task learning for durability prediction.

C. NDT Methods, Damage Types, and AI Integration in Concrete Structures

• Ultrasonic Testing: Evaluates internal voids and strength loss using regression models like ANN, Random Forest, and XGBoost.

• Acoustic Emission (AE): Monitors cracking and fatigue damage using CNNs and Random Forest models.

• Vibration-Based SHM: Assesses stiffness reduction and modal degradation with ANN and ensemble machine learning.

• Vision-Based Inspection: Detects surface cracks and delamination automatically using Convolutional Neural Networks (CNNs).

• Durability-Oriented NDT: Predicts chemical damage (e.g., corrosion) using interpretable XGBoost with SHAP models.

• Nanomaterial-Based Concrete: Tracks strain and micro cracking via IoT platforms and AI pattern recognition (ANN/CNN).

• Multi-Modal Hybrid Systems: Analyzes combined mechanical and environmental damage by fusing data across multiple sensors using ensemble AI.

• AI-Enabled Digital Twins: Forecasts progressive damage and remaining service life by continuously updating virtual structural models.

D. AI Models versus Performance Metrics in AI-Based NDT and SHM of Concrete Structures

• Artificial Neural Networks (ANN): Predicts concrete strength using ultrasonic data, outperforming standard regression but remaining sensitive to training data.

• Random Forest (RF): Robustly classifies damage from noisy Acoustic Emission (AE) and SHM data, though it has slightly lower accuracy than boosting models.

• Extreme Gradient Boosting (XGBoost): Achieves the highest reported prediction accuracy and stability for ultrasonic strength and durability testing.

• Convolutional Neural Networks (CNN): Acts as the dominant model for automated, pixel-level visual crack detection and segmentation.

• Explainable AI (XGBoost + SHAP): Accurately predicts durability (like corrosion) while explaining key influencing factors, which builds engineering trust.

• Hybrid AI Models (AI + IoT + Sensors): Enhances sensitivity for real-time, autonomous monitoring of strain and crack initiation.

• AI-Enabled Digital Twins: Continuously updates virtual structural models using sensor data to accurately forecast damage and support predictive maintenance.

E. Critical Research Gaps Identified from Literature

Despite significant progress, the reviewed literature reveals several persistent gaps that limit large-scale deployment of AI-based NDT and SHM systems. As evidenced in Tables 2 and 3, most studies rely on laboratory-scale datasets and single-damage scenarios, resulting in limited field-scale validation and poor generalization under real environmental and operational conditions [1], [4], [8]. The absence of standardized benchmarks and validation protocols further hinders objective comparison and reproducibility, slowing technology transfer from research to practice [2], [3], [8]. In addition, the black-box nature of many deep learning models restricts engineering acceptance, as predictions cannot be readily linked to physical damage mechanisms or design-code requirements [3], [4], [7]. Weak integration between physics-based models and data-driven AI also persists, limiting extrapolation beyond training data [4], [7], [8].

V. Future Research Roadmap

Physics-informed machine learning (PIML) can enhance generalization, reduce data dependency, and ensure physically consistent predictions. Emerging trends point to hybrid sensing, explainable AI, and digital twin–enabled SHM, supporting next-generation predictive maintenance. Techniques such as transfer and federated learning address data scarcity and privacy, while coupling AI-based NDT with digital twins enables damage forecasting, optimized inspections, and risk-informed asset management. Critical deployment challenges—including sensor survivability, cybersecurity, interoperability, and field validation—must be addressed to transition AI-based SHM from research to operational infrastructure management [1], [3]–[8].

VI. Conclusions

This paper has presented a comprehensive review of AI-based NDT and SHM techniques for concrete structures. AI-enhanced systems significantly improve damage detection and predictive capability compared to traditional approaches. However, challenges related to data availability, interpretability, and field deployment remain. The integration of hybrid sensing, explainable AI, and digital twins is expected to play a central role in next-generation smart infrastructure monitoring. By explicitly linking current research limitations to future solution pathways, this paper provides a structured and forward-looking roadmap for the development of intelligent, explainable, and sustainable SHM systems. The convergence of hybrid sensing, AI-driven analytics, and digital twins is expected to play a central role in ensuring the safety, resilience, and longevity of next-generation concrete infrastructure.

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