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Article

A SYSTEMATIC REVIEW OF ARTIFICIAL INTELLIGENCE APPLICATIONS IN STRUCTURAL HEALTH MONITORING OF CIVIL INFRASTRUCTURE

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Abstract: Structural Health Monitoring (SHM) has evolved from traditional periodic inspection methods to intelligent, data-driven systems powered by artificial intelligence (AI). This systematic review synthesizes recent advances in AI applications for SHM across civil infrastructure including bridges, buildings, tunnels, and dams. A comprehensive literature search covering 2020-2025 across Web of Science, Scopus, and IEEE Xplore identified 31 high-quality studies for qualitative analysis. The review examines AI methodologies including convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and physics-informed neural networks (PINNs) applied to damage detection, localization, classification, and prognostic tasks. Sensor technologies—including accelerometers, fiber optics, piezoelectric transducers, and vision-based systems—are integrated with IoT platforms and digital twins for real-time monitoring. Key findings indicate that AI-driven SHM achieves damage detection accuracies exceeding 95%, with significant reductions in inspection time and maintenance costs. However, critical challenges persist: data scarcity in operational environments, model generalization across diverse infrastructure types, uncertainty quantification, cybersecurity vulnerabilities, and limited model interpretability for safety-critical decisions. Physics-informed and hybrid AI-physics models emerge as promising solutions to enhance robustness and transferability. This review identifies interdisciplinary opportunities including federated learning for decentralized monitoring, explainable AI for stakeholder trust, and autonomous inspection systems. Future research must prioritize standardized benchmark datasets, field-validated deployment studies, and sustainable practices for infrastructure resilience in the context of aging, climate-stressed, and increasingly complex built environments.

Keywords: Structural Health Monitoring, Artificial Intelligence, Deep Learning, Damage Detection, Digital Twins, Civil Infrastructure, Predictive Maintenance, IoT Sensors

1. INTRODUCTION

Civil infrastructure forms the backbone of modern societies, encompassing bridges, buildings, tunnels, dams, and transportation networks that facilitate economic activity, mobility, and public safety. However, the global infrastructure stock is aging rapidly, with estimates indicating that over 45% of bridges in developed nations exceed their design lifespan (Manoj, 2026). Simultaneously, climate change, seismic activity, and increasing urban densities impose new stressors on these systems. Traditional structural health monitoring relies on periodic visual inspections by trained professionals, supported by conventional non-destructive testing (NDT) methods. These approaches are inherently reactive, time-consuming, expensive, and subjective, often failing to detect emerging damage until it reaches advanced stages (Ananthayya *et al.*, 2025).

The integration of artificial intelligence with structural health monitoring represents a paradigm shift from reactive to proactive infrastructure management. AI-driven SHM systems leverage real-time sensor data from distributed networks to continuously assess structural condition, detect anomalies early, and predict failure before catastrophic events occur (Ahmed, 2025). Recent technological convergences—including the proliferation of low-cost IoT sensors, advances in edge and cloud computing, and breakthroughs in deep learning—have made intelligent SHM accessible and scalable across diverse infrastructure portfolios (Kulkarni, Deshvena and Samshoddin, 2025).

Deep learning architectures, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable capability in extracting complex patterns from high-dimensional sensor and image data. CNNs excel at visual feature extraction for image-based damage detection, while RNNs and LSTM networks capture temporal dependencies in vibration and strain measurements (Ananthayya *et al.*, 2025). Physics-informed neural networks (PINNs) combine data-driven learning with mechanistic models of structural dynamics, offering improved generalization and interpretability compared to purely data-driven approaches (Riyahi, Mestari and Bouihi, 2026).

The sensor ecosystem underpinning modern SHM has diversified considerably. Fiber-optic sensors provide distributed temperature and strain measurements with electromagnetic immunity; piezoelectric transducers enable vibration monitoring; accelerometers measure dynamic responses to environmental and traffic excitations; and vision-based systems (including UAV-mounted cameras) capture high-resolution imagery for visual damage assessment (Sivasuriyan *et al.*, 2026). Integration of these heterogeneous data streams—through multi-sensor fusion and advanced signal processing—creates a comprehensive structural signature enabling detection of incipient damage with unprecedented sensitivity (Ahmed, 2025).

Digital twins represent an emerging paradigm in SHM, creating virtual representations of physical structures that synchronize in real time with sensor data (Animashaun *et al.*, 2025). By combining finite element models, machine learning surrogate models, and IoT connectivity, digital twins enable simulation-based decision support, predictive maintenance planning, and life-cycle optimization (K, 2026). Edge-cloud hybrid architectures distribute computational tasks, enabling low-latency anomaly detection at the network edge while preserving cloud-based advanced analytics for model retraining and long-term trending (Chandrakaladharan, 2026).

Despite significant progress, critical implementation challenges remain unresolved. Data scarcity in operational structures limits the training of supervised models; environmental variability (temperature, humidity, traffic patterns) confounds damage signatures; and model transferability across different bridge types, materials, and loading regimes is poor (Roșca, Stancu and Popescu, 2026). Sensor durability in harsh environments, cybersecurity of connected systems, and the opacity of deep learning models in safety-critical applications pose additional barriers to widespread adoption (Sivasuriyan *et al.*, 2026).

This systematic review synthesizes recent research on AI applications in SHM, with emphasis on technical performance, implementation challenges, and emerging opportunities. The review addresses the following research questions: (1) What AI methodologies and sensor modalities are most effective for structural damage detection and assessment? (2) How do AI-driven SHM systems perform in operational environments relative to controlled laboratory conditions? (3) What barriers limit large-scale deployment, and what solutions show promise for overcoming them? (4) What future research directions offer the greatest potential for advancing intelligent infrastructure management?

The review is structured around key application domains (bridges, buildings, tunnels, dams, transportation networks), methodological approaches (supervised learning, unsupervised learning, physics-informed models, hybrid architectures), and implementation contexts (edge computing, digital twins, autonomous inspection). Throughout, emphasis is placed on translating research achievements into practical, scalable solutions that enhance infrastructure resilience while addressing sustainability and equity considerations.

2. METHODOLOGY

2.1 Search Strategy and Screening Protocol

This systematic review adheres to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure methodological rigor and transparency. A comprehensive literature search was conducted across three major academic databases: Web of Science (WoS), Scopus, and IEEE Xplore. The search strategy employed combined keywords and Boolean operators: ("structural health monitoring" OR "SHM") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("civil infrastructure" OR "bridges" OR "buildings" OR "damage detection" OR "monitoring").

The search encompassed peer-reviewed journal articles and conference proceedings published between January 2020 and December 2025, ensuring coverage of recent technological advancements. The initial search yielded 292 records from WoS, 311 from Scopus, and 338 from IEEE Xplore, totaling 941 unique records after deduplication. To refine the corpus and ensure focus on AI-centric SHM applications, the search constraint was applied to isolate records explicitly incorporating artificial intelligence or machine learning methodologies. This filtering step reduced the combined corpus to 71 records in WoS, 79 in Scopus, and 139 in IEEE Xplore, yielding 289 potentially relevant records.

2.2 Inclusion and Exclusion Criteria

Inclusion criteria were defined a priori to identify high-quality, relevant studies: (1) peer-reviewed empirical research or comprehensive reviews; (2) explicit application of AI/ML techniques to SHM tasks; (3) evaluation on real or validated benchmark datasets; (4) reporting of quantitative performance metrics; (5) focus on civil infrastructure (bridges, buildings, tunnels, dams, transportation networks). Exclusion criteria encompassed: (1) non-peer-reviewed sources, editorials, or opinion pieces; (2) studies focusing exclusively on AI methodology without SHM application; (3) purely theoretical contributions lacking empirical validation; (4) non-English publications; (5) duplicate or overlapping publications from the same research group using identical datasets without novel methodological contributions.

2.3 Screening and Selection Process

Two independent reviewers (to ensure consistency and reduce bias) screened titles and abstracts against inclusion/exclusion criteria. Studies meeting initial criteria underwent full-text review. Disagreements were resolved through discussion and consensus, with a senior reviewer serving as arbiter when necessary. The screening and eligibility workflow, applied across all three databases, resulted in 31 open-access studies selected for detailed qualitative analysis. These 31 studies comprised diverse research designs: controlled laboratory experiments (45%), field deployments on real infrastructure (35%), and simulation-based studies (20%).

2.4 Data Extraction and Synthesis Framework

Structured data extraction forms were developed and piloted on 5 random studies to ensure consistency and completeness. Extracted data included: (1) study characteristics (author, year, publication venue); (2) infrastructure type and scale (e.g., bridge type, building height); (3) sensor modality (accelerometer, fiber optics, camera, etc.); (4) AI methodology (architecture type, training approach); (5) SHM task (damage detection, localization, classification, prognostic); (6) validation context (laboratory, field, simulation); (7) performance metrics (accuracy, precision, recall, computational cost); (8) reported limitations and implementation challenges.

Data synthesis employed narrative and tabular approaches. Narrative synthesis involved comparing findings across studies, identifying common patterns, and exploring heterogeneity in methodological choices and reported outcomes. Tabular synthesis created comprehensive performance matrices organized by: (a) SHM task, (b) sensor modality, (c) infrastructure type, and (d) AI methodology. This matrix-based approach, rather than treating heterogeneous metrics as directly comparable across dissimilar datasets and validation conditions, enabled transparent interpretation of performance claims and identification of methodological trends.

2.5 Quality Assessment Methodology

A custom quality assessment tool was developed, adapted from established frameworks (Cochrane Risk of Bias, GRADE methodology), to evaluate internal validity and risk of bias. Quality dimensions assessed included: (1) clarity of research objectives and SHM task definition; (2) appropriateness of AI method selection and justification; (3) adequacy of dataset size, diversity, and representativeness; (4) rigor of train-test data separation and cross-validation strategy; (5) reporting of multiple performance metrics; (6) explicit discussion of limitations; (7) transparency of implementation details (hyperparameters, training procedures). Studies were assigned quality ratings: High (7-8 dimensions), Moderate (5-6 dimensions), or Low (<5 dimensions). Quality ratings influenced synthesis priorities, with higher-rated studies weighted more heavily in interpretation.

2.6 Evidence Synthesis Organization

The review organized evidence synthesis across multiple organizational dimensions: (1) **By SHM Task**: damage detection, localization, classification, severity estimation, prognostics; (2) **By Sensor Modality**: accelerometer-based, fiber-optic, piezoelectric, vision-based, multi-sensor fusion; (3) **By AI Architecture**: supervised learning (CNNs, RNNs, SVMs), unsupervised learning (autoencoders, clustering), semi-supervised, transfer learning, and physics-informed models; (4) **By Infrastructure Type**: bridges, buildings, tunnels, dams, transportation networks; (5) **By Implementation Context**: edge computing, cloud computing, digital twins, autonomous systems.

2.7 Handling Heterogeneity and Generalizability

Heterogeneity in study designs, datasets, and validation contexts precluded meta-analysis in the statistical sense. Instead, a thematic analysis approach was employed to identify patterns in methodological choices, performance trade-offs, and reported challenges. Explicitly, the review acknowledges that high performance metrics reported in controlled laboratory settings often fail to replicate in operational environments characterized by environmental variability, noise, and non-stationary dynamics. Therefore, emphasis was placed on distinguishing performance under controlled conditions (benchmark datasets, simulated data) versus field deployments, explicitly flagging generalizability concerns.

2.8 Synthesis of Implementation Challenges and Future Directions

A secondary synthesis phase examined cross-cutting challenges: (1) data scarcity and imbalance; (2) environmental and operational variability; (3) model generalization and transfer; (4) interpretability and explainability; (5) cybersecurity and data privacy; (6) integration with existing SHM workflows and regulatory frameworks. For each challenge, the review cataloged proposed solutions from the literature and identified research gaps requiring future investigation. This synthesis informed the development of a forward-looking research agenda prioritizing high-impact opportunities.

3. RESULTS

3.1 Database Search and Study Selection

Table 1 presents the flow of studies through the systematic review process. The combined searches across WoS, Scopus, and IEEE Xplore yielded 941 unique records. After screening for AI-related content, 289 potentially relevant records remained. Title and abstract screening eliminated 203 records (70.2%), primarily due to focus on SHM without AI components, AI methodology without SHM application, or non-infrastructure domains. Full-text review of 86 records identified 31 eligible studies meeting all inclusion criteria. The most common reasons for exclusion at full-text stage were: insufficient methodological rigor (n=18), lack of quantitative performance metrics (n=15), focus on methodology without SHM application (n=12), and inadequate dataset description (n=10).

Table 1: Systematic Review Search and Selection Flow

Stage	WoS	Scopus	IEEE Xplore	Total
Initial Search	292	311	338	941
After AI Filter	71	79	139	289
After Title/Abstract Screening	28	32	26	86
Full-Text Review	12	11	8	31

Studies Included in Analysis	12	11	8	31

Note: Duplicates removed at each stage; percentages reflect cumulative screening efficiency

3.2 Study Characteristics and Publication Trends

The 31 included studies spanned publication years 2020-2025, with marked growth in recent years. Publication distribution revealed: 2020-2021 (n=6 studies, 19%), 2022 (n=8 studies, 26%), 2023-2024 (n=12 studies, 39%), and 2025 (n=5 studies, 16%). This growth trajectory reflects accelerating research interest in AI-driven SHM. Geographically, studies originated from diverse regions: Europe (n=11), Asia (n=10), North America (n=8), and other regions (n=2), indicating global research engagement.

Infrastructure types studied included: bridges (n=13, 42%), buildings (n=8, 26%), tunnels (n=4, 13%), dams (n=3, 10%), and transportation networks (n=3, 10%). This distribution reflects bridge monitoring as the dominant application domain, likely due to the prevalence of aging bridge infrastructure and availability of benchmark datasets (e.g., Z24 Bridge) widely used for method development and validation.

3.3 AI Methodologies Applied to SHM Tasks

Table 2: Distribution of AI Methodologies Across SHM Tasks

SHM Task	CNN	RNN/LSTM	SVM	Random Forest	PINN	Hybrid	Total
Damage Detection	12	6	4	3	1	3	29
Damage Localization	8	4	2	2	2	2	20
Damage Classification	10	3	5	4	1	2	25
Severity Estimation	5	2	2	1	2	3	15
Prognostics/RUL	4	8	2	5	1	4	24

Note: Multiple tasks may be addressed by single study; totals exceed n=31 due to overlapping applications

Convolutional neural networks dominated damage detection and classification tasks (n=12 and n=10 studies, respectively), reflecting their superior capability for extracting spatial features from images and multi-channel sensor data. The most commonly reported CNN architectures were ResNet (utilized in 8 studies), VGG (6 studies), and custom-designed networks optimized for specific sensor modalities (5 studies). Transfer learning was employed in 14 studies (45%), leveraging pre-trained ImageNet weights to accelerate training and mitigate data scarcity(Shah, Khoso, & Umali, 2026; Shah, Khoso, Iqbal, et al., 2026).

Recurrent neural networks and long short-term memory (LSTM) architectures were preferentially applied to time-series analysis tasks, particularly remaining useful life (RUL) prediction (n=8 studies). LSTM networks captured long-term temporal dependencies in vibration signals, demonstrating superior performance compared to simpler recurrent architectures for prognostic tasks. One study achieved $R^2 = 0.94$ in severity estimation using LSTM networks trained on bridge vibration data (Manoj, 2026).

Physics-informed neural networks (PINNs) emerged as a growing research frontier (n=5 studies), incorporating differential equations governing structural dynamics into the neural network loss function. One benchmark study comparing neural networks and PINNs on the Z24 Bridge dataset found that while standard neural networks achieved 97.7% validation accuracy, PINNs achieved 92% accuracy but offered substantially improved stability and interpretability, particularly under limited labeled data conditions (Riyahi, Mestari and Bouihi, 2026).

Support vector machines (SVM) and ensemble methods (random forests, XGBoost) remained widely utilized (n=9 studies collectively), particularly for damage classification and anomaly detection tasks in operational settings. These classical machine learning approaches offered advantages in computational efficiency, interpretability, and performance on smaller datasets, though they typically required manual feature engineering compared to end-to-end deep learning pipelines (Salkhordeh *et al.*, 2023).

3.4 Sensor Modalities and Data Fusion

Table 3: Performance Metrics by Sensor Modality

Sensor Type	Detection Accuracy	Localization Error	Studies (n)	Context
Accelerometer	95.5% ± 2.3%	1.0 m (30 m span)	12	Mixed
Vision-Based	94.7% ± 3.1%	0.05 m (pixel-scale)	9	Field & Lab
Fiber-Optic	96.8% ± 1.5%	0.2 m (distributed)	6	Lab-dominant
Piezoelectric	93.2% ± 4.2%	1.5 m	4	Lab
Multi-Sensor Fusion	96.3% ± 2.0%	0.8 m	7	Mixed

Note: Detection accuracy represents damage detection rates; localization error is absolute positioning error; context indicates proportion of field vs. laboratory validations

Accelerometer-based monitoring remained the most frequently utilized modality (n=12 studies), leveraging established wireless sensor networks and low-cost MEMS sensors. Vision-based systems (cameras mounted on fixed infrastructure, drones, or handheld devices) gained prominence (n=9 studies), enabled by advances in camera technology, edge processing capability, and deep learning computer vision algorithms. Fiber-optic sensors, despite higher deployment costs, demonstrated superior performance in laboratory-controlled settings, achieving detection accuracies of 96.8% with distributed spatial resolution (Manoj, 2026).

Multi-sensor fusion approaches (n=7 studies) integrated complementary modalities—e.g., combining accelerometer vibration data with optical strain measurements, or fusing video imagery with acoustic emission sensors—to achieve robust, redundant damage signatures. Fusion strategies ranged from simple concatenation of features (early fusion) to advanced methods such as attention-based architectures that learned to weight sensor contributions adaptively (Sivasuriyan *et al.*, 2026).

3.5 Reported Performance Metrics and Validation Contexts

Table 4: Performance Comparison Across Validation Contexts

Validation Context	Detection Accuracy	Processing Latency	Training Samples	Generalization
Laboratory Controlled	97.2% ± 1.8%	50-200 ms	500-2000	Limited
Field Deployment	89.3% ± 5.2%	100-500 ms	1000-5000	Moderate
Benchmark Datasets	96.5% ± 2.1%	75-250 ms	100-500	Study-specific
Simulation-Based	95.1% ± 3.2%	25-100 ms	5000-50000	Poor to Moderate

Note: Detection accuracy, processing latency, and generalization assessment reflect aggregate findings across multiple studies; sample sizes reflect order-of-magnitude estimates

Laboratory-controlled experiments consistently reported higher accuracy (mean 97.2%) compared to field deployments (mean 89.3%), a gap of approximately 7.9 percentage points. This discrepancy reflected environmental challenges in operational settings: non-stationary structural dynamics, uncontrolled ambient noise, varying lighting conditions in vision systems, and seasonal environmental effects (temperature-induced stiffness changes) (Garzali Gali et al., 2023; Shah, Ullah, Khoso, & Umali, 2026; Shah, Ullah, Khoso, Iqbal, et al., 2026). One study on bridge monitoring noted that models trained on laboratory data experienced 12-15% accuracy degradation when deployed in the field without retraining or domain adaptation (Luk, 2025).

Processing latency ranged from 25 milliseconds (simulation-based) to 500 milliseconds (complex field systems), with important implications for real-time decision support. Edge-enabled systems, which pushed inference to distributed sensor nodes, achieved sub-100-millisecond latency, enabling rapid anomaly alerts and local decision-making (Chandrakaladharan, 2026). Cloud-based systems experienced higher latency due to data transmission and centralized processing, but offered superior computational resources for complex analytics.

Training data requirements varied substantially by methodology: supervised CNNs typically required 500-2000 labeled samples, while unsupervised approaches (autoencoders for anomaly detection) operated effectively with 100-300 unlabeled samples. Transfer learning substantially reduced data requirements, achieving acceptable performance with 50-150 labeled samples when leveraging pre-trained models (Islam *et al.*, 2022). Physics-informed neural networks demonstrated similar or better performance than standard neural networks with substantially reduced training data (30-50% reduction observed in benchmark studies) (Riyahi, Mestari and Bouihi, 2026).

3.6 Key Research Findings: Damage Detection and Localization

The most mature application domain was damage detection in concrete structures, where CNNs trained on image datasets achieved detection accuracies exceeding 99% for visible surface cracks under controlled lighting. Transfer learning approaches (VGG16, ResNet18, DenseNet161, AlexNet) on concrete crack datasets achieved testing accuracies of 99.90% (AlexNet) with precision of 99.92% and F1-scores of 99.86% (Islam *et al.*, 2022). However, these exceptional accuracies were achieved on standardized benchmark datasets (CCIC, BWCI) under relatively controlled conditions; field application on structures with complex surface textures, variable weathering, and challenging lighting exhibited more modest performance (85-92% accuracy) (Roșca, Stancu and Popescu, 2026).

Damage localization—pinpointing the spatial coordinates of detected damage—achieved mean absolute errors of 0.8-1.5 meters on typical 30-meter bridge spans, or approximately 2.7-5% of structure length. The most precise systems, combining LiDAR-derived point clouds with deep learning segmentation, achieved sub-decimeter localization errors (Srivastava and Narkhede, 2025). One study integrating LiDAR point cloud segmentation with digital twin models achieved localization accuracy within 3.8 meters (12.7% of span) on multi-sensor bridge datasets (Manoj, 2026).

4. DISCUSSION

4.1 Assessment of Evidence Quality and Methodological Rigor

The included studies exhibited considerable variation in methodological rigor and evidence quality. Approximately 61% (n=19 studies) were rated as "High" quality on the adapted quality assessment tool, demonstrating clear research objectives, rigorous train-test protocols, comprehensive performance reporting, and transparent discussion of limitations. These high-quality studies typically employed cross-validation strategies (k-fold or time-series cross-validation), reported multiple performance metrics (accuracy, precision, recall, F1-score, AUC), and explicitly discussed limitations and assumptions (Riyahi, Mestari and Bouihi, 2026; Roșca, Stancu and Popescu, 2026).

Moderate-quality studies (n=9, 29%) often lacked explicit cross-validation reporting, reported limited performance metrics, or provided insufficient detail on dataset characteristics and hyperparameter selection. Low-quality studies (n=3, 10%) were predominantly simulation-based without field validation or exhibited potential data leakage issues (training and test data not properly separated temporally) (Luk, 2025).

A persistent concern across the literature was the reliance on benchmark datasets (particularly the Z24 Bridge in Switzerland, utilized in 8 studies) for validation. While benchmark datasets enable methodological comparison and reduce publication bias toward positive results, they may not represent the diversity of infrastructure typologies, materials, loading conditions, and environmental contexts encountered globally. Generalization from laboratory and benchmark-based results to operational structures remains an unresolved challenge (Roșca, Stancu and Popescu, 2026).

4.2 Environmental Variability and Model Robustness

Environmental factors—particularly temperature, humidity, traffic loading, and wind—significantly confound damage signatures in real infrastructure. Temperature-induced stiffness changes can produce modal frequency variations exceeding 5-10%, potentially misclassified as structural damage by naive algorithms (K, 2026). Several studies employed temperature compensation techniques (e.g., temperature-dependent baseline subtraction) or adopted machine learning approaches explicitly trained on temperature-variant data to mitigate this challenge. Physics-informed neural networks demonstrated superior robustness to environmental variability by constraining learned models to satisfy fundamental physical laws, reducing spurious correlations with environmental confounders (Riyahi, Mestari and Bouihi, 2026).

Operational variability—such as changing traffic patterns, pedestrian loads on bridges, or occupancy in buildings—similarly influenced structural response measurements. One study on operational modal analysis noted that modal frequencies tracked over 365 days exhibited seasonal variations of 3-4% attributed to temperature effects, overlaid on a non-stationary trend from structural aging and damage accumulation. Separating these signals required advanced signal processing and machine learning discrimination (Roșca, Stancu and Popescu, 2026).

4.3 Data Scarcity and Transfer Learning Solutions

A recurrent theme across reviewed studies was the scarcity of labeled training data from operational structures. Supervised learning algorithms require thousands to tens of thousands of labeled samples for optimal performance, yet collecting and annotating such datasets from real infrastructure is expensive, time-consuming, and requires domain expertise. Transfer learning emerged as a practical solution, leveraging pre-trained models from large generic datasets (ImageNet, benchmark SHM datasets) and fine-tuning on limited target-domain data. Studies employing transfer learning typically achieved 15-25% reduction in required labeled samples compared to training from scratch, while maintaining comparable or superior accuracy (Islam *et al.*, 2022).

Domain adaptation techniques—methods to adapt models trained on source domains (e.g., simulated data) to target domains (e.g., real structures) without explicit labeled target data—show promise but remain underdeveloped in SHM applications. Only 3 studies explicitly employed domain adaptation methods, representing a significant research gap (Avevor *et al.*, 2024).

4.4 Model Interpretability and Explainability Challenges

Deep learning models, despite superior predictive performance, suffer from limited interpretability—the difficulty of understanding why a model makes specific predictions. In safety-critical SHM applications where false positives trigger expensive maintenance interventions and false negatives risk catastrophic failures, model transparency is essential for engineering trust and regulatory approval. Several approaches toward explainability were identified:

1. **Feature visualization and saliency maps**: Gradient-based methods (Grad-CAM) and perturbation-based methods (SHAP) highlight input features most influential in model predictions. One study employing SHAP and Grad-CAM for defect detection achieved 95.3% classification accuracy while providing pixel-level interpretability (Kumar *et al.*, 2025).
2. **Physics-informed models**: By constraining neural networks to satisfy known physical laws, PINNs inherently improve interpretability. The learned model becomes directly relatable to structural mechanics principles (Riyahi, Mestari and Bouihi, 2026).
3. **Hybrid approaches**: Combining classical machine learning (SVMs, random forests) with deep learning, leveraging the interpretability of classical methods and the predictive power of deep learning (Rani, 2025).

Despite these advances, interpretability remains a bottleneck for regulatory approval and widespread adoption of AI in infrastructure management. Future research must prioritize development of certifiable, auditable AI systems suitable for critical applications.

4.5 Integration with Digital Twins and Predictive Maintenance

Digital twins—virtual representations of physical structures synchronized with real-time sensor data—represent an integrative paradigm combining SHM, AI analytics, and simulation-based decision support. Seven studies incorporated digital twin frameworks, with promising results in predictive maintenance scheduling and remaining useful life estimation. By coupling real-time sensor data with physics-based finite element models via machine learning surrogate models, digital twins enable scenario simulation and what-if analysis for maintenance planning (Animashaun *et al.*, 2025).

One study demonstrated that digital twin-enabled SHM systems could optimize maintenance scheduling, achieving 20-30% reductions in lifecycle maintenance costs compared to condition-independent scheduled maintenance while maintaining safety targets (K, 2026). However, high implementation costs ($100,000-$1,000,000+ for complex infrastructure), complexity, and workforce skill requirements currently limit adoption to high-value assets.

4.6 Edge Computing and Decentralized SHM

Edge-artificial-intelligence (edge-AI) architectures, which push inference to distributed sensor nodes rather than centralizing processing in cloud servers, emerged as a solution to latency, bandwidth, and privacy concerns. One study implementing 1D CNNs on resource-constrained edge devices achieved 95.5% damage detection accuracy at 15 dB signal-to-noise ratio while reducing latency from 1850 milliseconds (cloud-only pipeline) to 95 milliseconds and decreasing uplink bandwidth by 93% (Chandrakaladharan, 2026). Edge-AI approaches enable real-time decision-making critical for autonomous infrastructure management and support deployment in remote or GPS-denied environments.

4.7 Limitations and Research Gaps

Critical limitations undermining current progress include:

1. **Dataset standardization**: Lack of standardized, publicly available benchmark datasets for diverse infrastructure types, materials, and loading conditions impedes methodological advancement and limits cross-study comparisons (Roșca, Stancu and Popescu, 2026).
2. **Environmental robustness**: Limited field validation under diverse environmental conditions; unclear how models generalize across climate zones, seasonal variations, and extreme weather events (Ahmed, 2025).
3. **Uncertainty quantification**: Most reviewed studies provide point predictions without quantifying prediction uncertainty or confidence intervals, essential for risk-informed decision-making in infrastructure management (Sivasuriyan *et al.*, 2026).
4. **Cybersecurity and data privacy**: Networked SHM systems face cyber vulnerabilities; limited literature addresses security protocols and privacy-preserving analytics in connected infrastructure (Sivasuriyan *et al.*, 2026).

5. CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Key Findings

This systematic review synthesizes evidence on artificial intelligence applications in structural health monitoring of civil infrastructure, identifying substantial progress in methodological development and demonstrated performance, alongside persistent implementation challenges. Key findings include: (1) AI-driven SHM achieves high detection accuracies (95-97%) for damage identification under controlled conditions, substantially surpassing traditional visual inspection; (2) convolutional neural networks dominate image-based damage detection, while LSTM networks excel at prognostic tasks; (3) sensor fusion approaches combining complementary modalities (accelerometers, fiber optics, vision) improve robustness and redundancy; (4) physics-informed models enhance interpretability and robustness to environmental variability; (5) significant accuracy degradation (7-9 percentage points) occurs when models transition from laboratory to operational environments, highlighting generalization challenges; (6) edge-enabled distributed intelligence enables real-time decision support with reduced latency and bandwidth; (7) digital twins coupled with machine learning offer transformative potential for predictive maintenance and lifecycle optimization.

5.2 Critical Research Gaps Requiring Future Investigation

1. **Standardized Benchmark Datasets**: Development of large, diverse, open-access datasets spanning multiple infrastructure types, materials, damage scenarios, and environmental conditions would substantially accelerate methodological development and enable rigorous cross-study comparisons (Roșca, Stancu and Popescu, 2026).

2. **Field Validation Studies**: Greater emphasis on field deployments with rigorous documentation of environmental conditions, comparison with ground-truth damage assessments, and long-term performance tracking under diverse operational scenarios (Ahmed, 2025).

3. **Transfer Learning and Domain Adaptation**: Systematic investigation of transfer learning effectiveness across infrastructure types, materials, and environmental domains; development of domain adaptation techniques enabling models trained on one structure type to generalize to dissimilar structures (Avevor *et al.*, 2024).

4. **Uncertainty Quantification**: Integration of Bayesian inference, ensemble methods, and probabilistic deep learning to provide prediction uncertainty estimates essential for risk-informed maintenance decisions (Sivasuriyan *et al.*, 2026).
5. **Explainable AI for Infrastructure Applications**: Development and validation of explainability methods appropriate for safety-critical SHM applications; integration with regulatory frameworks for AI certification in infrastructure management (Kumar *et al.*, 2025).
6. **Cybersecurity and Privacy**: Comprehensive investigation of security vulnerabilities in networked SHM systems; development of privacy-preserving analytics techniques enabling sensitive data analysis without revealing individual measurements (Sivasuriyan *et al.*, 2026).
7. **Physics-Informed Neural Networks**: Continued development and validation of PINN architectures incorporating structural mechanics principles, enabling robust models with reduced data requirements and improved interpretability (Riyahi, Mestari and Bouihi, 2026).

5.3 Recommendations for Practitioners and Policymakers

1. **Pilot Projects with Rigorous Documentation**: Infrastructure agencies should initiate pilot SHM deployments on high-value assets, with careful documentation of environmental conditions, maintenance histories, and model performance to build practical evidence base (K, 2026).
2. **Workforce Development**: Substantial investment in training programs to develop workforce capability in AI-enabled SHM technologies, bridging traditional civil engineering and modern data science disciplines (Roșca, Stancu and Popescu, 2026).
3. **Regulatory Framework Development**: Development of standards and certification pathways for AI applications in safety-critical infrastructure monitoring, analogous to aviation and medical device regulatory frameworks, enabling confident adoption while managing risks (Sivasuriyan *et al.*, 2026).
4. **Open Science Initiatives**: Funding and institutional support for open-science initiatives enabling sharing of infrastructure datasets, model architectures, and comparative evaluations while managing intellectual property and confidentiality concerns (Ahmed, 2025).
5. **Sustainable and Equitable Implementation**: Integration of AI-driven SHM within broader frameworks for sustainable infrastructure management, addressing equity in resource allocation and ensuring benefits reach underserved communities and developing nations (K, 2026).

6. Conclusion

Artificial intelligence presents transformative opportunities for structural health monitoring, enabling transition from reactive to predictive infrastructure management. However, successful translation of research achievements into operational practice requires addressing critical gaps in model generalization, environmental robustness, interpretability, and regulatory acceptance. By prioritizing field validation, developing standardized datasets, advancing physics-informed and hybrid methodologies, and fostering interdisciplinary collaboration among engineers, data scientists, and policymakers, the built environment can achieve unprecedented safety, resilience, and sustainability. The convergence of AI, IoT sensors, edge computing, and digital twins positions infrastructure management for a fundamental paradigm shift toward intelligent, autonomous, and adaptive systems capable of safeguarding critical assets and public welfare in the face of aging infrastructure, climate change, and urbanization challenges.

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