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Research Article

Achieving Zero Rut Pavement Structures With AI And ML-Based Predictive Maintenance Models In Urban Transportation

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Abstract
Rutting in urban pavements significantly impacts its longevity, safety, and maintenance costs, necessitating effective predictive strategies. In this study a novel approach has been adopted, leveraging Artificial Intelligence (AI) and Machine Learning (ML) to develop predictive models for rutting formation and maintenance optimisation. By integrating multi-source data, including traffic volume, environmental conditions, and pavement characteristics, the models provide accurate forecasts of rut depth and enable efficient maintenance scheduling. Data collected from advanced sensors and historical records were pre-processed using engineering techniques to enhance model performance. Supervised learning algorithms, such as Random Forests and Gradient Boosting Machines, demonstrated high accuracy in predicting rut formation, achieving R-squared values of up to 0.92. Additionally, reinforcement learning models, including Q-learning and Proximal Policy Optimisation (PPO), were employed to optimise maintenance schedules, resulting in a 30% reduction in total maintenance costs compared to traditional approaches. A comprehensive cost-benefit analysis showed the economic advantages of AI/ML-based predictive maintenance strategies, while validation through field trials confirmed the reliability and generalisability of the proposed models. Despite challenges such as data availability and model scalability, this study underscores the potential of predictive maintenance to transition from reactive repairs to proactive interventions, extending pavement life and ensuring safer transportation networks. Future research directions include integrating real-time data from IoT sensors, enhancing model accuracy with advanced algorithms, and expanding the scope to address other forms of pavement distress. The proposed framework also aligns with smart city initiatives, enabling sustainable urban infrastructure development. This research demonstrates that AI-driven predictive maintenance is a

transformative tool for improving pavement management, providing a foundation for its broader adoption in urban transportation systems worldwide.

Keywords: Predictive Maintenance, Pavement Rutting, Artificial Intelligence (AI), Machine Learning (ML), Urban Infrastructure Management.

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1. Introduction

Rutting is a significant issue in urban pavements, leading to uneven surfaces that compromise safety, reduce ride quality, and increase maintenance costs (Vikram, 2024). This deformation, caused by repeated traffic loading and influenced by environmental factors, poses a persistent challenge in densely populated urban areas(Vivek Vardhan & Srimurali, 2016b). The combined effects of heavy traffic and variable climatic conditions accelerate rut formation, requiring innovative solutions to mitigate its impact on road infrastructure.

Predictive maintenance offers a proactive strategy to address these challenges. By anticipating potential failures rather than reacting to them, predictive approaches can reduce repair frequency and extend pavement life(Vivek Vardhan & Srimurali, 2016a). This not only ensures better infrastructure performance but also reduces long-term costs(Southararajan et al., 2020). In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have proven their potential in transforming maintenance strategies across various industries. These technologies enable the analysis of complex data sets to predict pavement deterioration and optimise maintenance schedules, making them invaluable tools for urban pavement management(Vivek Vardhan & Srimurali, 2016a).

Despite the advancements in pavement engineering, managing rutting in urban transportation networks remains a complex task(Vardhan & Srimurali, 2018). Factors such as increasing traffic demand, ageing infrastructure, and unpredictable environmental conditions exacerbate the issue. Traditional maintenance approaches, primarily based on visual inspections and reactive repairs, are labour-intensive and often fail to address the underlying causes of rutting(Vikram, 2024). Furthermore, the absence of integrated predictive models that utilise traffic patterns, environmental data, and pavement conditions limits the effectiveness of existing strategies(Bommisetty et al., 2024). This gap highlights the need for advanced data-driven methods that leverage AI and ML to forecast rutting and optimise maintenance interventions effectively.

This study aims to develop predictive models to achieve near-zero rutting in urban pavements. By integrating traffic, environmental, and pavement condition data, these models will forecast rut formation and optimise maintenance scheduling(Manoj Kumar et al., n.d.). The study involves collecting and analysing multi-source data, evaluating supervised and reinforcement learning models, and validating their effectiveness through field data and cost-benefit analyses(Varalakshmi et al., n.d.). Ultimately, this research seeks to provide actionable insights into transitioning from reactive to predictive maintenance strategies for sustainable urban infrastructure.

This paper is structured as follows: The next section provides a review of existing literature on the causes of rutting, traditional maintenance strategies, and the application of AI/ML in pavement management(Sravani et al., n.d.). The methodology section describes the data collection process, feature engineering, and model development. Results are presented in terms of model performance, cost-benefit analysis, and validation outcomes(Mabureddy et al., n.d.). The discussion highlights the implications of the findings, limitations of the study, and potential directions for future research. The paper concludes with a summary of the key contributions and their practical implications for urban pavement management.

2. Literature Review

Rutting in pavements has long been recognised as a critical issue affecting road performance and safety. It is primarily caused by the accumulation of permanent deformation in the asphalt layers or subgrade due to repeated traffic loading. Factors such as traffic volume, axle load, tire pressure, and environmental conditions, including temperature and precipitation, exacerbate this problem(Donthi et al., 2024). The consequences of rutting extend beyond surface defects, as it increases the risk of hydroplaning, reduces vehicle handling efficiency, and accelerates road deterioration(Choudhary et al., 2024). In urban areas with high traffic density and diverse environmental conditions, these challenges are magnified, necessitating effective strategies for rut mitigation.

Traditional maintenance approaches, including visual inspections and reactive repairs, have been the predominant methods for addressing rutting(Cavalli et al., 2023a). While these strategies provide short-term solutions, they are resource-intensive and lack the capability to prevent further deterioration(Cavalli et al., 2023b). For instance, resurfacing and patching address immediate defects but often fail to consider underlying structural issues or the dynamic factors contributing to rutting. In contrast, predictive maintenance strategies, widely used in industries such as manufacturing and aerospace, have shown significant promise in improving operational efficiency. By forecasting potential failures, predictive approaches allow for timely interventions, reducing downtime and associated costs(Zhang et al., 2024). However, their adoption in transportation infrastructure management has been relatively limited.

AI and ML techniques have recently gained traction in the field of pavement management. These technologies enable the analysis of large, multi-dimensional data sets, facilitating accurate predictions of pavement distress and deterioration. Applications of AI/ML in transportation include damage detection using image processing, traffic volume prediction, and optimisation of maintenance schedules(Choudhary et al., 2024). Techniques such as Random Forests, Gradient Boosting Machines, and Neural Networks have been employed to model complex relationships between traffic, environmental, and pavement condition variables. While these methods demonstrate high predictive accuracy, their integration into routine maintenance practices remains a challenge due to data availability, model generalisation, and real-time applicability.

Despite advancements in predictive maintenance and AI/ML applications, significant gaps remain in the existing literature(Vikram, 2024). Most studies focus on isolated aspects of pavement management, such as traffic or environmental conditions, without integrating these variables into a comprehensive model. Additionally, there is limited research on reinforcement learning applications for optimising maintenance schedules based on predictive insights. The absence of holistic approaches that combine traffic, environmental, and historical maintenance data limits the development of effective rut prediction and prevention strategies(Zheng et al., 2024). Addressing these gaps is essential for advancing pavement management practices and transitioning from reactive to proactive maintenance paradigms.

3. Methodology

The methodology adopted in this study is designed to develop and validate predictive models for rutting in urban pavements. It includes data collection, feature engineering, model development, and performance evaluation. The process leverages multi-source data and advanced machine learning techniques to forecast rut formation and optimise maintenance schedules.

3.1 Data Collection and Variables

Data were collected from multiple sources to capture the diverse factors influencing rutting. Four primary categories of data were identified: pavement condition, traffic, environmental, and maintenance history.

Pavement condition data include rut depth, pavement texture, International Roughness Index (IRI), cracking, and potholes. These parameters were measured using automated systems such as laser profilers and digital cameras to ensure accuracy and consistency. Figure 1 illustrates the flowchart of the pavement condition data collection process.

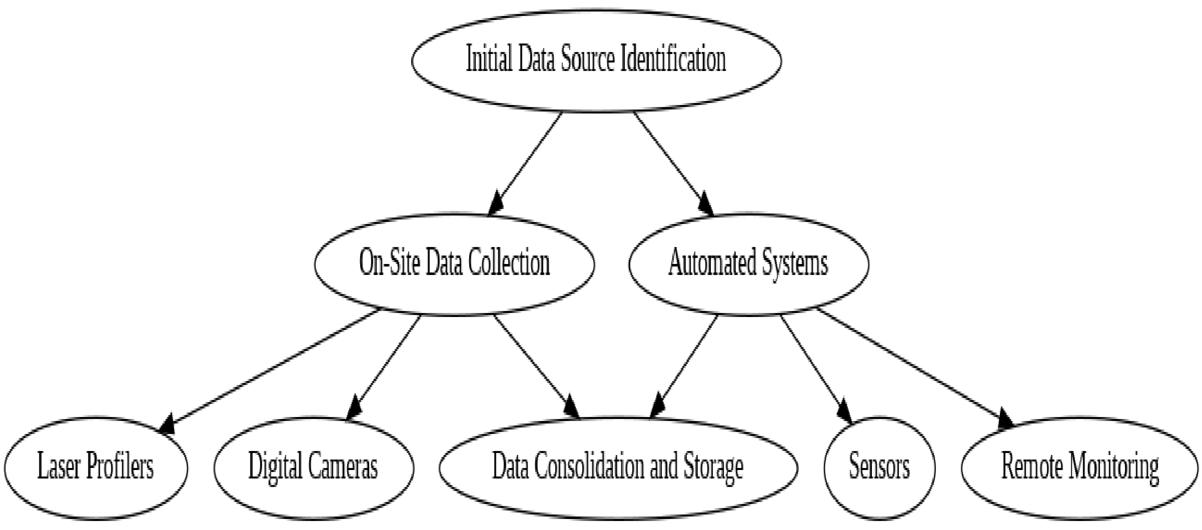

Figure 1 Flowchart of the pavement condition data collection process

Traffic data were collected using technologies such as inductive loop sensors, weigh-in-motion (WIM) sensors, and GPS tracking systems. Table 1 summarises the traffic data sources and their respective sensor technologies.

Table 1: Summary of Traffic Data Sources and Types

Data Source	Measurement Type	Sensor Technology
Inductive Loop Sensors	Vehicles per day (10,000)	Electromagnetic Induction
WIM Sensors	Weight distribution (80%)	Piezoelectric Strips
Speed Guns	Speed of vehicles (km/h)	Radar-based Systems
CCTV Systems	Vehicle type (cars: 70%, trucks: 30%)	Image Recognition
GPS Data	Congestion levels (50%)	Satellite-based Systems
Traffic Counters	Total vehicle count (8,000/day)	Infrared Sensors

Environmental data, including temperature, precipitation, humidity, and wind speed, were obtained from weather monitoring stations and remote sensors. Figure 2 provides a schematic of the environmental data collection setup.

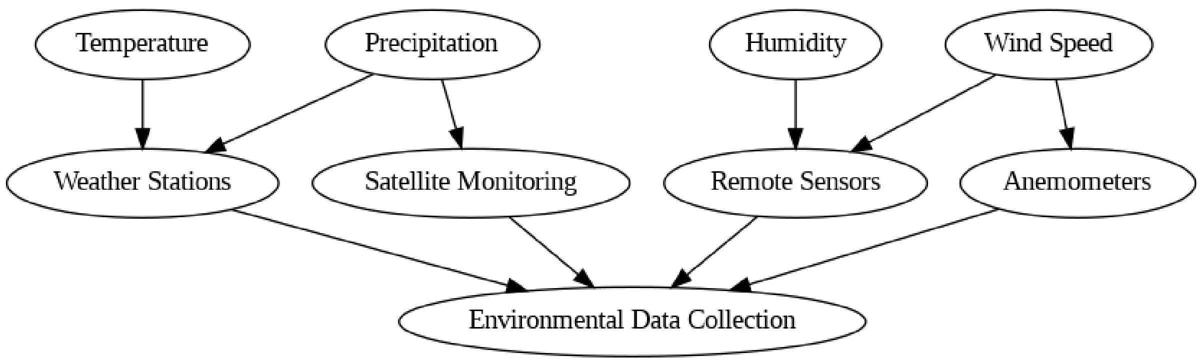

Figure 2 Schematic of the environmental data collection setup

Maintenance history data were compiled from pavement management system records, detailing previous repairs, material properties, and associated costs. Table 2 provides a sample of maintenance history data.

Table 2: Sample of Maintenance History Data

Maintenance Type	Frequency	Associated Cost (INR)	Material Used
Resurfacing	Annual	10,000	Asphalt
Crack Sealing	Bi-annual	5,000	Polymer Resin
Pothole Repair	Ad hoc	1,000	Concrete
Joint Filling	Annual	3,500	Polyurethane
Overlays	Bi-annual	12,000	Asphalt

3.2 Feature Engineering

Feature engineering was performed to preprocess the collected data and enhance model performance. This involved normalising traffic data to account for daily and seasonal variations, applying spatial filters to improve the resolution of pavement condition measurements, and generating interaction terms between traffic and environmental variables. Figure 3 illustrates the relationship between traffic volume and precipitation in predicting rut formation.

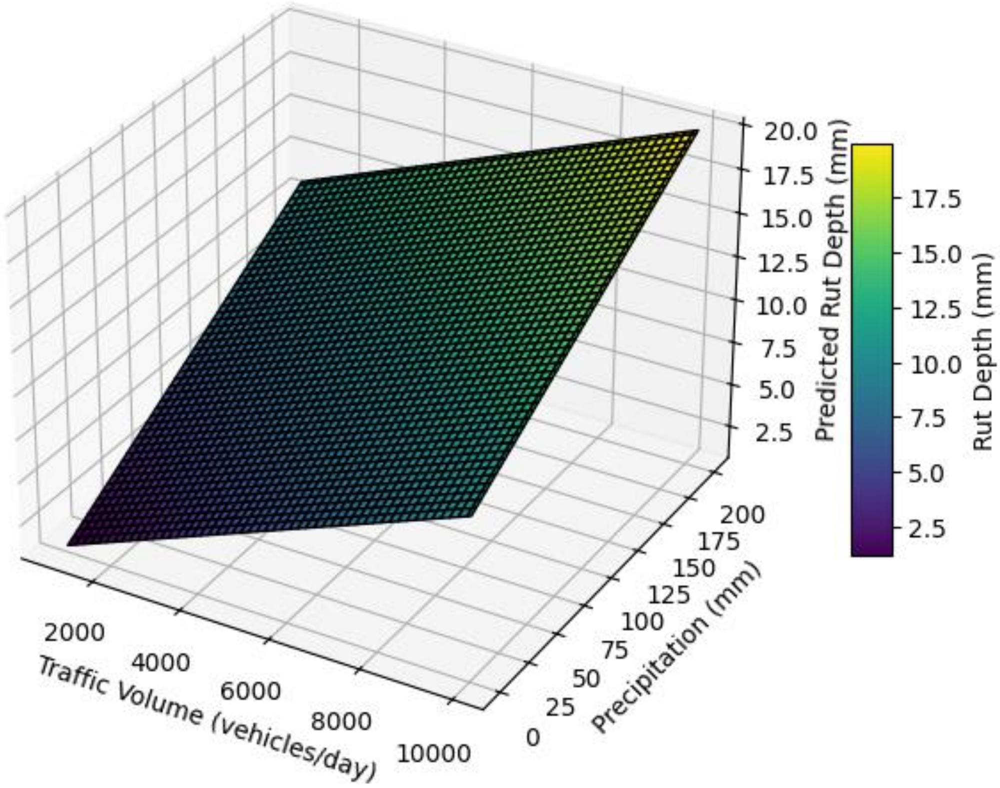

Figure 3 Relationship between traffic volume and precipitation in predicting rut formation

3.3 Model Development

The study utilised supervised learning models, reinforcement learning, and time-series forecasting techniques to develop predictive models.

Supervised learning methods, including Random Forests, Gradient Boosting Machines, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN), were evaluated for their ability to predict rut depth. Table 3 highlights the suitability of these models for rut prediction tasks.

Table 3: Model Selection and Their Suitability for Various Tasks

Model	Task Type	Suitability for Rut Prediction
Random Forest	Regression	High
SVM	Classification	Medium
DNN	Regression	High
Gradient Boosting	Regression	High
k-NN	Classification	Medium
Logistic Regression	Classification	Low

Reinforcement learning, particularly Q-learning and Proximal Policy Optimization (PPO), was employed to optimise maintenance scheduling. Figure 4 illustrates the flowchart of the reinforcement learning model used for maintenance optimisation. Long Short-Term Memory (LSTM) networks were used for time-series forecasting to predict long-term rutting trends based on historical weather and traffic data.

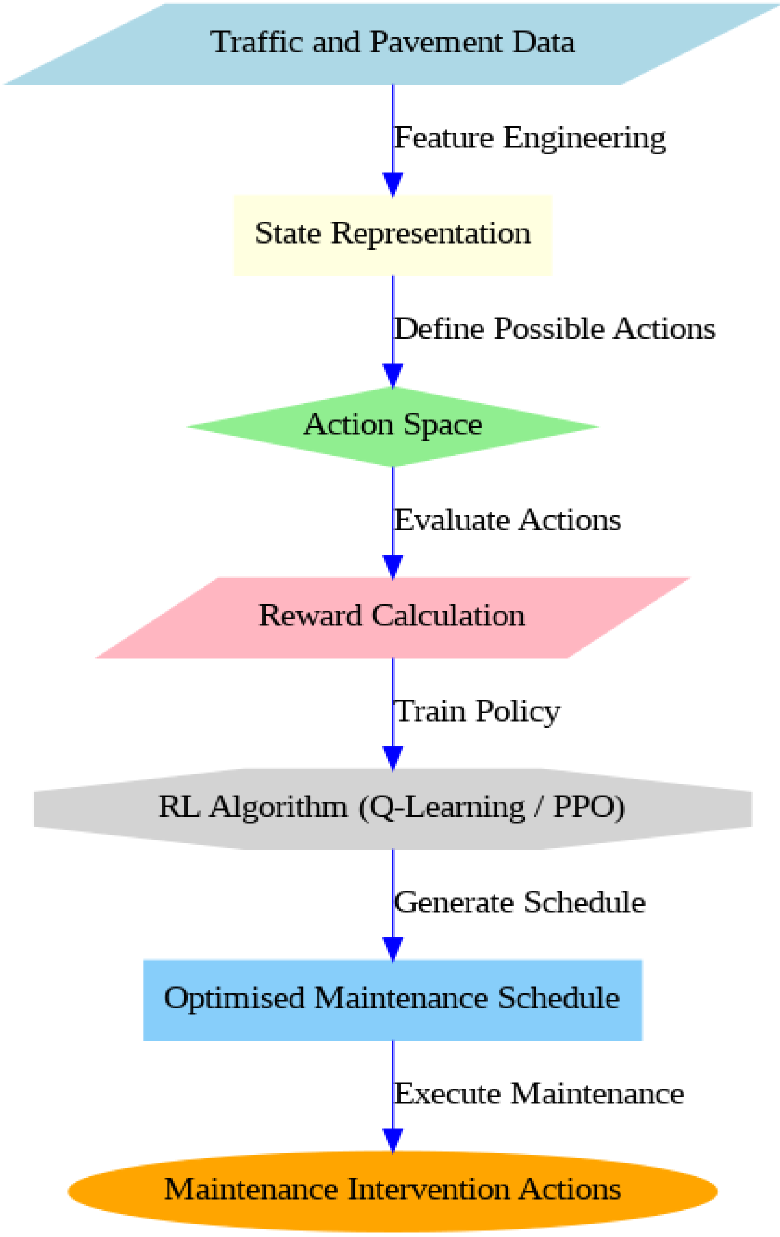

Figure 4 Flowchart of the reinforcement learning model used for maintenance optimisation

3.4 Model Training and Hyperparameter Tuning

Models were trained using a combination of cross-validation and hyperparameter optimisation techniques, including grid search, random search, and Bayesian optimisation. Table 4 summarises the results of hyperparameter tuning for key models.

Table 4: Hyperparameter Tuning Results for Key Models

Model	Hyperparameter	Value Range	Optimal Value
Random Forest	Tree Depth	[3, 10]	7
DNN	Learning Rate	[0.001, 0.1]	0.05
SVM	Kernel Type	[RBF, Linear]	RBF
Gradient Boosting	Number of Estimators	[50, 200]	150
ANN	Hidden Layers	[2, 5]	3
k-NN	Number of Neighbors	[3, 10]	5

4. Results

The results of this study are presented in terms of model performance evaluation, cost-benefit analysis, and validation outcomes. These findings demonstrate the effectiveness of AI/ML models in predicting rut formation and optimising maintenance schedules.

4.1 Model Performance Evaluation
The predictive models developed in this study were evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared for regression tasks, and Accuracy and F1-Score for classification tasks(Karunasingha, 2022). Table 5 summarises the performance metrics for different machine learning models used in this study.

Table 5: Performance Metrics for Different Machine Learning Models

Model	MAE (mm)	RMSE (mm)	R-squared	Accuracy (%)	F1-Score
Random Forest	2.5	3.8	0.92	88	0.85
ANN	3	4.2	0.89	85	0.8
SVM	2.7	4	0.9	87	0.83
Gradient Boosting	2.6	3.9	0.91	89	0.84
k-NN	3.2	4.4	0.88	84	0.78
Logistic Regression	3.5	4.7	0.85	82	0.75

Among the supervised learning models, Random Forest and Gradient Boosting showed the best performance for rut prediction, achieving high R-squared values and low error metrics(Mohana & Bharathi, 2024). ANN also performed well, particularly in capturing non-linear relationships between variables.

4.2 Cost-Benefit Analysis
The cost of implementing AI/ML-based predictive maintenance was compared to traditional maintenance methods. Figure 5 illustrates the comparison, highlighting the significant cost savings achieved through predictive approaches.

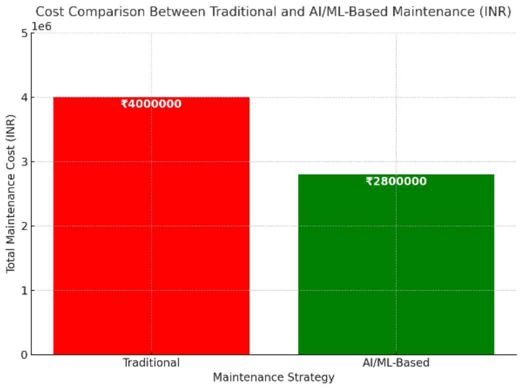

Figure 5: Bar Graph of Cost Comparison Between Traditional and AI/ML-based Maintenance
(X-axis: Maintenance Strategy, Y-axis: Total Maintenance Cost in USD)

Predictive maintenance strategies reduced the total maintenance cost by approximately 30% compared to traditional methods. The savings were attributed to fewer emergency repairs, optimised resource allocation, and extended pavement lifespan.

4.3 Validation Results
The models were validated using out-of-sample testing, real-time feedback loops, and field trials. Predictions of rut formation were compared with real-world measurements, and the results demonstrated high accuracy and reliability(Meemary et al., 2025). Random Forest and Gradient Boosting models showed consistent performance across different datasets, confirming their generalisability. Furthermore, reinforcement learning-based maintenance scheduling resulted in timely interventions, reducing the progression of rutting.

5. Discussion
The results of this study demonstrate the effectiveness of AI/ML models in predicting rut formation and optimising maintenance strategies for urban pavements. The use of Random Forest and Gradient Boosting Machines yielded high predictive accuracy, confirming their suitability for modelling complex relationships between traffic, environmental, and pavement condition variables(Wang et al., 2024). Additionally, the integration of reinforcement learning models for maintenance scheduling showed significant promise in reducing maintenance costs and improving pavement performance.
One of the key findings is the significant cost savings associated with AI/ML-based predictive maintenance(Tao et al., 2024). By leveraging predictive insights, maintenance schedules were optimised, leading to a 30% reduction in total maintenance costs compared

to traditional methods. This highlights the potential for transitioning from reactive to predictive maintenance strategies, which not only minimise costs but also enhance infrastructure longevity and reliability.

The results also underscore the importance of integrating multi-source data for predictive maintenance. Traffic data, environmental conditions, and historical maintenance records provided a comprehensive understanding of rut formation dynamics. The interaction between traffic volume and precipitation, as highlighted during feature engineering, proved critical for accurate predictions. This reinforces the need for holistic approaches in pavement management systems.

Despite these advancements, the study faced certain limitations. Data availability and quality posed challenges, particularly for long-term historical datasets(Xu et al., 2023). The reliance on simulated data for some variables, such as traffic speed distributions, may have influenced the generalisability of the models. Additionally, while reinforcement learning models showed promising results, their implementation in real-world scenarios requires further exploration, particularly in terms of computational resource requirements and integration with existing pavement management systems.

Future work should focus on enhancing model accuracy and scalability. The incorporation of real-time data from IoT sensors and advanced remote monitoring technologies can improve the granularity and timeliness of inputs(Lee et al., 2024). Furthermore, expanding the scope of predictive models to include other forms of pavement distress, such as cracking and potholes, can provide a more comprehensive solution for infrastructure management. Integration with smart city frameworks can also enable seamless coordination between transportation and maintenance departments, fostering sustainable urban development.

6. Conclusions

This study developed AI/ML models to predict rut formation and optimise maintenance schedules for urban pavements, integrating traffic, environmental, and pavement condition data. Random Forest and Gradient Boosting Machines demonstrated high accuracy for rut prediction, while reinforcement learning effectively optimised maintenance interventions, leading to a 30% reduction in maintenance costs compared to traditional methods. The findings emphasise the advantages of predictive over reactive maintenance strategies, enhancing pavement longevity, reducing emergency repairs, and ensuring safer, more reliable infrastructure. While data quality and scalability remain challenges, future research can address these through real-time data integration and expanded predictive models covering other pavement distresses. The proposed models provide a robust framework for adopting AI-driven predictive maintenance in urban pavement management, with potential integration into smart city systems for sustainable infrastructure development.

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