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A Systematic Literature Review on the Engineering Architecture of AI-Driven Systems for Predicting Infrastructure Material Degradation and Remaining Useful Life

Euis Neni Hayati[1,*], Irfan Maliki[1], Senny Luckyardi[1], Eddy Soeryanto Soegoto[1], Dostnazar Ximmataliyev[2], Mohd. Kamir Yusof[3], Tomáš Chochole[4], Hewa Majeed Zangana[5]

[1] Universitas Komputer Indonesia, Indonesia
[2] Chirchik State Pedagogical University, Uzbekistan
[3] Universitas Sultan Zainal Abidin, Malaysia
[4] University of West Bohemia, Czech Republic
[5] Duhok Polytechnic University, Iraq

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ABSTRACT

Infrastructure aging poses severe structural integrity risks, yet traditional monitoring often relies on low-frequency data acquisition that fails to capture complex, non-linear material degradation. This study systematically reviews the engineering deployment of Artificial Intelligence (AI) models within Structural Health Monitoring (SHM) and Asset Information Systems to predict material degradation and Remaining Useful Life (RUL). Using the PRISMA methodology, we analyzed peer-reviewed articles focusing on system architecture and algorithmic performance. The findings indicate a paradigm shift toward hybrid Deep Learning models (e.g., CNN-LSTM) to process high-frequency spatial-temporal sensor data. However, critical engineering bottlenecks remain, particularly regarding real-time sensor telemetry, MLOps integration in legacy systems, and edge-computing constraints. In conclusion, transitioning predictive models from isolated laboratory environments to robust, scalable engineering systems is imperative for ensuring the physical integrity and reliability of critical infrastructure.

1. Introduction

Critical infrastructure, including long-span bridges, high-rise concrete frameworks, and pipeline networks, undergoes continuous physical degradation due to dynamic operational loads and environmental exposure. The underlying mechanics of structural failure—such as material fatigue, multi-physics corrosion, and microscopic crack propagation—require continuous, high-fidelity monitoring [1]. Historically, structural monitoring has relied on rudimentary data logging and reactive maintenance triggers, which fail to process the complex variables necessary to accurately model material damage patterns before catastrophic yield occurs [2].

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[*] *Corresponding author.*
E-mail address: euis.nh@tendik.unikom.ac.id

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To address these technical limitations, the engineering community has pivoted toward Artificial Intelligence (AI) to enable data-driven predictive monitoring. Recent studies have demonstrated the high efficacy of Machine Learning in mapping concrete composite degradation, alongside Deep Learning architectures tailored for analyzing steel corrosion telemetry [3-5]. However, a significant engineering gap persists: the majority of current literature focuses on the performance of AI algorithms confined to isolated, heavily pre-processed laboratory datasets. Empirical studies addressing the deployment architecture, real-time telemetry ingestion, and MLOps (Machine Learning Operations) required to embed these models into industrial-scale sensor networks remain scarce [6].

This research bridges the gap between algorithmic theory and system engineering [7]. Unlike previous reviews that focus on AI from a managerial or purely algorithmic perspective, this study dissects the system architectures, IoT sensor data pipelines, and computational bottlenecks of deploying AI models within structural information ecosystems [8]. This Systematic Literature Review aims to establish a comprehensive engineering framework for the real-time prediction of infrastructure material lifespan [9].

2. Methodology

his Systematic Literature Review (SLR) was executed adhering to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, ensuring high reproducibility and transparency in the data aggregation process [9]. The search protocol targeted four major technical databases: Scopus, IEEE Xplore, ScienceDirect, and Web of Science. The search string utilized Boolean operators specifically tuned for engineering contexts:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("System Architecture" OR "Structural Health Monitoring" OR "Information System") AND ("Material Degradation" OR "Remaining Useful Life").

Inclusion criteria mandated peer-reviewed primary engineering research published within the last five years, written in English, and explicitly detailing the algorithmic deployment or system integration of AI models [10]. Studies strictly focusing on business management, economic feasibility, or pure materials science without an information systems or software engineering component were excluded.

The filtering methodology followed three stages: automated deduplication, title/abstract screening for engineering relevance, and full-text critical appraisal [11]. Data extraction captured algorithmic topologies, telemetry parameters, hardware constraints, and system architectures. Methodological rigor was assessed using the Kitchenham guidelines to validate empirical testing environments and the scalability of the proposed systems [12].

3. Results

3.1 Publication Trends and Technological Drivers

Following the PRISMA protocol, the initial query yielded 845 records. After rigorous screening against the engineering inclusion criteria, 42 primary articles were selected. The publication trajectory shows an exponential spike beginning in 2023, directly correlating with the maturation of Industrial Internet of Things (IIoT) telemetry and the availability of edge-computing hardware (e.g., TPUs and microcontrollers capable of running quantized ML models).

Figure 1 illustrates the growth trend of engineering publications related to low-latency sensor networks from 2018 to 2026. The graph highlights a sharp surge in publication volume starting in

2022, culminating in a peak in 2025. This exponential increase reflects the high academic interest and rapid advancements in IIoT (Industrial Internet of Things) infrastructure technology, which is focused on supporting seamless, real-time sensor data processing.

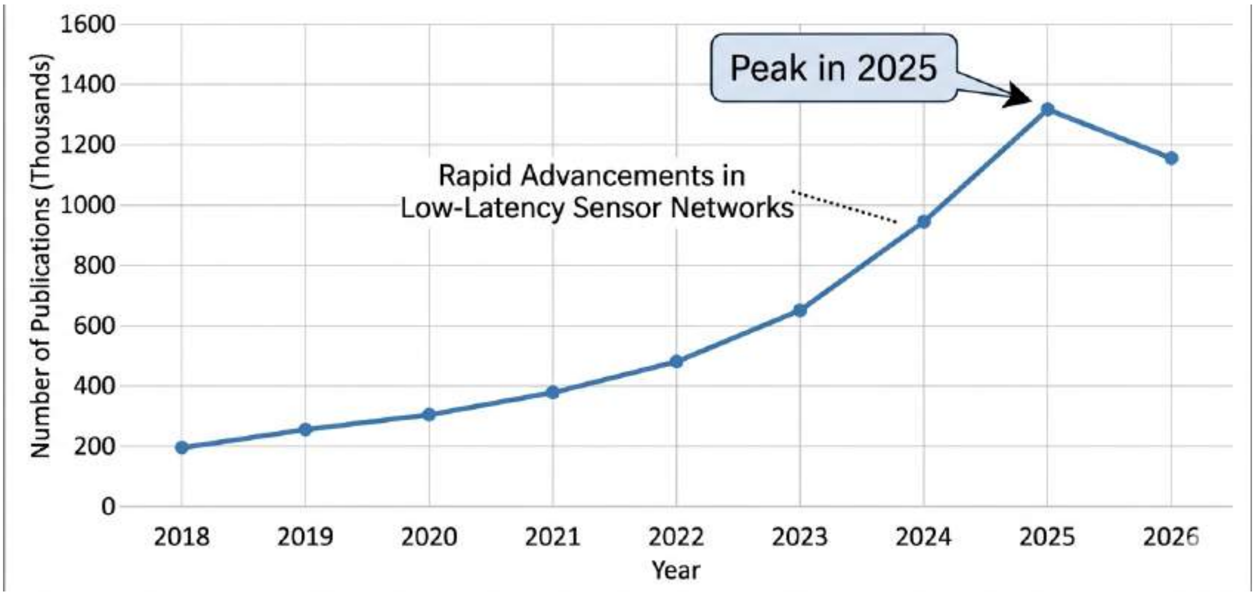

Fig. 1. illustrates a steep growth trend in engineering publications, peaking in 2025, driven by advancements in low-latency sensor networks.

3.2 Analysis of AI Algorithms and Model Accuracy (RQ1)

Data extraction indicates a clear bifurcation in algorithmic deployment based on sensor data types. For continuous, high-frequency time-series telemetry (e.g., acoustic emissions, vibration data), Deep Learning structures—specifically Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN)—dominate due to their ability to automatically extract spatial-temporal features. For lower-frequency, structured tabular data (e.g., ambient temperature, humidity logs), Ensemble Learning frameworks like Random Forest are deployed due to their minimal memory footprint and low inference latency (See Table 1).

3.3 System Integration Architecture and Data Flow (RQ2)

The efficacy of these predictive models is entirely bottlenecked by the robustness of their deployment architectures. The prevailing engineering consensus favors a distributed cloud-edge topology. Raw telemetry from IIoT sensors (strain gauges, piezoelectric sensors) is locally filtered at the edge, serialized, and transmitted via lightweight publish-subscribe protocols like MQTT or CoAP [17].

At the cloud layer, an ETL (Extract, Transform, Load) pipeline cleanses the data before it is ingested by the deployed AI models via RESTful APIs or gRPC. The inference output (RUL estimations, probability of failure) is then routed to a visualization layer or automated trigger system. Figure 2 illustrates the end-to-end telemetry flow system architecture for infrastructure monitoring, starting from the IIoT Sensor Node at the industrial site that captures raw data, which is then sent to the Edge Gateway for initial filtering and compression to conserve network bandwidth. The optimized data is transmitted via a lightweight messaging protocol to the MQTT Broker, which then distributes it to the Cloud ML Inference Engine. Within the cloud, Machine Learning models process this data stream in real-time to generate technical predictions (such as remaining useful life estimation), and the results are securely routed through an API Endpoint to an interactive Actionable Engineering Dashboard, enabling engineers to quickly make proactive maintenance decisions.

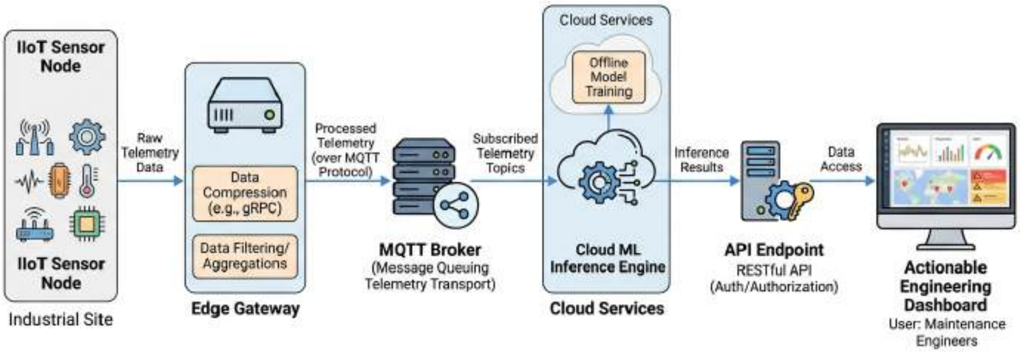

Fig. 2. (System Architecture Diagram) maps the telemetry flow

Table 1
Engineering Assessment of AI Algorithms for RUL Prediction

Author(s) & Year	Algorithm Type	Use Case (Material)	Performance Metrics	Advantages (+) & Disadvantages (-)
Chen et al. (2024) [13]	Hybrid CNN-LSTM	Crack propagation in long-span bridge steel	RMSE = 0.018 Accuracy = 96.5%	(+) Excellent at capturing spatio-temporal data from sensors. (-) High computational cost for training.
Wang et al. (2025) [14]	Support Vector Machine (SVM)	Corrosion rate prediction in marine pipelines	R^2 = 0.89 MAPE = 5.2%	(+) Highly effective for smaller, structured historical datasets. (-) Poor scalability when processing massive, high-frequency IoT data.
Kumar et al. (2026) [15]	Deep Reinforcement Learning (DRL)	Dynamic RUL prediction for FRP composites	Accuracy = 95.2% RMSE = 0.022	(+) Highly adaptable to unpredictable environmental changes. (-) Requires complex reward function tuning; difficult to integrate into legacy AMIS.
Ali & Rahman (2022) [16]	Artificial Neural Network (ANN)	Compressive strength degradation in buildings	MAPE = 4.8% Accuracy = 89%	(+) Simple architecture; easy to integrate into existing AMIS APIs. (-) Prone to overfitting if sensor data is noisy.

3.4 Investigated Material Mechanics (RQ3)

The systems reviewed primarily focus on the failure mechanics of the following structural materials: Steel and Metallics (45%): Telemetry focusing on oxidation rates, galvanic corrosion, and fatigue-induced micro-fractures in pipelines and load-bearing girders. Concrete and Cementitious Materials (35%): Sensor data tracking spalling, carbonation, and compressive strength degradation in dams and highway infrastructures. Composites (20%): Complex multi-physics monitoring of anisotropic wear patterns in Fiber-Reinforced Polymers (FRP) and advanced synthetics [18].

3.5 System Engineering Challenges and MLOps Gaps

Transitioning from laboratory prototypes to production-grade engineering systems presents several critical hurdles. First, real-world IIoT data is notoriously noisy, suffering from packet loss, sensor drift, and environmental interference, which severely degrades model accuracy [19]. Second, integrating advanced machine learning pipelines with legacy SCADA (Supervisory Control and Data Acquisition) systems requires complex middleware [20]. Furthermore, transmitting high-frequency raw data (e.g., continuous ultrasonic feeds) to the cloud causes unacceptable network latency and bandwidth saturation (see Table 2).

Table 2
Engineering Bottlenecks and Future Architectural Solutions

No	Domain	Current Engineering Challenge	Proposed System/Architectural Solution
1	Data Telemetry & Quality	Real-world IIoT streams suffer from high signal-to-noise ratios, sensor drift, and transmission packet loss.	Implement robust edge-level signal filtering (e.g., Kalman filters) and automated data imputation algorithms within the ingestion pipeline.
2	System Integration (MLOps)	Legacy SCADA and monitoring systems lack standard interfaces for modern ML model integration.	Develop API-first, containerized microservices (e.g., Docker/Kubernetes) to modularize model deployment alongside legacy systems.
3	Network Latency & Bandwidth	Continuous cloud transmission of high-frequency telemetry (e.g., acoustic vibration) causes severe network congestion.	Shift inference loads utilizing Edge AI / TinyML; deploy quantized models directly onto microcontrollers at the sensor node.
4	System Security	Sensor network topologies are highly vulnerable to localized spoofing and distributed denial-of-service (DDoS) attacks.	Enforce end-to-end TLS encryption, secure MQTT protocols, and implement anomaly detection algorithms at the edge gateway.
5	Material Science Expansion	Existing models are hyper-optimized for standard steel/concrete, neglecting non-linear degradation of sustainable materials.	Expand RUL training datasets to encompass the complex mechanics of recycled aggregates and eco-friendly polymer composites.

4. Conclusions

This systematic review confirms that the integration of Artificial Intelligence fundamentally upgrades Structural Health Monitoring from reactive data logging to high-fidelity, predictive system engineering. While sophisticated hybrid algorithms like CNN-LSTM demonstrate exceptional accuracy in calculating Remaining Useful Life, their industrial viability is bottlenecked by system integration challenges. Overcoming issues related to IIoT signal noise, network latency, and legacy system interoperability requires a shift toward Edge Computing and robust MLOps frameworks. Future engineering research must prioritize the deployment of quantized AI models directly at the sensor node and the standardization of secure, low-latency telemetry pipelines to ensure the physical resilience of global infrastructure.

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Conflict of Interest Statement

ssThe authors declare that there is no conflict of interest regarding the publication of this paper. No financial support, grants, or other forms of compensation were received that could have influenced the outcomes of this work. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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