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Edge-Cloud Artificial Intelligence Predictive Maintenance Model for Road Infrastructure Management

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Abstract
The deterioration of road infrastructure presents a persistent challenge to transportation efficiency, safety, and economic productivity, particularly in resource-constrained environments where maintenance is often reactive rather than preventive. This study proposes an edge-cloud artificial intelligence predictive maintenance conceptual model designed to enhance real-time monitoring, early fault detection, and proactive decision-making for road infrastructure systems using a qualitative, design science research (DSR) approach. The model integrates edge computing nodes, Internet of Things (IoT) sensor networks, and lightweight machine learning deployed at the edge to enable low-latency data processing and reduce dependence on centralized cloud infrastructures. By leveraging continuous data streams, the model will facilitate timely identification of structural anomalies including cracks, potholes, and subsurface degradation. The proposed model further incorporates adaptive learning mechanisms to improve predictive accuracy over time while optimizing bandwidth usage and operational costs. In addition, a decision-support layer is introduced to assist infrastructure managers in prioritizing maintenance interventions based on risk and severity indices. The conceptual model demonstrates the potential of decentralized AI architectures to transform traditional road maintenance practices into intelligent, predictive, and scalable systems suitable for both urban and rural contexts.

Keywords: Artificial Intelligence, Conceptual Model, Edge–Cloud Computing, Predictive Maintenance, Real-Time Condition Monitoring.

1. Introduction

Road infrastructure constitutes a critical pillar of socio-economic development, facilitating mobility, trade, and regional connectivity. However, maintaining the integrity and performance of road networks remains a persistent challenge, particularly in developing contexts where maintenance strategies are often reactive, fragmented, and resource-constrained. Conventional approaches rely on periodic inspections and centralized data processing, which are frequently associated with delayed responses, high operational costs, and limited scalability (Zhang et al., 2016; Ceriani et al., 2025). In recent years, the convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and edge computing has introduced transformative possibilities for infrastructure management. Edge computing, in particular, enables real-time data processing at or near the point of data generation, thereby reducing latency, bandwidth dependency, and reliance on centralized systems (Quy et al., 2023). When integrated with AI-driven analytics, edge-based systems can support continuous monitoring and early detection of road defects such as cracks, potholes, and structural degradation, thereby significantly enhancing road maintenance efficiency (Ejaz, Alam & Choudhury, 2025).

Despite these technological advancements, current road maintenance systems remain predominantly reactive, resulting in increased lifecycle costs, safety hazards, and service disruptions. The dependence on centralized cloud-based analytics further compounds these challenges, especially in regions with limited connectivity, where latency and data transmission constraints hinder timely decision-making (Villaverde et al., 2026). Moreover, many existing AI-driven maintenance solutions lack effective integration with edge computing frameworks, leading to delayed insights and reduced operational responsiveness (Sathupadi et al., 2024). The absence of a unified and scalable conceptual model that integrates real-time data acquisition, edge analytics, machine learning, and intelligent decision support systems continues to limit the practical implementation of predictive maintenance strategies in road infrastructure management.

In response to these challenges, this study aims to develop a comprehensive conceptual model for an edge-based AI predictive maintenance systems tailored to road infrastructure. The model is designed to enable real-time monitoring, early fault detection, and proactive maintenance decision-making. Specifically, the study seeks to examine existing predictive maintenance approaches, identify their limitations, and explore the integration of edge computing and AI technologies for real-time data processing. It further aims to design a multi-layered framework incorporating sensor-based data acquisition, edge analytics, machine learning models, and decision support mechanisms, while also addressing key considerations such as scalability, interoperability, and adaptability across diverse environmental and infrastructural contexts.

The significance of this study lies in its potential to advance both theoretical and practical dimensions of intelligent infrastructure management. By proposing a novel edge-based AI conceptual framework, the research addresses critical gaps in current maintenance paradigms and contributes to the growing body of knowledge on smart infrastructure systems. Practically, the model offers a pathway to reducing maintenance costs, extending the lifespan of road assets, and improving road safety through timely and data-driven interventions. This is particularly valuable in developing regions, where decentralized processing and efficient resource utilization are essential. Furthermore, the study provides a foundation for future empirical validation and implementation, thereby supporting the transition toward more resilient, efficient, and intelligent road infrastructure systems.

2. Literature Review

The maintenance of road infrastructure remains a persistent global challenge, particularly in rapidly urbanizing regions where traffic loads, environmental stressors, and constrained maintenance budgets exacerbate deterioration rates. Traditional maintenance strategies, primarily reactive or time-based are increasingly inadequate for addressing complex degradation patterns such as cracking, rutting, and pothole formation. Studies have shown that deferred maintenance significantly increases lifecycle costs and compromises road safety and serviceability (World Bank, 2019; Huang et al, 2024). In many developing contexts, fragmented data collection systems, limited monitoring technologies, and inefficient asset management practices further hinder timely intervention. Consequently, there is a growing imperative to transition toward intelligent, data-driven maintenance paradigms that enhance decision-making precision and optimize resource allocation.

Predictive maintenance has emerged as a transformative approach within civil infrastructure management, leveraging historical and real-time data to anticipate failures before they occur. Unlike preventive maintenance, which follows fixed schedules, predictive maintenance utilizes condition-based monitoring to estimate the remaining useful life (RUL) of infrastructure components (Chen, Cao & Zhu, 2023; Molęda et al., 2023). In road systems, predictive models have been applied to forecast pavement deterioration using parameters such as traffic volume, material properties, and environmental conditions (Famewo & Shokouhian, 2025). These approaches have demonstrated significant potential in reducing maintenance costs and improving infrastructure reliability. However, conventional predictive systems often rely on centralized data processing architectures, which may introduce latency, bandwidth constraints, and limited scalability, particularly in geographically dispersed road networks.

The integration of artificial intelligence (AI) into infrastructure monitoring has significantly enhanced the capability to analyse complex, high-dimensional datasets. Machine learning and deep learning techniques have been widely applied for automated damage detection, classification, and severity assessment using data from sensors, drones, and satellite imagery (Al Shafian & Hu, 2024; Braik & Koliou, 2024; Hütten et al., 2024). Convolutional neural networks (CNNs), for example, have demonstrated high accuracy in detecting pavement distress from image data (Wang et al., 2025), while recurrent neural networks (RNNs) and hybrid models have been used for temporal prediction of infrastructure degradation trends (Sowemimo et al., 2024). Despite these advancements, AI-driven systems often depend on cloud-centric architectures, which can be susceptible to latency issues, data privacy concerns, and network reliability challenges, limitations that are particularly pronounced in real-time and mission-critical applications.

Edge computing has gained prominence as a complementary paradigm to address the limitations of centralized processing by enabling data computation closer to the source. In smart infrastructure systems, edge devices such as embedded sensors, Internet of Things (IoT) nodes, and roadside units can perform localized data processing, thereby reducing latency, bandwidth usage, and dependency on continuous cloud connectivity (Mollah, Sultana & Kudapa, 2023). In the context of road infrastructure, edge computing facilitates real-time monitoring and immediate anomaly detection, enabling faster maintenance response (Patrikar & Parate, 2022). The convergence of AI and edge computing, often referred to as edge intelligence has further expanded the potential for deploying lightweight machine learning models directly on edge devices (Hua et al., 2023). This integration supports scalable, distributed analytics and enhances system resilience, particularly in environments with limited connectivity.

Notwithstanding the growing interest in AI-driven and edge-enabled infrastructure systems, existing models and frameworks remain fragmented and often lack holistic integration. Many studies focus either on AI-based prediction models or edge computing architectures in isolation, with limited emphasis on unified, end-to-end conceptual frameworks tailored to road infrastructure maintenance (Wang et al., 2025). Furthermore, challenges such as model optimization for resource-constrained edge devices, data heterogeneity, interoperability, and real-world deployment scalability remain insufficiently addressed. Notably, there is a paucity of research that contextualizes these technologies within the specific operational and socio-economic constraints of developing regions. This study addresses these gaps by proposing a comprehensive conceptual model that integrates edge computing and AI for predictive maintenance of road infrastructure, emphasizing real-time analytics, decentralized decision-making, and adaptive system architecture

3. Theoretical and Conceptual Foundation

The proposed edge-based artificial intelligence (AI) predictive maintenance model for road infrastructure is grounded in an interdisciplinary synthesis of theoretical perspectives spanning cyber-physical systems (CPS) theory, distributed computing theory, and reliability-centred maintenance (RCM) theory. At its core, the model draws upon CPS theory, which conceptualizes the integration of physical infrastructure with computational intelligence and communication capabilities to enable real-time monitoring and adaptive control (Lee, Bagheri, & Kao, 2015). Complementing this is the paradigm of distributed (edge) computing, which decentralizes data processing closer to data sources, thereby reducing latency, bandwidth consumption, and reliance on centralized cloud systems (Shi et al., 2016). Additionally, reliability-centred maintenance (RCM) theory provides a foundational lens for prioritizing maintenance interventions based on system criticality and failure probabilities (Moubray, 1997). Together, these theoretical underpinnings establish a robust basis for leveraging AI-driven analytics at the network edge to enhance proactive maintenance decision-making in road infrastructure systems. The model's theoretical foundational concept is represented in figure 1.

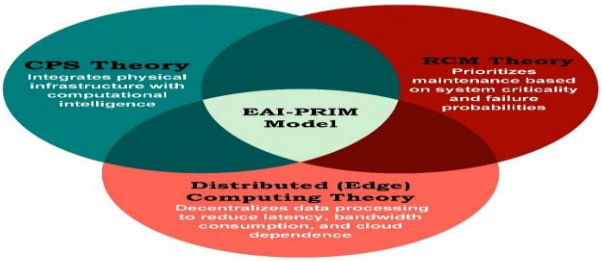

Figure 1. The Model's Theoretical Foundational Concept

The conceptual model development is also guided by established principles of systems thinking, modularity, and scalability. Systems thinking ensures that road infrastructure is treated as a complex, interconnected ecosystem involving physical assets, sensing devices, data pipelines, and decision-support mechanisms (Meadows, 2008). Modularity facilitates the decomposition of the model into functional layers, data acquisition, edge analytics, communication, cloud integration, and decision support, allowing for flexibility and incremental deployment. Scalability is achieved through distributed architecture design, enabling the model to adapt to varying geographic and operational contexts, particularly in resource-constrained environments. Furthermore, the model adheres to the design science research paradigm by emphasizing solution creation, iterative refinement, and contextual relevance (Hevner et al., 2004), thereby ensuring that the model is both theoretically sound and practically implementable.

Furthermore, the model incorporates several key constructs and variables that collectively define its operational dynamics. Primary constructs include data acquisition, such as IoT sensors, mobile devices, and satellite imagery; edge intelligence, the machine learning algorithms deployed at edge nodes; communication infrastructure like wireless networks enabling data transmission; and decision support systems like interfaces for maintenance planning. Critical variables encompass pavement condition indicators, such as roughness, cracking, rutting; traffic load intensity; environmental factors like temperature and precipitation, and system performance metrics such as prediction accuracy and latency. These constructs are interrelated through a data-driven feedback loop, where real-time data is continuously analysed to generate predictive insights, which in turn inform maintenance actions. The integration of supervised learning techniques enhances anomaly detection and failure prediction capabilities, aligning with contemporary advances in AI-enabled infrastructure monitoring (Chen, Yongchareon & Knoche, 2023).

The assumptions underlying the proposed model are essential for defining its scope and applicability. First, it is assumed that sufficient sensor coverage and data quality can be achieved to support reliable predictive analytics. Second, the model presumes the availability of edge computing resources with adequate processing capabilities to execute machine learning algorithms in near real-time. Third, it assumes the existence of stable and secure communication networks to facilitate seamless data exchange between edge nodes and centralized systems when necessary. Additionally, the model is expected to operate under the assumption that stakeholders, including transportation agencies and maintenance personnel, possess the institutional capacity to adopt data-driven decision-making processes. These assumptions, while idealized, are grounded in ongoing technological advancements and increasing investments in smart infrastructure systems globally.

Finally, the integration of these theoretical and conceptual elements culminates in a holistic model that advances the state of predictive maintenance for road infrastructure. By embedding intelligence at the edge, the model addresses critical limitations of traditional centralized approaches, particularly in terms of latency, scalability, and resilience. The conceptual foundation emphasizes a shift from reactive and schedule-based maintenance to predictive and condition-based strategies, thereby optimizing resource allocation and extending asset lifespan. Moreover, the model is particularly relevant for emerging and developing regions, where infrastructure challenges are compounded by limited resources and fragmented data systems.

4. Methodology

This study adopts a qualitative, design science research (DSR) approach to develop a conceptual framework for an edge-based artificial intelligence (AI) predictive maintenance model tailored to road infrastructure systems. Design science is particularly appropriate as it emphasizes the creation and evaluation of innovative solutions that address complex real-world problems (Hevner et al., 2004; Tuunanen, Winter & Brocke, 2024). The research is further underpinned by systems engineering perspective, integrating principles from intelligent transportation systems (ITS), edge computing, and machine learning. A conceptual modelling strategy is employed to synthesize interdisciplinary insights and propose a scalable and adaptive architecture capable of real-time condition monitoring and predictive maintenance. This approach is justified given the exploratory nature of the study and the need to bridge theoretical advancements with practical infrastructure management challenges (Gregor, 2022).

The conceptual model development process follows a structured, iterative procedure comprising problem identification, requirements analysis, solution design, and theoretical validation. Initially, a comprehensive literature synthesis is conducted to identify key components of predictive maintenance systems, including sensing technologies, data acquisition layers, edge analytics, and decision-support mechanisms (Gong et al., 2023; Dabboussi & Jammal, 2023). This is followed by abstraction and integration, where critical system elements are mapped into a layered architecture encompassing data ingestion, edge intelligence, communication protocols, and maintenance optimization modules. The model emphasizes decentralised processing through edge nodes to reduce latency, bandwidth consumption, and reliance on centralized cloud systems. Iterative refinement ensures alignment with real-world operational constraints such as connectivity limitations, environmental variability, and scalability requirements.

The proposed model conceptualizes diverse data sources and requirements essential for effective predictive maintenance. These include heterogeneous datasets derived from Internet of Things (IoT) sensors, such as vibration, strain, temperature; remote sensing technologies like satellite imagery and LiDAR; mobile crowdsourcing platforms; and historical maintenance records (Dabboussi & Jammal, 2023). Data preprocessing, feature extraction, and anomaly detection are envisioned to occur at the edge layer using lightweight AI models optimized for resource-constrained environments. The model assumes the integration of both structured and unstructured data, necessitating robust data fusion techniques to enhance predictive accuracy. Additionally, the model accounts for temporal and spatial data dependencies critical for road deterioration modelling, aligning with established infrastructure asset management practices (Xin et al., 2026). The Design Science Research (DSR) methodology adopted in this study, outlining the sequential stages underpinning the development of the proposed model is illustrated in Figure 2.

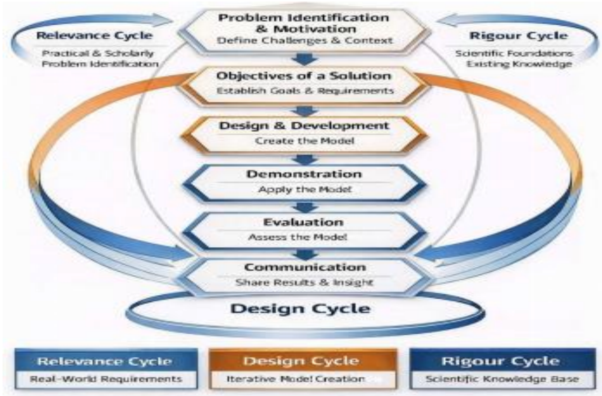

Figure 2. The Adopted Design Science Research (DSR) methodology guide delineating the sequential stages underpinning the development of the proposed model (Source: The Authors)

Given the conceptual nature of the study, the model validation is conducted through theoretical and analytical evaluation rather than empirical implementation. The validation strategy includes expert review, logical consistency analysis, and benchmarking against existing predictive maintenance frameworks. Scenario-based simulations are proposed as a future step to assess the model's robustness under varying operational conditions. Ethical considerations are integral to the research design, particularly concerning data privacy, surveillance risks, and algorithmic transparency. The model advocates for privacy-preserving data processing at the edge, minimizing the transmission of sensitive data to centralized systems (Ometov et al., 2022). Furthermore, the study emphasizes responsible AI principles, including fairness, accountability, and explainability, to ensure that predictive decisions do not disproportionately impact specific regions or communities.

5. Mathematical Modelling and Formulation

5.1. Problem Formulation

The edge-based predictive maintenance problem for road infrastructure is formulated as a dynamic optimization problem in which road sections are continuously monitored through embedded sensors, unmanned aerial systems, vehicle-mounted cameras, and IoT devices deployed along the road network. In this study, the road network is assumed to consist of (N) pavement segments, where each segment $i \epsilon \{1, 2, 3, \dots \dots \dots N\}$ is characterized at time t by a vector, as illustrated in equation (1).

$$\boldsymbol{X}_i(t) = [PCI_i(t) + IRI_i(t) + CR_i(t) + RD_i(t) + W_i(t) + T_i(t) \quad \dots \qquad (1)$$

where PCI denotes Pavement Condition Index, IRI is the International Roughness Index, CR is crack ratio, RD is rut depth, W represents traffic loading, and T denotes environmental variables such as temperature and rainfall.

The edge AI module processes these data locally and estimates the future deterioration state $\dot{X}_i(t+\Delta t)$ using lightweight machine learning models or spatio-temporal learning models. The deterioration process is represented as shown in equation (2):

$$\dot{X}_i(t+\Delta t) = f_0(\boldsymbol{X}_i(t) + \boldsymbol{u}_i(t) + \boldsymbol{e}_i(t) \quad \dots \quad (2)$$

where $f_0(.)$ is the trained edge-based prediction model, $\boldsymbol{u}_i(t)$ denotes maintenance decisions, and $\boldsymbol{e}_i(t)$ represents environmental and operational uncertainties. The principal objective is to minimize the long-term degradation and maintenance expenditure while maintaining road quality above a predefined threshold. Recent studies show that AI-based deterioration models significantly outperform traditional empirical regression methods in forecasting infrastructure distress (Famewo & Shokouhian, 2025; Sarkar & Sinha, 2026).

Furthermore, for the maintenance decision problem, the model seeks an optimal maintenance action $\boldsymbol{a}_i(t)$ for each road segment from a finite set, as in equation (3):

$$\boldsymbol{a}_i(t) \in \{0,1,2,3\} \quad \dots \quad (3)$$

where (0) denotes no action, (1) preventive maintenance, (2) corrective rehabilitation, and (3) full reconstruction.

5.2. Predictive Maintenance Optimization Model

The predictive maintenance strategy is formulated as a multi-objective optimization model. The primary objective is to minimize the total expected maintenance cost while simultaneously maximizing road condition and network availability over the planning horizon H, as in equation (4):

$$min\ Z = \sum_{t=1}^{H}\sum_{i=1}^{N}[C_i^m(a_{i,}t) + C_i^f(t) + C_i^d(t)] \quad \dots \ (4)$$

Where C_i^m is the maintenance intervention cost, C_i^f is the expected failure cost, and C_i^d is the delay or user disruption cost.

The optimization is constrained by the predicted road condition, given in equation (5):

$$PCI_i(t+1) = PCI_i(t) - D_i(t) + R_i((a_{i,}t) \quad \dots \ (5)$$

where $D_i(t)$ is the predicted deterioration and $R_i((a_{i,}t)$ is the restoration gain due to maintenance. However, the operational constraint as represent in equation (6) must be satisfied to ensure that no road segment falls below the minimum acceptable serviceability threshold.

$$PCI_i(t) \geq PCI_{min} \quad \dots \quad (6)$$

5.3. Cost–Benefit and Lifecycle Analysis

The lifecycle cost analysis evaluates the economic feasibility of deploying the edge-cloud AI predictive maintenance model across the entire road network. The total lifecycle cost of road segment is defined as in equation (7):

$$LCC_i = C_i^0 + \sum_{t=1}^{H}\frac{C_i^m(t) + C_i^u(t) + C_i^c(t)}{(1+r)^t} \quad \dots \ (7)$$

where C_i^0 is the initial installation cost of sensors and edge devices, $C_i^m(t)$ is the maintenance cost, $C_i^u(t)$ is the user cost arising from traffic delays, $C_i^c(t)$ is the environmental cost, and (r) is the discount rate.

The net benefit of implementing predictive maintenance instead of conventional reactive maintenance is expressed in equation (8):

$$NB = \sum_{t=1}^{H}\frac{B_t - C_t}{(1+r)^t} \quad \dots \quad (8)$$

where B_t denotes the avoided failure, congestion, and reconstruction costs, and C_t represents the cost of deploying and operating the predictive maintenance system. A positive value of (NB) indicates that the edge-cloud AI-driven approach is economically advantageous.

The benefit–cost ratio is similarly represented in equation (9):

$$BCR = \frac{\sum_{t=1}^{H}\frac{B_t}{(1+r)^t}}{\sum_{t=1}^{H}\frac{C_t}{(1+r)^t}} \quad \dots \quad (9)$$

The (BCR>1) indicates a financially sustainable investment. Studies on intelligent road infrastructure management systems report that predictive maintenance can reduce lifecycle costs by 20–30% while significantly extending road service life and minimizing major reconstruction frequency (Asadi, 2025).

5.4. Reliability and Failure Prediction Models

Reliability analysis is required to estimate the probability that a road segment will continue to operate without failure over a specified time horizon. The random time to failure of a road section is denoted by T_f. The reliability function is therefore represented as in equation (10):

$$R(t) = P(T_f > t) \quad \dots \quad (10)$$

While the probability of failure is represented in equation (11):

$$P_f(t) = 1 - R(t) \quad \dots \quad (11)$$

In this study, for road deterioration, Weibull reliability model (Elmahdy, 2015) is adopted, a robust and versatile statistical technique for analysing time-to-failure data and predicting product lifespan, characterized by its capacity to model varying failure rate behaviours, including decreasing, constant, and increasing failure rates. The Weibull reliability model is depicted in equation (12):

$$R(t) = exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right] \quad \dots \quad (12)$$

where α is the characteristic life parameter and β is the shape parameter governing the failure trend.
Therefore, the corresponding failure rate, which represents the instantaneous probability of road failure, is given as in equation (13):

$$h(t) = \frac{\beta}{\alpha}\left(\left(\frac{t}{\alpha}\right)^{\beta-1}\right) \quad \ldots \quad (13)$$

A value of $\beta > 1$ indicates that the probability of failure increases as the road ages. The edge-cloud AI model will predict this failure probability in real-time and triggers maintenance once the predicted risk exceeds a predefined threshold P_f^{max}. Reliability-based maintenance decision rules therefore take the form:

$$\text{If } P_f(t) \geq P_f^{max}$$
$$\text{then initiate maintenance action}$$

The recent reliability-oriented road studies emphasize that probabilistic deterioration models provide more robust maintenance schedules than deterministic approaches because they explicitly account for uncertainty in traffic loads, material properties, and environmental conditions (Martyushev et al., 2023; Shanmugasundaram et al., 2024)

6. Proposed Edge-Cloud Artificial Intelligence Predictive Maintenance Model

6.1. Model Overview and Architecture

The proposed Edge-Cloud Artificial Intelligence (AI) Predictive Maintenance Model for road infrastructure is designed as a multi-layered, distributed architecture that integrates real-time sensing, localized edge analytics, and centralized intelligence. The conceptual model addresses critical limitations of traditional infrastructure maintenance systems, namely latency, bandwidth dependency, and delayed decision-making by shifting computational intelligence closer to the data source.
At its core, the architecture adopts a hierarchical paradigm consisting of interconnected layers: (i) Data Acquisition, (ii) Edge Processing, (iii) Artificial Intelligence/Machine Learning Analytics, (iv) Communication Network, (v) Cloud Integration, (vi) User Interface and Decision Support, and (vii) Feedback and Self-Learning. This layered design enables scalable, resilient, and low-latency operations, particularly suited for geographically distributed road networks in resource-constrained environments.
The model emphasizes real-time condition monitoring, anomaly detection, and predictive analytics to facilitate proactive maintenance scheduling, reduce lifecycle costs, and enhance road safety. By leveraging edge intelligence, the model ensures operational continuity even under intermittent connectivity conditions.

6.2. Data Acquisition Layer (Sensors, IoT Devices)

The data acquisition layer forms the foundational component of the model, responsible for continuous monitoring of road infrastructure conditions through a network of heterogeneous sensors and Internet of Things (IoT) devices. These include embedded pavement sensors (such as, strain gauges, accelerometers), environmental sensors (for temperature, humidity), and mobile sensing platforms such as vehicle-mounted cameras and smartphones.
Advanced sensing technologies such as Light Detection and Ranging (LiDAR), ground-penetrating radar (GPR), and high-resolution imaging systems can be integrated to capture structural and surface-level anomalies, including cracks, potholes, rutting, and deformation. Data streams are to be generated in high frequency and diverse formats (structured and unstructured), necessitating efficient preprocessing mechanisms.
To ensure data reliability and integrity, the layer incorporates calibration protocols, noise filtering, and redundancy mechanisms. The use of edge-compatible IoT devices will minimize power consumption while enabling continuous, autonomous data collection (Duan et al., 2022; Hemmati et al., 2024). The architecture of the proposed model is illustrated in Figure 3

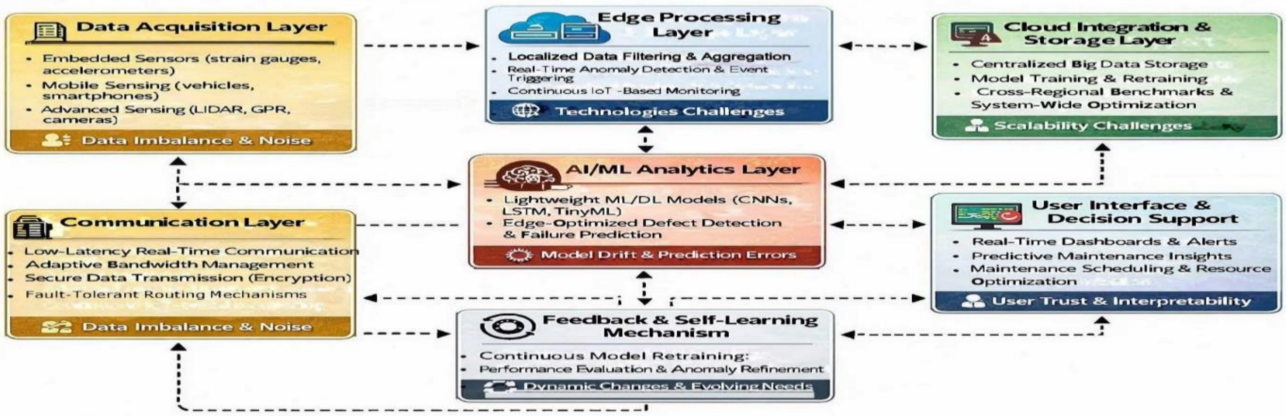

Figure 3. The Proposed Road Predictive Maintenance Model Architecture

The mode architecture provides a comprehensive depiction of the system's structural design. It elucidates the interactions among core components and outlines the integration of embedded technologies that collectively enable the effective operation of the edge–cloud artificial intelligence predictive maintenance model for road infrastructure management.

6.3. Edge Processing Layer (Real-Time Analytics)

The edge processing layer constitutes a critical component of the proposed model architecture, enabling localized data handling and real-time analytics while substantially reducing dependence on continuous cloud communication. Edge nodes, strategically deployed at roadside units and embedded within smart infrastructure, execute preliminary operations including data filtering, aggregation, and transformation. Core functionalities encompass data compression and normalization, real-time anomaly detection, event-driven processing, and latency-sensitive decision-making.

Positioned close to the road network, edge devices pre-process raw sensor data streams to minimize latency and optimize bandwidth utilization prior to transmission to cloud servers. This edge–cloud synergy is particularly vital in developing regions, where network connectivity may be intermittent and the need for rapid, context-aware maintenance decisions is paramount.

By shifting computational intelligence closer to the data source, the model will achieve ultra-low latency and enhanced bandwidth efficiency, facilitating the immediate detection of critical infrastructure anomalies. Supporting technologies such as edge gateways and micro data centres underpin this distributed computing paradigm, strengthening system resilience, scalability, and fault tolerance (Ergun et al., 2022).

6.4. AI/ML Layer (Prediction and Decision Models)

The AI/ML layer (Prediction and Decision Models) constitutes the intelligence core of the model, where predictive maintenance algorithms are deployed. This layer leverages machine learning (ML) and deep learning (DL) techniques to analyse historical and real-time data for forecasting road infrastructure degradation probabilities.

Several algorithms can be combined to improve predictive performance, including Convolutional Neural Networks (CNNs) for image-based defect detection, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for temporal degradation prediction, and Random Forests, Gradient Boosting, and Multilayer Perceptron for classification and risk assessment.

The algorithms will be optimized for edge deployment using lightweight architectures, such as TensorFlow Lite or TinyML to ensure computational efficiency without compromising accuracy. This layer estimates the probability that a road segment or structural component will exceed a critical deterioration threshold within a specified time horizon expressed in equation (14):

$$P(F_t) = f(X_{s,} X_{e,} X_h) \quad \ldots \quad (14)$$

where $P(F_t)$ denotes the probability of infrastructure failure at time (t), X_s represents sensor-derived variables, X_e denotes environmental and traffic variables, and X_h captures historical maintenance information.

Similarly, the remaining useful life (RUL) of a road segment is estimated using the equation (15):

$$RUL = T_f - T_c \quad \ldots \quad (15)$$

where T_f is the predicted time to failure and T_c is the current time.

These predictive outputs enable infrastructure managers to intervene before severe deterioration occurs, thereby reducing maintenance costs, minimizing traffic disruption, and improving road safety. Studies have shown that AI-enabled predictive maintenance systems can reduce maintenance expenditure by approximately 30% while significantly improving operational efficiency and infrastructure availability (Bitam et al., 2025).

6.5. Communication Layer (Network Infrastructure)

The communication layer facilitates seamless data transmission between edge devices, cloud systems, and user interfaces. It leverages a hybrid networking approach combining wireless technologies such as 5G or 6G, Long Range Wide Area Network (LoRaWAN), Narrowband Internet of Things (NB-IoT), and Wireless Fidelity (Wi-Fi) to ensure reliable connectivity across diverse geographical regions. Key design considerations include: Low-latency communication for real-time alerts, adaptive bandwidth management, secure data transmission using encryption protocols, and fault-tolerant routing mechanisms

This layer is to support both synchronous and asynchronous communication, enabling efficient data flow under varying network conditions. The integration of software-defined networking (SDN) is to further enhance network flexibility and scalability (Qureshi, Hussain & Jeon, 2020).

6.6. Cloud Integration and Storage Layer

While edge processing layer handles real-time processing, the cloud integration layer provides centralized storage, large-scale data analytics, and long-term model training capabilities. This hybrid edge-cloud architecture ensures optimal resource utilization. The functions of this layer include: Big data storage and management, model training and retraining using historical datasets, cross-regional analytics and benchmarking, and system-wide optimization.

Cloud platforms enable the aggregation of data from multiple edge nodes, facilitating advanced analytics and continuous improvement of AI models. The synergy between edge and cloud enhances system intelligence and scalability (Liu et al., 2026).

6.7. User Interface and Decision Support Systems

The user interface (UI) and decision support system (DSS) layer provides stakeholders, including engineers, policymakers, and maintenance teams with intuitive access to actionable insights. This layer integrates visualization tools, dashboards, and alert systems. The layer's key features include: Real-time monitoring dashboards, predictive maintenance alerts and notifications, geospatial visualization of road conditions, and maintenance scheduling and resource optimization tools.

The decision support system (DSS) translates the outputs of the predictive analytics engine into actionable maintenance decisions. Rather than simply identifying defects, the DSS prioritizes maintenance interventions according to urgency, cost, risk, traffic importance, and available resources. The model ranks road segments and infrastructure assets using a composite maintenance priority index. A model's generalized maintenance priority function is expressed in equation (16):

$$MPI = (\alpha R + \beta C + \gamma T + \delta S) \quad \ldots \quad (16)$$

where R represents risk severity, C denotes estimated maintenance cost, T indicates traffic criticality, S refers to structural condition, and α, β, γ, δ are weighting coefficients.

Using this prioritization model, the DSS can automatically recommend whether an asset requires immediate repair, preventive treatment, or total reconstruction. The model can also generate optimized maintenance schedules, allocate repair crews, estimate budget requirements, and simulate alternative intervention scenarios. When integrated with geographic information systems and dashboard interfaces, the DSS provides infrastructure managers with intuitive visualizations of road conditions and maintenance priorities across the network. Reinforcement learning and adaptive optimization may further improve decision quality by identifying the most cost-effective intervention strategy over time (Ong, Niyato & Yuen, 2020). Advanced DSS capabilities incorporate explainable AI (XAI) techniques, ensuring transparency and interpretability of model outputs. This enhances user trust and facilitates informed decision-making (Kostopoulos, Davrazos & Kotsiantis, 2024).

6.8. Feedback and Continuous Learning Mechanism

A defining feature of the proposed model is its continuous learning capability. Following each maintenance intervention, new operational data, inspection results, repair histories, and post-maintenance performance indicators are fed back into the model. This feedback loop enables the predictive algorithms to update themselves and improve their accuracy over time.

The continuous learning mechanism operates through periodic retraining, drift detection, and adaptive parameter adjustment. If the model identifies discrepancies between predicted deterioration and actual infrastructure performance, it recalibrates its weights and thresholds accordingly. Such adaptive learning is essential because road conditions evolve continuously due to changing climate patterns, traffic intensity, construction quality, and material aging. Without continuous updating, predictive models may become less reliable and produce inaccurate recommendations.

The model therefore supports a closed-loop intelligent maintenance cycle in which sensing, prediction, decision-making, intervention, and learning are repeatedly integrated. This approach enhances predictive precision, as well as strengthens long-term sustainability by extending asset life, reducing unnecessary maintenance, conserving resources, and supporting resilient transportation infrastructure. According to Li, He & Li (2024), continuous integration and deployment of AI models have been identified as critical enablers of next-generation intelligent maintenance systems.

Table 1 presents the comprehensive ecosystem of the proposed edge–cloud artificial intelligence (AI) predictive maintenance model for road infrastructure management. It outlines the model's architectural components (layers), their respective core functions, and the associated inputs and enabling technologies. Furthermore, the table explicates the underlying processing mechanisms and methodological approaches embedded within each layer, culminating in the corresponding outputs that collectively drive intelligent, data-driven maintenance decision-making.

Table 1. The Edge-Cloud AI Predictive Maintenance Model Ecosystem for Road Infrastructure

Model Component / Layer	Core Function	Key Inputs & Technologies	Processing Mechanisms / Methods	Outputs / Outcomes
Data Acquisition Layer (Sensors & IoT Devices)	Continuous real-time monitoring of road infrastructure conditions	Embedded pavement sensors (accelerometers), environmental sensors (temperature, humidity), mobile sensing (vehicles), LiDAR, GPR, high-resolution imaging systems	Data calibration, noise filtering, redundancy management, multi-modal data fusion, edge-enabled data capture	High-frequency heterogeneous datasets (structured & unstructured), raw defect indicators (cracks, potholes, deformation), environmental condition streams
Edge Processing Layer (Real-Time Analytics)	Localized preprocessing and real-time analytics for	Edge nodes, roadside units, micro data centres, IoT gateways	Data compression, normalization, event-triggered processing, anomaly detection, real-time	Ultra-low latency alerts, filtered/processed data, detected anomalies, bandwidth-optimized data streams

	rapid decision support		filtering, distributed computing	
AI/ML Layer (Prediction & Decision Intelligence)	Predictive modelling of infrastructure degradation and failure risk	Historical + real-time datasets, lightweight ML/DL frameworks (TensorFlow Lite, TinyML), CNN, LSTM, RNN, Random Forest	Feature extraction, deep learning-based defect detection, temporal forecasting, risk classification, model optimization for edge deployment	Predictive maintenance outputs (failure probability, severity scoring, degradation forecasting, intervention timing, prioritization maps)
Communication Layer (Network Infrastructure)	Seamless and secure data transmission across edge-cloud-user systems	5G, LoRaWAN, NB-IoT, Wi-Fi, SDN-enabled networking infrastructure	Low-latency routing, adaptive bandwidth allocation, encrypted transmission, fault-tolerant communication, hybrid synchronous/ asynchronous data exchange	Reliable data transfer, real-time alerts dissemination, resilient connectivity, network-optimized data exchange
Cloud Integration & Storage Layer	Centralized storage, large-scale analytics, and long-term model training	Cloud platforms, data lakes, distributed storage systems, historical datasets	Big data analytics, model training/retraining, cross-regional benchmarking, system-wide optimization, edge-cloud orchestration	Long-term predictive models, aggregated infrastructure intelligence, large-scale insights, optimized AI model updates
User Interface & Decision Support System (UI/DSS)	Visualization, interpretation, and decision facilitation for stakeholders	Dashboards, GIS tools, visualization engines, alert systems, explainable AI (XAI) modules	Data visualization, explainability modelling, decision rule engines, geospatial mapping, predictive alert generation	Actionable insights, maintenance schedules, real-time dashboards, geospatial road health maps, interpretable AI decisions
Feedback & Self-Learning Mechanism	Continuous system adaptation and performance improvement	Multi-layer feedback signals, maintenance records, user inputs, environmental updates	Reinforcement learning, continuous retraining, adaptive threshold tuning, error correction, performance evaluation loops	Self-optimizing system behaviour, improved prediction accuracy, adaptive models, evolving maintenance strategies

7. Discussion

7.1. Key Insights

The integration of edge-based artificial intelligence with predictive maintenance represents a paradigm shift in how urban road infrastructure resilience can be achieved. Traditional reactive maintenance models, where interventions are initiated only after a failure are inherently inefficient, costly, and disruptive to mobility and safety. AI-driven predictive maintenance (PdM), particularly when deployed at the network edge, enables real-time interpretation of heterogeneous sensor data, early detection of structural degradation, and accurate forecasting of component failures before they manifest as service interruptions or hazardous conditions. Prior work demonstrates that edge AI can forecast equipment degradation using lightweight models and multimodal sensing inputs, significantly reducing latency and communication overhead compared to centralized cloud approaches, while maintaining high predictive accuracy in real-world conditions (Sharanya et al., 2022)

By processing data locally, edge AI reduces reliance on distant cloud servers, addressing latency, bandwidth, and privacy concerns that can undermine centralized models, especially in safety-critical domains such as transport infrastructure. This aligns with current evidence that edge computing within smart city ecosystems enhances decision-making speed at the point of data generation, improves system resilience under degraded networks, and supports continuous, context-aware analysis across distributed assets (Velaga et al., 2025). These insights confirm the feasibility and added value of embedding intelligent PdM capabilities directly into roadside infrastructure nodes rather than solely at remote data centres.

7.2. Practical Implications for Smart Cities

This study demonstrates the practical implications of deploying an edge-based AI predictive maintenance model for road infrastructure are profound, including:

(1) **Real-Time Operational Intelligence:** By enabling inference on or near assets (e.g., sensors positioned within road pavements, traffic cabinets, or vehicle-mounted nodes), cities can detect anomalies such as road surface cracks, potholes, drainage failures, or signalling malfunctions in near real time, rather than relying on periodic manual inspections or delayed cloud analytics (Zhumadillayeva et al., 2025)

(2) **Asset Life-Cycle Optimization:** Predictive insights support prioritization of maintenance interventions based on risk and remaining useful life estimates, thus optimizing expenditure, reducing unplanned outages, and extending infrastructure lifespan. This is particularly critical for agencies with constrained budgets and complex asset portfolios.

(3) **Enhanced Mobility and Safety:** Low-latency edge analytics contribute to smoother traffic flows and safer travel environments by avoiding abrupt maintenance closures and enabling dynamic rerouting informed by real-time asset health data.

(4) **Data Governance and Citizen Trust:** On-device analytics mitigates the need to transmit raw personal or geospatial data to central servers, offering privacy advantages that align with responsible smart city data governance frameworks.

Combined, these benefits help transition smart cities from reactive maintenance operations to proactive, data-driven infrastructure management strategies that are both efficient and citizen-centric.

7.3. Policy and Governance Considerations

Implementing edge-AI PdM at city scale introduces non-trivial policy and governance dimensions that must accompany technological deployment, including

(1) **Regulatory Alignment on Data Flows:** Smart infrastructure solutions, especially those that integrate heterogeneous data streams and cross-sector systems must comply with local privacy frameworks and interoperability standards. Policymakers should define clear rules for permissible data flows, minimum anonymization requirements, and retention schedules to uphold civil liberties while enabling predictive analytics (Velaga et al., 2025).

(2) **Model Auditability and Liability:** The distributed nature of edge inference complicates traditional governance approaches. When autonomous predictive models influence maintenance decisions or safety critical alerts, authorities need mechanisms for model provenance tracking, auditability, and clear delineation of responsibilities across municipal agencies, vendors, and operators.

(3) **Procurement and Standardization:** Public procurement policy can mandate baseline interoperability, explainability, and security practices for edge AI solutions. Standardization of metadata for models and sensor interfaces is vital for cross-vendor system cohesion and long-term sustainability.

These considerations emphasize the need for governance frameworks that balance innovation with accountability, ensuring that smart infrastructure systems remain transparent and responsive to civic expectations.

7.4. Scalability and Deployment Challenges

Despite promising advantages, the scalability and practical deployment of edge AI predictive maintenance models face several challenges:

(1) **Computational and Energy Constraints:** Edge nodes often operate under limited hardware resources and power budgets. Designing lightweight AI models that strike an optimal balance between predictive accuracy, inference speed, and energy consumption remains a core research challenge. Techniques such as model compression, quantization, and dynamic inference scheduling are necessary to meet operational constraints without compromising performance (Liu et al., 2025).

(2) **Heterogeneous Sensor Integration:** Road networks comprise diverse sensor types and communication protocols, leading to data heterogeneity that complicates fusion across modalities. Failure to align multiple data sources can undermine model robustness and generalizability.

(3) **Network Reliability and Synchronization:** Edge systems must deal with intermittent connectivity and timing discrepancies among distributed devices. Ensuring consensus and synchronization across a dispersed sensor field is crucial for temporal coherence and timely anomaly detection (Velaga et al., 2025).

(4) **Validation at Scale:** Current studies often demonstrate predictive maintenance solutions at small scale or in controlled environments. Advancing these systems requires large-scale field validation across varied climatic, traffic, and infrastructure conditions to ensure models remain robust over time. Addressing these challenges is essential for widespread adoption, requiring interdisciplinary collaboration between AI researchers, infrastructure engineers, city planners, and policymakers.

8. Conclusion and Future Research Directions

8.1. Summary of Findings

This study proposed a comprehensive conceptual model for an edge-cloud artificial intelligence (AI) predictive maintenance model tailored to road infrastructure systems. The model integrates distributed edge computing, real-time data acquisition from heterogeneous sources (e.g., IoT sensors, vehicular data, and remote sensing), and advanced machine learning algorithms to enable proactive detection of road deterioration. By decentralizing data processing and embedding intelligence closer to the data source, the model addresses critical limitations of traditional centralized systems, including latency, bandwidth constraints, and delayed decision-making.

The findings underscore the transformative potential of edge-based AI in enhancing infrastructure resilience, operational efficiency, and cost-effectiveness. The model is designed to facilitate near real-time analytics, enabling early identification of defects such as cracks, potholes, and structural weaknesses, thereby reducing maintenance backlogs and preventing catastrophic failures. Furthermore, the integration of human-centred interfaces within the architecture supports informed decision-making by infrastructure managers and policymakers, bridging the gap between technical outputs and actionable insights.

Overall, the study demonstrates that combining edge computing with AI-driven predictive maintenance offers a scalable and context-sensitive solution, particularly suited to resource-constrained and rapidly urbanizing regions where infrastructure demands are intensifying.

8.2. Contributions to Knowledge

This research makes several significant contributions to the existing body of knowledge in intelligent infrastructure management. First, it advances the conceptual understanding of predictive maintenance by introducing a novel edge-centric architectural paradigm that shifts computation from centralized cloud environments to distributed edge nodes. This paradigm enhances system responsiveness and reliability, contributing to the growing discourse on decentralized AI systems in smart infrastructure.

Second, the study presents an integrated, multi-layered framework that unifies data acquisition, edge analytics, machine learning inference, and decision-support mechanisms within a single coherent model. Unlike existing approaches that often treat these components in isolation, this work emphasizes their interdependencies, thereby offering a holistic perspective on the design and deployment of intelligent maintenance systems.

Third, the research contributes to practical and policy-oriented discussions by highlighting the model's applicability in diverse socio-economic contexts, including developing regions. It provides a foundation for aligning technological innovation with sustainable infrastructure development goals, emphasizing efficiency, scalability, and adaptability. In doing so, the study bridges theoretical advancements with real-world implementation considerations, positioning edge-cloud AI as a critical enabler of next-generation road asset management systems.

8.3. Recommendations for Future Research

While the proposed conceptual model provides a robust foundation, several avenues for future research remain open. Empirical validation of the framework through pilot implementations and real-world case studies is essential to assess its operational feasibility, performance metrics, and cost-benefit implications. Future studies should focus on deploying prototype systems across varied geographic and environmental conditions to evaluate robustness, scalability, and adaptability under dynamic constraints.

Further research is also needed to refine machine learning models for improved accuracy, interpretability, and generalization across different road types and degradation patterns. This includes exploring advanced techniques such as federated learning, transfer learning, and hybrid AI models that can operate efficiently within resource-constrained edge environments. Additionally, addressing data-related challenges, such as data quality, heterogeneity, and standardization remains a critical priority for ensuring reliable model performance.

Finally, future investigations should examine broader systemic and interdisciplinary considerations, including cybersecurity risks in edge networks, ethical implications of AI-driven decision-making, and governance frameworks for data sharing and infrastructure management. Integrating emerging technologies such as digital twins and autonomous inspection systems could further enhance the model's capabilities. By addressing these research directions, scholars and practitioners can accelerate the transition from conceptual frameworks to fully operational, intelligent road maintenance ecosystems that are resilient, sustainable, and responsive to evolving infrastructure demands.

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