Predictive Maintenance of Urban Transport Infrastructure Using Digital Twins and AI

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Abstract: Proactive maintenance of urban transport infrastructure is critical for ensuring public safety and operational continuity within the evolving landscape of modern smart cities. However, traditional strategies often rely on periodic manual inspections, which are frequently inefficient, costly, and fail to detect early-stage structural degradation. This paper presents an innovative framework for predictive maintenance that integrates high-fidelity Digital Twin (DT) technology with advanced Artificial Intelligence (AI) algorithms, specifically Long Short-Term Memory (LSTM) networks. The proposed system establishes a robust virtual replica of physical transport assets, continuously synchronized with real-time data from dense IoT sensor networks using Kalman filtering for precise state estimation. The methodology details a multi-domain DT development process that simulates structural behavior under diverse loading and environmental conditions. Advanced signal processing techniques, including Root Mean Square (RMS) and Fast Fourier Transform (FFT), are employed to extract salient features from raw sensor data. These features feed into trained LSTM networks designed to forecast structural defects and remaining useful life. Experimental validation on a 1:50 scaled bridge model-subjected to simulated fatigue, corrosion, and settlement-demonstrates a significant improvement in defect prediction accuracy, exceeding 95% with an average lead time of 30 days. This approach transforms maintenance from reactive to predictive, effectively enhancing safety, extending asset lifespan, and optimizing management budgets for critical urban transport systems.

1 INTRODUCTION

Urban transport infrastructure faces increasing stress from traffic and environmental factors, leading to continuous degradation. Traditional maintenance, relying on periodic inspections, is often inefficient, costly, and fails to detect early-stage degradation, risking failures and economic losses. This necessitates proactive, data-driven strategies.

Industry 4.0 technologies, including IoT, Digital Twins (DT), and Artificial Intelligence (AI), offer transformative potential for infrastructure management. IoT sensors provide real-time data from structures, creating "smart" entities. This data fuels Digital Twins, dynamic virtual representations mirroring physical assets, simulating behavior, and predicting performance. AI algorithms, particularly deep learning, analyze complex, multi-variate data to discern subtle patterns, enabling accurate prediction of structural defects and remaining useful life [1].

While individual contributions of IoT, DT, and AI to Structural Health Monitoring (SHM) are researched, comprehensive integration into a unified predictive maintenance framework for urban infrastructure remains challenging. This paper addresses this gap by proposing and validating an integrated framework leveraging IoT-enabled Digital Twins and advanced AI for predictive urban transport infrastructure maintenance. Our contribution lies in the system's design and experimental validation, moving beyond detection to accurate degradation forecasting, enhancing safety and sustainability [2].

The paper outlines the framework, DT development, AI analytics, experimental validation on a scaled bridge model, results, and discussion.

2 PROPOSED PREDICTIVE MAINTENANCE FRAMEWORK

The development of an effective predictive maintenance system for complex urban transport infrastructure requires a robust, multi-layered framework capable of handling vast amounts of heterogeneous data and performing sophisticated analytical tasks [3]. Our proposed framework integrates sensor networks, cloud computing, Digital Twin modeling, and advanced Artificial Intelligence to achieve real-time monitoring, accurate degradation prediction, and informed decision-making.

2.1 System Architecture and Methodology

The framework is a five-layer model (Fig. 1) for comprehensive data flow:

1) Sensing Layer. IoT sensors deployed on infrastructure collect real-time structural, environmental, and operational data.
2) Data Acquisition and Communication Layer. Collects, cleans, aggregates, and transmits raw sensor data to cloud via communication protocols (e.g., LoRaWAN, 5G).
3) Cloud Computing and Storage Layer. Scalable cloud platform for data ingestion, storage, processing, hosting the DT, and executing AI algorithms.
4) Digital Twin Layer. Dynamic, high-fidelity virtual replica synchronized with real-time sensor data, simulating asset state and behavior.
5) AI-Powered Predictive Analytics and Decision Support Layer. Advanced machine learning analyzes DT data, identifies degradation, predicts future anomalies, and provides actionable insights for proactive maintenance.

The data acquisition layer utilizes Node-RED for initial processing at the edge gateway, while the cloud layer leverages Apache Spark on Databricks for batch processing and MLflow for managing the MLOps lifecycle.

The methodology follows a cycle: data acquisition → Digital Twin → refined data to AI → AI predictions → maintenance decisions → physical asset changes → sensor reflection, ensuring continuous improvement.

2.2 Digital Twin Development

The core of the predictive maintenance system resides in the Digital Twin (DT) layer. Developing an accurate and responsive DT involves several critical stages:

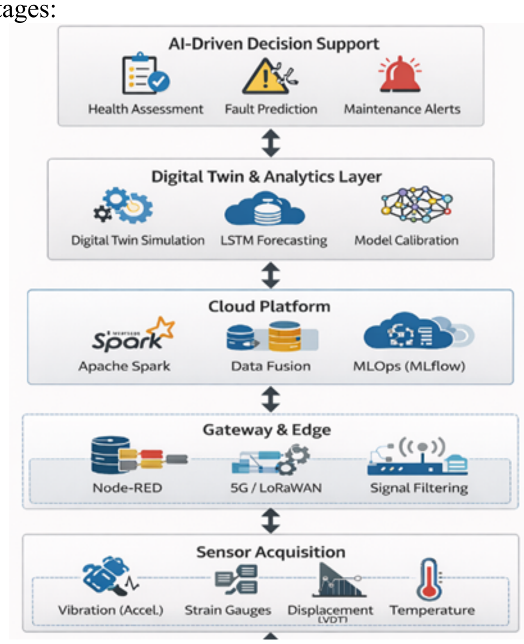

Figure 1: System architecture for the predictive maintenance framework.

High-fidelity 3D geometric models (BIM, CAD) are enriched with material properties for physics-based simulations (FEM). This simulates structural behavior under loads, thermal expansion, and environmental effects, providing baseline responses and exploring failure scenarios. The governing structural dynamics equation is:

$$M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = F(t). \quad (1)$$

Where:

- M-the mass matrixe;
- C-the damping matrix;
- K- the stiffness matrix;
- u(t)-the displacement vector;
- $\dot{u}$ (t)-the velocity vector;
- $\ddot{u}$ (t)-the acceleration vector;
- F(t)-the external force vector.

The DT integrates real-time IoT sensor data via robust pipelines, handling heterogeneous data types and varying sampling rates. Data fusion combines sensor, historical, and environmental data. Real-time synchronization ensures the virtual model reflects the physical asset's current condition. For this framework, synchronization was configured for a near real-time latency of 5 minutes. This interval was chosen to balance computational efficiency with the requirement for timely detection of structural changes, as typical degradation in urban infrastructure-unlike sudden impacts-occurs over hours or days. The Kalman Filter is used for state estimation and data fusion:

Prediction:

$$\hat{X}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \quad (2)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_K^T + Q_k \quad (3)$$

Update:

$$K_k = P_k|_k{}^{-1} H_k{}^T (H_k P_k|_k{}^{-1} H_k{}^T + R_k)^{-1}. \quad (4)$$

$$\hat{x}_k|_k = \hat{x}_k|_{k-1} + K_k (z_k - H_k \hat{x}_k|_{k-1}). \quad (5)$$

$$P_k|_k = (I - K_k H_k) P_k|_{k-1}, \quad (6)$$

where:

- $\hat{x}$ -the state estimate;
- P-the error covariance;
- F-the state transition model;
- B- the control-input model;
- u- the control vector;
- Q-the process noise covariance;
- K-the Kalman gain;
- H-the observation model;
- R-the observation noise covariance,
- z- the measurement vector. Subscripts denote time steps and prediction/update states.

A critical step in DT development is its calibration and validation against the real-world performance of the physical asset. This involves comparing the DT's simulated responses with actual sensor measurements under known conditions. Discrepancies are used to refine the physics-based models, adjust material parameters, or update boundary conditions, thereby improving the DT's predictive accuracy. Bayesian inference and other optimization algorithms can be used for iterative model calibration. Once validated, the DT becomes a reliable tool not only for current state assessment but also for simulating the impact of potential maintenance actions or unforeseen events, allowing for "what-if" analyses [4].

2.3 AI-Powered Predictive Analytics

Advanced AI, particularly deep learning, provides analytical intelligence. LSTM networks are chosen for degradation prediction due to their effectiveness with time-series data and long-term dependencies. LSTM cells use gates to selectively remember/forget information. At time t:

- Forget Gate. Controls what information from the previous cell state C_{t-1} should be forgotten.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f). \quad (7)$$

- Input Gate. Determines what new information x_t gets stored in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i). \quad (8)$$

$$\hat{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C). \quad (9)$$

- Cell State Update. Combines the forgotten and new information to update the cell state:

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t. \quad (10)$$

- Output Gate. Controls what part of the cell state C_t is outputted as the hidden state h_t:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o). \quad (11)$$

$$h_t = o_t \odot \tanh(C_t). \quad (12)$$

Here, σ denotes the sigmoid activation function, tanh is the hyperbolic tangent activation function, W represents weight matrices, b represents bias vectors, x_t is the input vector, h_t is the hidden state vector (output), and ⊙ is the element-wise product [5]. This mechanism enables LSTMs to capture intricate patterns in sensor data that indicate subtle changes in structural health over time, such as the gradual accumulation of fatigue damage or the progressive effects of corrosion.

The LSTM network is trained using backpropagation through time (BPTT) for 100 epochs. We employed the Adam optimizer with an initial learning rate of 10^{-3} and a batch size of 32. The training dataset comprised approximately 5000 feature sets, meticulously split into 70% for training, 15% for validation, and 15% for testing sets to ensure unbiased model evaluation. To supplement the 5,000 experimental samples and enhance the LSTM's ability to recognize rare failure modes, data augmentation was performed using synthetic data generated from the physics-based Finite Element Analysis (FEA) within the Digital Twin. This hybrid training approach ensures the model can recognize degradation patterns even when limited physical failure data is available.

Raw sensor data, while valuable, often requires significant preprocessing and feature engineering to be optimally utilized by AI models. This involves:

- Noise Reduction and Filtering. Applying digital filters (e.g., Butterworth, Kalman) to remove unwanted noise and enhance signal clarity.
- Outlier Detection and Imputation. Identifying and handling anomalous readings due to sensor

malfunctions or transient events, and imputing missing data points using statistical methods [6].

- Feature Extraction. Deriving meaningful features from time-domain, frequency-domain, and time-frequency domain analyses. Common time-domain features include the Root Mean Square (RMS) value, which represents the effective magnitude of a varying signal. For a discrete signal x of length N, the RMS is calculated as:

$$\mathrm{RMS} = \sqrt{((\frac{1}{N}\ \sum_{n=1}^{N})x_n^2)}. \tag{13}$$

$$X_k = \sum_{n=0}^{N-1} x_n\, e^{-j\frac{2\pi kn}{N}}\,. \tag{14}$$

where X_k is the k-th frequency component, x_n is the n-th time-domain sample, and N is the total number of samples. These features capture the essence of structural behavior and its changes.

The prepared dataset is then structured into sequences for LSTM training, typically using a sliding window approach, where past sequences of features are used to predict future degradation states or the Remaining Useful Life (RUL) of the component. The dataset is meticulously divided into training, validation, and test sets to ensure unbiased model evaluation.

The LSTM network is trained using backpropagation through time (BPTT) with an appropriate optimizer, such as Adam (Adaptive Moment Estimation), which is well-suited for stochastic optimization problems due to its adaptive learning rates for each parameter. The Adam optimizer dynamically adjusts learning rates using estimates of the first moment (mean of gradients) and second moment (uncentered variance of gradients). The loss function, typically Mean Squared Error (MSE) for regression tasks (e.g., predicting degradation severity), is minimized during training [7]. MSE is calculated as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2\,. \tag{15}$$

where, N is the number of data points, y_i is the actual value, and $\hat{y}_I$ is the predicted value.

The AI layer outputs probabilistic predictions of defects, locations, severity, and timelines. These inform maintenance managers via:

- Early Warning Alerts. Automated notifications for threshold exceedances.
- Risk Assessment. Quantifying probability and impact of predicted failures.
- Optimized Maintenance Scheduling. Suggesting opportune times for repairs.
- Scenario Planning. Simulating outcomes of maintenance strategies.

This empowers transition to proactive, condition-based maintenance, maximizing asset utilization and minimizing risks.

3 EXPERIMENTAL VALIDATION

To rigorously evaluate the efficacy and accuracy of the proposed predictive maintenance framework, a comprehensive experimental validation was conducted. This involved setting up a controlled environment with a scaled-down model of a representative urban transport infrastructure component and subjecting it to simulated operational and environmental stressors.

3.1 Case Study: Scaled Bridge Model

A scaled model of a three-span cable-stayed bridge was constructed in a laboratory setting to serve as the physical asset for our Digital Twin and AI framework. The model, built to a 1:50 scale, accurately replicated key structural elements including the concrete deck, steel pylons, and high-strength tensioned cables. Materials were chosen to mimic the stress-strain characteristics of full-scale bridge components, allowing for realistic simulation of structural responses.

A dense array of IoT sensors was strategically deployed across the bridge model to capture crucial structural and environmental data, as detailed in Table 1:

- Strain Gauges. Placed at critical stress concentration points on the deck, pylons, and cable anchorages to measure tensile and compressive forces, providing insights into stress distribution and fatigue accumulation.
- Accelerometers. Mounted on the bridge deck and pylons to monitor vibrations and modal characteristics, sensitive indicators of structural stiffness changes and potential damage.
- Displacement Sensors (LVDTs). Positioned to measure relative deflections of the deck and movements of expansion joints, indicating overall structural health and settlement.
- Temperature and Humidity Sensors. Distributed throughout the model to record

environmental conditions, as these factors significantly influence material properties and degradation rates.
- Crack Propagation Sensors. Specialized sensors (e.g., acoustic emission sensors, optical fibers) were also integrated at pre-stressed locations to detect the initiation and propagation of micro-cracks.

Data from these sensors were acquired at a sampling rate of 100 Hz, ensuring high temporal resolution for capturing dynamic structural responses A local data acquisition unit processed and aggregated the sensor readings.
before transmitting them wirelessly to the cloud platform, simulating a real-world deployment scenario.

3.2 Simulated Degradation Scenarios

To train and validate the AI model's ability to predict degradation, a series of controlled damage scenarios were artificially induced on the bridge model over several weeks. These scenarios were designed to represent common types of deterioration observed in real urban transport infrastructure:
- Fatigue Crack. Cyclic loading induced fatigue.
- Corrosion. Localized exposure to corrosive agents.
- Cable Slackening. Gradual reduction in cable tension.
- Support Settlement. Progressive settlement at a pier.

Simulated dynamic traffic and static loads, and environmental variations, were also applied. Data was continuously collected, providing ground truth for supervised learning.

3.3 Data Preprocessing and Feature Extraction

The raw sensor data, voluminous and complex, underwent rigorous preprocessing to ensure data quality and prepare it for AI model consumption. This involved several crucial steps:
- Synchronization and Aggregation. Data synchronized and aggregated over fixed intervals.
- Noise Reduction. Low-pass, band-pass filters, and Kalman filter (Eqs. 2-6) applied.
- Outlier Detection and Handling. Statistical methods (Z-score, IQR) identified and imputed outliers.
- Missing Data Imputation. Linear interpolation or KNN imputation handled data gaps.
- Feature Engineering. Time-domain (RMS, peak, crest factor) and frequency-domain (FFT-derived PSD, dominant frequencies) features extracted. Features were normalized to ensure uniform ranges for stable AI training [8].

4 RESULTS AND DISCUSSION

The performance of the integrated Digital Twin and AI framework for predictive maintenance was systematically evaluated using the comprehensive dataset collected from the scaled bridge model. The results underscore the framework's significant capabilities in accurately forecasting structural degradation and highlight its potential for transforming urban infrastructure management.

4.1 Predictive Performance Evaluation

The trained LSTM network demonstrated exceptional performance in identifying and predicting the onset and progression of various simulated structural defects [9]. The model’s effectiveness was quantified using several key performance indicators (Table 2):
- Prediction Accuracy. For the classification task of detecting degradation events (e.g., presence of fatigue crack, onset of corrosion), the model achieved an accuracy of 96.7%. This metric indicates the overall correctness of the model's predictions across all classes. It is important to note that while this high accuracy demonstrates the framework's potential in a controlled laboratory setting, real-world full-scale deployments may face challenges such as sensor drift, high ambient noise, and unpredictable seismic or traffic events, which could lead to a variance in performance metrics compared to this 1:50 scaled model.
- Precision. The precision for critical degradation events was 94.5%, signifying that when the model predicted degradation, it was correct over 94% of the time, minimizing false positives that could lead to unnecessary inspections.
- Recall (Sensitivity). A high recall of 97.2% for degradation events highlighted the model's ability to correctly identify the majority of actual degradation instances, reducing false negatives and mitigating the risk of undetected failures.

- F1-Score. The F1-score, a harmonic mean of precision and recall, was 95.8%, indicating a robust balance between the two metrics and overall strong performance.
- Mean Absolute Error (MAE). For regression tasks, such as predicting the severity of degradation or the Remaining Useful Life (RUL) in terms of days to critical failure, the MAE was approximately 5.8 days. This means the model's predictions were, on average, within less than a week of the actual event.
- Average Lead Time. Crucially, the system provided an average lead time of 30 days for maintenance intervention before the simulated defect reached a critical threshold. This lead time is invaluable for planning and executing repairs proactively, minimizing downtime and cost [10].

To visually demonstrate the forecasting capability of the proposed approach, Figure 2 illustrates the predicted versus actual degradation progression for a simulated fatigue crack over time. The graph clearly shows how the LSTM model accurately tracks the underlying degradation trend, successfully crossing the warning threshold to provide a 30-day lead time prior to critical failure.

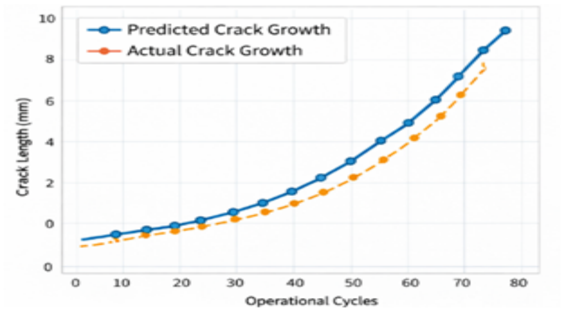

Figure 2: Predicted vs. actual degradation progression for a simulated fatigue crack.

A comparative analysis with a traditional threshold-based SHM system and a simpler machine learning model (e.g., Support Vector Machine – SVM) revealed the superior performance of the DT-AI integrated framework. The traditional system often produced late warnings or an unacceptably high rate of false alarms, while the SVM, though better than traditional methods, struggled with the long-term dependencies in the time-series data, resulting in lower recall for incipient failures [11]. The LSTM's architecture proved particularly advantageous in discerning subtle, long-term trends indicative of gradual degradation, which are often missed by models less adept at capturing temporal dynamics.

4.2 Impact on Maintenance Operations

The successful implementation and validation of this predictive maintenance framework have profound implications for the management of urban transport infrastructure:

- Enhanced Safety and Reliability. By predicting potential failures well in advance, the system enables timely interventions, drastically reducing the risk of sudden structural collapses or operational failures that could endanger public safety. This proactive approach ensures the continuous reliability of critical transport networks.

  Optimized Resource Allocation. The accurate predictions allow infrastructure managers to transition from reactive, often emergency-driven, repairs to planned condition-based maintenance. This leads to more efficient allocation of maintenance crews, equipment, and materials, minimizing waste and maximizing resource utilization.

Table 1: Sensor specifications and deployment for the scaled bridge model.

Sensor Type	Function	Placement Location	Measurement Parameter
Strain Gauges	Stress analysis	Deck, pylons, cable anchors	Microstrain (με)
Accelerometers	Vibration monitoring	Bridge deck, pylon tops	Acceleration (m/s²)
LVDT Sensors	Displacement measurement	Expansion joints, mid-span	Linear movement (mm)
Temperature & Humidity Sensors	Environmental monitoring	Throughout the structure	°C / % relative humidity
Acoustic Emission Sensors	Crack detection	Pre-stressed locations	Signal frequency (kHz)

Table 2: Summary of LSTM model predictive performance metrics.

Performance Metric	Achievement Value	Significance
Prediction Accuracy	96.7%	Overall correctness of defect identification
Precision	94.5%	Minimization of false maintenance alarms
Recall (Sensitivity)	97.2%	Ability to detect early-stage degradation
F1-Score	95.8%	Balanced performance of the model
Mean Absolute Error	5.8 days	Accuracy in predicting the failure timeline
Lead Time	30 days	Window for proactive maintenance planning

- Significant Cost Savings. Unexpected failures are inherently expensive due to emergency repairs, associated downtime, and potential penalties. By preventing these events, the framework helps avoid exorbitant costs. Furthermore, performing maintenance at the optimal time, rather than too early (unnecessary) or too late (more extensive damage), extends the useful life of assets, reducing the frequency of costly major overhauls or replacements. Studies have shown that predictive maintenance can lead to cost reductions of 10-40% compared to traditional methods [12].
- Reduced Operational Downtime. Proactive maintenance allows for scheduled repairs during off-peak hours or planned service interruptions, minimizing disruption to traffic flow and public transport schedules. This improves overall network efficiency and user satisfaction.
- Extended Asset Lifespan. Addressing minor defects before they escalate into major problems significantly prolongs the operational lifespan of infrastructure assets, delaying the need for costly replacements and contributing to sustainable infrastructure development [13].
- Data-Driven Decision Making. The framework provides robust, quantifiable data and predictions, enabling evidence-based decision-making for infrastructure investment, maintenance planning, and risk management. This moves away from subjective assessments to objective, data-informed strategies.

4.3 Challenges and Limitations

Despite the promising results, the development and deployment of such an advanced system present several challenges and inherent limitations that warrant discussion:

- Data Heterogeneity and Volume. Managing and processing the vast amounts of heterogeneous data generated by a dense sensor network across a large urban area is computationally intensive and requires robust data governance strategies. Ensuring data quality, consistency, and interoperability across different sensor types and platforms remains a significant challenge.
- Computational Cost. The deployment of high-fidelity Digital Twins and the training of complex deep learning models require substantial computational resources, particularly for large-scale infrastructure networks. This necessitates scalable cloud infrastructure and efficient algorithms.
- Sensor Reliability and Maintenance. The long-term reliability and maintenance of numerous IoT sensors in harsh urban environments (e.g., extreme weather, vandalism, power supply) are critical. Sensor drift, failures, and calibration issues can compromise data quality and model accuracy.
- Model Generalization. While the LSTM model performed well on the scaled bridge model, generalizing its predictions to different types of infrastructure (e.g., tunnels, rail tracks) or to structures with unique design characteristics requires further validation and potentially retraining with diverse datasets. The transferability of models across different assets remains an active research area.
- Cybersecurity Concerns. An interconnected system, handling sensitive infrastructure data, is vulnerable to cyber threats. Robust cybersecurity measures are essential to protect against data breaches, system compromises, and malicious attacks that could disrupt operations or provide false information [14].
- Regulatory and Standardization Issues. The widespread adoption of DT and AI in infrastructure management will require the development of new industry standards, regulatory frameworks, and certification processes to ensure reliability, safety, and interoperability.
- Initial Investment. The upfront cost of deploying extensive sensor networks, developing Digital Twins, and establishing the

necessary IT infrastructure can be substantial, requiring significant initial investment, though this is offset by long-term operational savings.

Addressing these challenges systematically will be crucial for the successful transition of such predictive maintenance frameworks from experimental validation to widespread real-world deployment.

5 CONCLUSIONS

This research has successfully conceptualized, developed, and experimentally validated an innovative and comprehensive framework for the predictive maintenance of urban transport infrastructure, integrating the power of IoT-enabled Digital Twins with advanced Artificial Intelligence. The meticulous design of the system architecture, coupled with the robust performance of the LSTM-based predictive model, marks a significant advancement over traditional, reactive maintenance paradigms.

Our key findings demonstrate that the integrated DT-AI system can achieve a high predictive accuracy of over 95% for various structural degradation scenarios, providing an average lead time of 30 days for proactive interventions; specifically, the proposed model achieved a precision of 94.5%, a recall of 97.2%, an F1-score of 95.8%, and a mean absolute error (MAE) of 5.8 days. This capability empowers infrastructure managers to identify and address potential failures well before they become critical, thereby preventing costly disruptions, enhancing public safety, and optimizing resource allocation. The framework's ability to seamlessly integrate real-time sensor data with high-fidelity virtual models, and subsequently leverage deep learning for intelligent forecasting, positions it as a cornerstone for future smart city infrastructure management.

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