Research Article

A Data-driven Framework for Automated Pavement Maintenance Strategy Generation: A Case Study of Florid

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Abstract

Road infrastructure in climate-sensitive regions such as the Southeastern United States faces increasing risks under climate change. Intense rainfall, hurricanes, storm surges, and freeze–thaw cycles accelerate pavement deterioration and disrupt roadway functionality. Developing adaptive and transparent maintenance strategies is therefore essential for sustaining performance and enhancing resilience. Current pavement management systems rely on static knowledge bases and empirical rules, which limits flexibility and interpretability. This study proposes a data-driven framework that combines Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) to generate context-aware and interpretable pavement maintenance strategies. A comprehensive knowledge base was constructed using Long-Term Pavement Performance (LTPP) data, Florida Department of Transportation manuals, regional climate information, and historical maintenance records. Structured indicators such as Annual Average Daily Truck Traffic, precipitation, and freeze index guided the retrieval process. Given pavement distress, climate, and traffic conditions, the RAG module retrieved relevant cases and technical standards, enabling the LLM to produce evidence-based recommendations. Validation on 30 pavement sections in Florida achieved an exact prediction accuracy of 76.7% with 23 correct classifications. Predictions were dominated by Mill and Overlay (15 cases, 50%) and Surface Treatment (9 cases, 30%), followed by Patch Repair (3 cases, 10%), Rigid Pavement Repair (2 cases, 6.7%), and Thin Overlay (1 case, 3.3%). Crack Sealing and Recycled Treatment were not predicted. The framework showed strong performance for structural and surface renewal actions, while preventive strategies remain underrepresented. Generated reports included condition summaries, historical references, recommendations, and assumptions, which improved interpretability and partially reduced the risk of hallucination compared with traditional black-box models. The proposed framework provides a replicable decision-support tool that improves accuracy, adaptability, and interpretability in pavement management, contributing to infrastructure resilience and sustainable transportation planning.

Keywords: Pavement Maintenance, Large Language Model (LLM), Retrieval-Augmented Generation (RAG), LTPP, Climate Resilience, Data-driven Decision Making, Florida

Highlights

- Develops a retrieval-augmented knowledge base integrating multi-dimensional LTPP data on climate, traffic, performance, and maintenance.
- Implements a standardized classification scheme that consolidates 23 actions into 7 categories, enhancing balance and interpretability.
- Demonstrates an LLM-RAG framework that generates age-sensitive, interpretable, and case-informed pavement maintenance recommendations.

1 Introduction

Pavement infrastructure is a critical component of global transportation networks, yet pavement maintenance management systems (PMS) face mounting challenges from aging assets, climate variability, and increasing traffic loads (Faris et al., 2023; Piryonesi & El-Diraby, 2021). Traditional PMS relies on deterministic deterioration models, expert judgment, and decision trees to schedule Maintenance and Repair (M&R) activities (Basnet et al., 2023; Khichad & Vishwakarma, 2024). While these approaches provide baseline functionality, they often lack adaptability, consistency, and scalability under evolving conditions (Gong, Dong, Huang, & Jia, 2015; Marcelino, Antunes, Fortunato, & Gomes, 2021).

The Long-Term Pavement Performance (LTPP) program, initiated in the 1980s, has transformed pavement research by providing over 30 years of systematically collected performance, climate, and traffic data across diverse environments (Chen, Deng, Li, & Shi, 2023; Younos, Abd El-Hakim, El-Badawy, & Afify, 2020) Although widely used in deterioration and prediction models, most studies emphasize prediction accuracy rather than interpretable decision support that practitioners can directly implement.

Recent advances in artificial intelligence, particularly Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG), present new opportunities. LLMs can generate context-aware, human-interpretable outputs, while RAG grounds these outputs in verified engineering knowledge, mitigating black-box concerns (Wang, Liu, Lu, & Jia, 2025; Siddharth & Luo, 2024). Unlike traditional case-based reasoning (CBR), which relies solely on similarity-based retrieval, the LLM-RAG approach combines generative reasoning with historical precedents to deliver transparent and traceable recommendations.

Despite advances in predictive modeling and artificial intelligence applications, current PMS still lack an integrated framework that can: (1) leverage historical cases from comprehensive datasets such as LTPP; (2) provide transparent, explainable recommendations consistent with engineering judgment; (3) generate standardized, professional outputs suitable for integration with agency workflows.

To address these shortcomings, this study proposes a LLM-RAG framework that embeds multidimensional pavement records into a vector database, retrieves relevant historical cases, and generates professional-grade maintenance reports using structured LLM prompts. Its contributions are reflected in three aspects:

1) Constructing a retrieval-enhanced knowledge base that integrates climate, traffic, structural, and performance attributes from LTPP.
2) Implementing a standardized seven-category maintenance classification system to consolidate different historical processing methods into actionable categories consistent with industry practices.
3) Demonstrating an explainable recommendation framework that has been validated against historical engineering decisions, highlighting its potential for real-world application.

2 Literature Review

2.1 Pavement Performance Prediction with LTPP Data

Numerous studies have leveraged the LTPP dataset to build pavement deterioration and performance models. Gong et al. (2015) evaluated preventive maintenance treatments across multiple climates, showing their long-term benefits. Marcelino et al. (2021) applied machine learning to forecast pavement conditions, marking a shift from deterministic to data-driven models. Younos et al. (2020) and Zhang & Wang (2023) further integrated traffic, climate, and geospatial analyses, identifying key factors influencing rutting and cracking. More recently, Chen et al. (2023) employed a long-and-short-term memory network with attention mechanisms to achieve high-accuracy predictions, highlighting the growing importance of deep learning with large-scale LTPP data. Despite these advancements, most models prioritize prediction accuracy over decision-making interpretability.

2.2 Case-Based Reasoning and Historical Knowledge in Maintenance Decisions

Case-Based Reasoning (CBR) has long been recognized as a promising approach for maintenance planning. Chou (2008) introduced an AHP-based CBR system for pavement cost estimation, while L. Li & Wang (2012) applied CBR to rehabilitation strategy selection. Abu Dabous et al. (2022) advanced this line of research by integrating CBR with Random Forests to improve case retrieval accuracy, demonstrating robust performance with LTPP data. Similar approaches were applied in building retrofit, where Y. Li, Du, & Kumaraswamy (2024) confirm the broader applicability of case-informed reasoning. These studies underscore the value of leveraging historical maintenance records for decision support, though scalability and integration with modern AI remain underexplored.

2.3 Retrieval-Augmented Generation in Engineering Domains

The RAG framework has recently gained traction in engineering knowledge management. Siddharth & Luo (2024) demonstrated its use in design knowledge retrieval, while Wang et al. (2025)developed a hybrid RAG framework combining embeddings and graph search for building lifecycle queries. These works highlight RAG's ability to ground LLM responses in verified domain knowledge, mitigating hallucinations. Applications in infrastructure remain nascent, though early examples, Deng et al. (2024) show that RAG-enhanced LLMs can act as maintenance advisors, converting predictive alerts into prescriptive recommendations.

2.4 Artificial Intelligence and LLMs in Pavement Maintenance

AI has steadily advanced in pavement management, from computer vision-based maintenance detection (Xiong, Zayed, & Abdelkader, 2024) to AI-enabled strategy reviews (Basnet et al., 2023). The recent introduction of LLMs into pavement maintenance is groundbreaking. Oguntoye et al. (2025) employed ChatGPT-4 to classify M&R records and improve prediction models, while Deng et al. (2024) used an LLM agent with RAG to generate maintenance recommendations. These pioneering efforts illustrate the feasibility of LLM-driven maintenance systems, though systematic frameworks that integrate structured datasets like LTPP with RAG-enhanced LLM reasoning are still lacking.

The literature reveals a clear evolution in pavement management approaches, from deterministic models to sophisticated AI systems. However, three critical gaps persist:(1) While LTPP-based models provide predictive capabilities and CBR systems offer precedent-based reasoning, no existing framework systematically integrates these complementary approaches with modern AI capabilities. (2) Advanced machine learning models achieve high prediction accuracy but lack the transparency required for professional engineering decision-making, particularly in maintenance strategy selection, where justification is crucial. (3)Existing AI applications in pavement management generate ad-hoc outputs that are difficult to integrate with established pavement management workflows and reporting standards. This study addresses these gaps by developing an integrated LLM-RAG framework that combines the predictive power of LTPP data with the interpretability of case-based reasoning and the reasoning capabilities of modern AI, generating standardized professional outputs suitable for practical implementation.

3 Methodology

This study adopts a quantitative, data-driven research design to develop and validate a Retrieval-Augmented Generation (RAG) enhanced Large Language Model (LLM) for pavement maintenance strategy recommendation. Unlike traditional decision support systems, which rely on deterministic deterioration models and rule-based decision trees, this framework leverages historical precedents and AI reasoning to provide transparent, interpretable, and standardized recommendations. The methodology consists of three stages: (i) data collection and preprocessing, (ii) development of the RAG-enhanced LLM framework, and (iii) evaluation through training and validation experiments. Figure 1 provides an overview of the methodological framework, while the following subsections describe each component in detail.

3.1 Data Collection and Process

The dataset used in this study is derived from the Long-Term Pavement Performance (LTPP) program, a comprehensive pavement monitoring database covering road sections across North America. To support the development of the proposed framework, five modules were selected from the LTPP dataset: pavement basic information, climate, traffic, pavement performance, and maintenance records.

The variables were carefully chosen to represent the key factors influencing pavement condition and maintenance decisions. Specifically, the basic information module provides state code, pavement type, construction number, and structural layer material and thickness. The climate module includes precipitation, freeze–thaw cycles, temperature indicators, wind speed, humidity, and solar radiation. The traffic module covers annual average daily truck traffic (AADTT) and cumulative axle load measures (kESAL). The performance module contains pavement roughness (MRI/IRI), rutting, and multiple cracking indices for both flexible (AC) and rigid (PCC) pavements. Finally, the maintenance module records maintenance type, thickness, material, and layer information. A detailed variable dictionary is provided in Table 1 (Appendix).

To reduce data sparsity and improve robustness, the 23 original maintenance actions in the LTPP dataset were consolidated into seven standardized categories: Crack Sealing, Patch Repair, Surface Treatment, Thin Overlay, Recycled Treatment, Mill and Overlay, and Rigid Pavement Repair. This consolidation was based on technical characteristics and functional similarity, aligned with FDOT practices and AASHTO guidelines, ensuring that the categories remain operationally meaningful while minimizing noise from rarely applied treatments. A mapping of original actions to the seven categories is shown in Table 2 (Appendix).

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Table 3 Pavement type distribution in training and validation sets

Pavement Type	Historical Cases	Validation Cases	Total

AC	95	27	122
PCC	15	3	18
Total	110	30	140

3.2 Development of RAG-enhanced Pavement Maintenance LLM

Intelligent pavement maintenance decision-making has become a critical requirement for ensuring transportation infrastructure resilience under climate change and traffic loading. This research proposes an LLM-based pavement maintenance framework built upon RAG. Figure 1 illustrates the overall workflow of the proposed RAG-enhanced pavement maintenance framework. Historical pavement records, including basic information, climate, traffic, performance, and maintenance features, are embedded and stored in a vector database. When a new pavement case is queried, the system performs a similarity search and metadata filtering to identify the most relevant historical cases. These retrieved cases, along with the contextual features of the current pavement section, are then passed into the LLM through a structured prompt. The LLM processes the input and generates a standardized maintenance recommendation report that specifies the most suitable maintenance category, confidence score, technical justification, and assumptions or limitations. This workflow ensures that the framework leverages both quantitative data and historical precedents, producing recommendations that are interpretable, transparent, and aligned with engineering practice. The framework is composed of three modules: (i) Vector Database, (ii) Retrieval Component, and (iii) Generation Component.

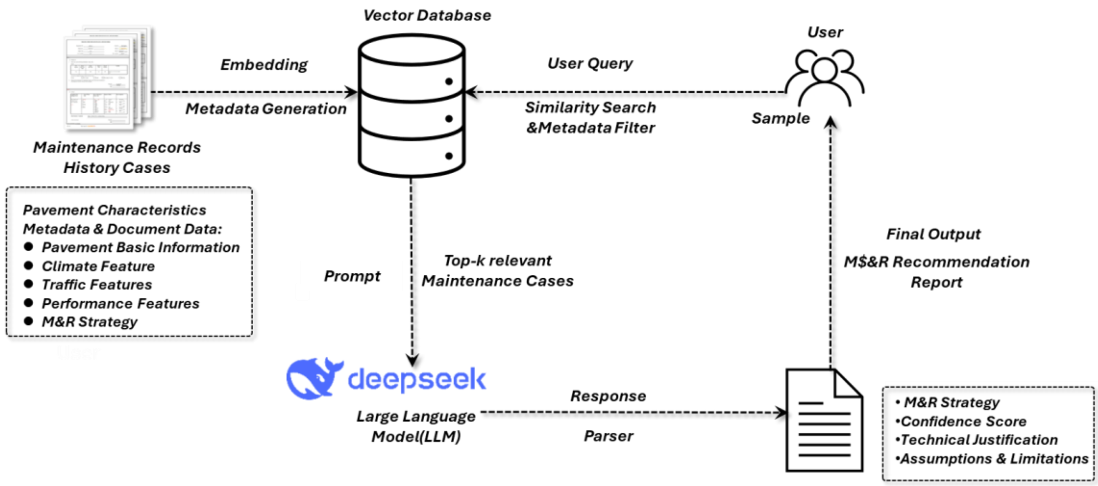

Figure 1. Framework of the RAG-enhanced LLM for Pavement Maintenance Strategy Generation

3.2.1 Vector Database

The vector database, established from historical pavement sections and their maintenance records, acts as an external knowledge base for the LLM. It facilitates the matching of historical cases with current pavement conditions by embedding features from five modules: basic information, climate, traffic, pavement performance, and maintenance records. Specifically, the database integrates variables such as pavement type, age, base/subbase materials, precipitation, freeze–thaw cycles, AADTT, rutting, and cracking indices, as summarized in Table 1 (Appendix).

To reduce sparsity and complexity, the original 23 maintenance actions in the LTPP dataset are consolidated into seven standardized categories, including —Crack Sealing, Patch Repair, Surface Treatment, Thin Overlay, Recycled Treatment, Mill and Overlay, and Rigid Pavement Repair, based on technical characteristics and functional similarity (Table 2 (Appendix)). This classification ensures balanced data distribution, enhances prediction robustness, and aligns with practical maintenance management practices.

3.2.2 Retrieval Component

The retrieval component is responsible for similarity search. Each new pavement case is processed into a compact document embedding that captures its essential features. Using cosine similarity as the primary metric, the system retrieves the top-K most relevant historical cases (K=3 in this study). Both the feature vectors and contextual metadata (e.g., pavement type, age, climate conditions) of the retrieved cases are passed to the LLM as comparative benchmarks.

3.2.3 Generation Component

The generation component is developed to consist of a structured prompt template and the LLM. The engineered prompt template guides the LLM by providing explicit instructions that shape both input processing and output generation. These instructions ensure consistency, interpretability, and technical alignment with pavement management practices.

Table 4 (Appendix) illustrates the designated prompt template for pavement maintenance recommendations. The parameters contained in the braces {} are placeholders that dynamically change according to the input data. Initially, the system captures and organizes the basic information of the pavement section. This includes the section ID, year of record, pavement type, age, and structural characteristics, as well as climate indicators (temperature, precipitation, freeze–thaw cycles), traffic loadings (ESAL, AADTT), and current performance measures such as roughness, rutting, and cracking. In addition to these direct indicators, the template incorporates relevant historical maintenance cases retrieved from the knowledge base. This comparative approach enriches the context for the LLM, enabling it to leverage both quantitative thresholds and past precedents to improve decision-making.

To ensure clarity and transparency, the LLM is instructed to generate its outputs in a structured JSON format. The output dictionary contains several key elements:

(1) Primary Maintenance Category: One of the seven standardized actions.

(2) Confidence Score: A numerical measure of certainty in the prediction.

(3) Technical Justification: A concise explanation linking the recommendation to climate, traffic, performance conditions, and historical references.

(4) Assumptions and Limitations: Explicit notes on data quality, missing variables, or the need for field verification.

This framework ensures that the recommendations are not only data-driven but also professionally interpretable, providing engineers with transparent and context-aware maintenance strategies that align with best practices.

3.3 Evaluation

The framework was validated on 30 pavement sections using accuracy of predicted maintenance categories as the primary metric. Results were compared with historical decisions, and incorrect predictions were analyzed to identify common patterns. While the dataset size constrains statistical generalization, the evaluation demonstrates the feasibility, interpretability, and practical alignment of the proposed framework, laying the foundation for future large-scale testing.

4 Results

The RAG+LLM framework was validated on 30 pavement sections and achieved an accuracy of 76.7% (23/30 cases), comparable to baseline rule-based decision matrices. Reports were structured and interpretable, including condition summaries, historical case references, technical justifications, and explicit assumptions, ensuring transparency and practical usability.

Predicted categories showed a preference for structural and renewal measures: mill and overlay (15, 50%), surface treatment (9, 30%), patch repair (3, 10%), rigid repair (2, 6.7%), and thin overlay (1, 3.3%). Crack sealing (0/2) and recycled treatment (0/1) were never predicted, and the thin overlay was also misclassified (0/2 correct). These results highlight the framework's strength in mainstream practices but its limited ability to recommend preventive or innovative actions.

Error analysis showed that most of the 7 misclassifications occurred in underrepresented categories, confirming the impact of dataset imbalance. Additionally, borderline performance thresholds (e.g., roughness and rutting) contributed to errors. Environmental and traffic variables influenced outcomes logically: high rainfall, frequent freeze–thaw, and heavy traffic increased structural recommendations, while low-traffic sections received more preventive or surface treatments. Performance thresholds also acted as decisive cutoffs, with higher roughness/rutting leading to structural interventions. Each case was processed in under 5 seconds, showing good computational efficiency.

5 Discussion

The framework aligns with established pavement management practices: overlays dominate mid-life pavements, while patch and rigid repair address localized or structural needs. However, preventive measures such as crack sealing and thin overlays were not predicted, and recycled treatments were absent. This reflects both imbalanced LTPP data and the framework's reliance on performance thresholds, which bias results toward corrective actions once deterioration is evident.

This limitation is critical for practice, as agencies rely on preventive strategies to extend service life and optimize budgets. Without such coverage, the framework risks favoring costlier interventions. Future work should address this by balancing training data, refining retrieval weighting, and incorporating lifecycle stage constraints to improve preventive treatment recognition.

Despite this gap, the framework showed strong interpretability and transparency, clearly explaining recommendations and assumptions. Combined with its computational efficiency, this highlights potential for integration into PMS workflows.

6 Conclusions

This study developed and validated an RAG-LLM framework for standardized pavement maintenance strategy generation. Key findings are:

1. 76.7% prediction accuracy across 30 validation cases, comparable to traditional PMS.
2. Predictions dominated by mill and overlay (50%) and surface treatment (30%), consistent with practice.
3. Decisions logically incorporated age, climate, traffic, and performance indicators.
4. Reports were structured, interpretable, and supported by historical case references.

Limitations include the absence of crack sealing (0/2), thin overlay (0/2), and recycled treatments (0/1), simplified environmental and traffic inputs, and a small validation set. Future work should expand preventive and innovative coverage, refine inputs, and scale validation.

Overall, the framework demonstrates strong potential for intelligent, interpretable, and standardized pavement maintenance planning, with both academic and practical value.

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Data Availability Statement

All pavement data used in this study are publicly available through the Long-Term Pavement Performance (LTPP) database maintained by the Federal Highway Administration (FHWA) at https://infopave.fhwa.dot.gov/. The processing scripts and analysis codes developed in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest related to the publication of this work.

7 Appendix

Table1Variable dictionary

Type	Name of Input Variable	Variable Source
Basic Information	State Code	STATE_CODE
	Pavement Age	Calculation based on CONSTRUCTION_NO
	Pavement Type	AC / PCC / Combination
	Material of Base	MATL_CODE_EXP
	Material of Subbase	MATL_CODE_EXP
	Thickness of Base/Subbase	REPR_THICKNESS
Climate Information	Precipitation	PRECIPITATION
	Freeze–Thaw Cycles	FREEZE_THAW
	Thermal Indicators	TEMP_AVG, TEMP_MEAN_AVG, DAYS_ABOVE_32_C, DAYS_BELOW_0_C, FREEZE_INDEX
	Wind	WIND_VELOCITY_AVG, WIND_VELOCITY_MAX
	Humidity	HUM_AVG_AVG, HUM_AVG_MAX, HUM_AVG_MIN
	Radiation	SHORTWAVE_SURFACE_AVG, EMISSIVITY_AVG
Traffic Information	AADTT (Annual Average Daily Truck Traffic)	AADTT_ALL_TRUCKS_TREND
	kESAL (Cumulative Equivalent Single Axle Loads)	ANNUAL_ESAL_TREND, ANNUAL_GESAL_TREND
	Roughness (IRI/MRI)	MRI

Pavement Performance	Rutting	MAX_MEAN_DEPTH_1_8
	Cracking – Flexible (AC)	HPMS16_CRACKING_PERCENT_AC, MEPDG_CRACKING_PERCENT_AC, MEPDG_TRANS_CRACK_LENGTH_AC, MEPDG_LONG_CRACK_LENGTH_AC, ME_PERCENT_WHEEL_PATH_CRACK
	Cracking – Rigid (JPCC)	HPMS16_CRACKING_PERCENT_JPCC, MEPDG_CRACKING_PERCENT_JPCC, ME_PERCENT_CRACKED_SLABS
Maintenance Information	Maintenance Type	Maintenance Category
	Maintenance Thickness	IMP_THICKNESS
	Maintenance Material	MATL_CODE_EXP
	Maintenance Layer	LAYER_NO

Table2 simplified maintenance classification.

Maintenance Measure	Specific Measure
Crack Sealing	Transverse Joint Sealing
	Lane–Shoulder Longitudinal Joint Sealing
	Crack Sealing
	Manual Premix Spot Patch
	Patch Potholes (Hand Spread, Compacted with Truck)
	Full Depth Patch of AC Pavement
	Partial Depth Patching of PCC Pavement Other Than at Joint
	Full Depth Patching of PCC Pavement Other Than at Joint
Surface Treatment	Aggregate Seal Coat
	Slurry Seal Coat
	Surface Treatment – Single Layer
	Surface Treatment – Double Layer
Thin Overlay	Asphalt Concrete Overlay
	Thin Hot-Mix Overlay
Recycled Treatment	Hot-Mix Recycled Asphalt Concrete Overlay
	Warm-Mix Recycled Asphalt Concrete Overlay
	Cold In-Place Recycling
Mill and Overlay	Mill Off AC and Overlay
	Mill Existing Pavement and Overlay with Hot-Mix Recycled AC
	Mill Existing Pavement and Overlay with Warm-Mix Recycled AC
Rigid Pavement Repair	PCC Slab Replacement
	Full Depth Transverse Joint Repair Patch
	Grinding Surface

Table 4 The prompt for pavement maintenance recommendations

Prompt

```
{
  "Section ID": "{SHRP_ID}_{ID}_{Year}",
  "Year": "{Year}",
  "Report Date":"{current date}",
  "Condition Summary": {
    "Climate Traffic": "Comprehensive 2-3 sentence analysis of climate conditions (temperature, precipitation, freeze-thaw) and traffic loading (ESAL, AADTT) impacts on pavement deterioration.",
    "Roughness Deterioration": "Detailed assessment of current performance status including MRI, rutting depth, and cracking patterns with performance thresholds evaluation.",
    "Pavement Context": "Summary of pavement type, age, structural characteristics, and maintenance history context affecting treatment selection."
  },
  "Historical Reference": {
    "Relevant cases ID": ["List of 3 most relevant historical case IDs"],
    "Relevant Records Summary": "Summary of historical cases with similar pavement type, age, climate, and traffic conditions, focusing on applied treatments and effectiveness.",
    "Relevance Reason": "Technical explanation of why selected cases are applicable, including quantitative similarity in key parameters (age ±5 years, similar climate zone, comparable traffic loading)."
  },
  "Recommended Maintenance Plan": {
    "Maintenance": [
      "SELECT EXACTLY ONE FROM: Crack Sealing, Surface Treatment, Thin Overlay, Recycled Treatment, Mill and Overlay, Patch Repair, Rigid Pavement Repair"],
    "Justification": "Technical justification linking current conditions to recommended treatment, referencing performance thresholds, historical case outcomes, and engineering best practices. Include quantitative analysis where possible.",
    "Age_Appropriateness": "Specific analysis of why the recommended treatment is suitable for the pavement's current age, considering remaining service life and cost-effectiveness."
  },
  "Assumptions Limitations": "Clear statement of analysis assumptions, data limitations, and recommendations for field verification or additional testing."
}
```

8 References

Abu Dabous, S., Hamad, K., Al-Ruzouq, R., Zeiada, W., Omar, M., & Obaid, L. (2022). A case-based reasoning and random forest framework for selecting preventive maintenance of flexible pavement sections. *The Baltic Journal of Road and Bridge Engineering*, *17*(2), 107–134. https://doi.org/10.7250/bjrbe.2022-17.562

Basnet, K. S., Shrestha, J. K., Shrestha, R. N., Basnet, K. S., Shrestha, J. K., & Shrestha, R. N. (2023). Pavement performance model for road maintenance and repair planning a review of predictive techniques. *Digital Transportation and Safety*, *2*(DTS-2023-0021), 253–267. https://doi.org/10.48130/DTS-2023-0021

Chen, C., Deng, Y., Li, M. Y., & Shi, X. M. (2023). Investigation of key climatic factors affecting asphalt pavement roughness in different climate regions. *TRANSPORTATION RESEARCH PART D-TRANSPORT AND ENVIRONMENT*, *122*. https://doi.org/10.1016/j.trd.2023.103877

Chou, J.-S. (2008). Applying AHP-based CBR to estimate pavement maintenance cost. *Tsinghua Science and Technology*, *13*(S1), 114–120. https://doi.org/10.1016/S1007-0214(08)70136-6

Deng, H., Namoano, B., Zheng, B., Khan, S., & Ahmet Erkoyuncu, J. (2024). From prediction to prescription: Large language model agent for context-aware maintenance decision support. *Phm Society European Conference*, *8*(1), 10. https://doi.org/10.36001/phme.2024.v8i1.4114

Faris, N., Zayed, T., Abdelkader, E. M., & Fares, A. (2023). Corrosion assessment using ground penetrating radar in reinforced concrete structures: Influential factors and analysis methods. *Automation in Construction*, *156*, 105130. https://doi.org/10.1016/j.autcon.2023.105130

Gong, H., Dong, Q., Huang, B., & Jia, X. (2015). *Effectiveness analyses of flexible pavement preventive maintenance treatments with LTPP SPS-3 experiment data*. Retrieved from https://ascelibrary.org/doi/10.1061/%28ASCE%29TE.1943-5436.0000818

Khichad, J. S., & Vishwakarma, R. J. (2024). Overview and discussion of pavement performance prediction techniques for maintenance and rehabilitation decision-making. *International Journal of Pavement Research and Technology*. https://doi.org/10.1007/s42947-024-00435-x

Li, L., & Wang, K. C. P. (2012). *Strategies for flexible pavement rehabilitation based on case-based reasoning | proceedings | vol , no*. Retrieved from https://ascelibrary.org/doi/10.1061/41167%28398%294

Li, Y., Du, H., & Kumaraswamy, S. B. (2024). Case-based reasoning approach for decision-making in building retrofit: A review. *Building and Environment*, *248*, 111030. https://doi.org/10.1016/j.buildenv.2023.111030

Marcelino, P., Antunes, M. de L., Fortunato, E., & Gomes, M. C. (2021). Machine learning approach for pavement performance prediction. *Taylor & Francis*. (world). Retrieved from https://www.tandfonline.com/doi/abs/10.1080/10298436.2019.1609673

Oguntoye, K. S., Ceylan, H., Kim, S., Sourav, A. A., Gulmezoglu, B., Mo, Y., & Candidate, P. D. (n.d.). *Automatic pavement maintenance predictions using large language and machine learning models*.

Piryonesi, S. M., & El-Diraby, T. (2021). Climate change impact on infrastructure: A machine learning solution for predicting pavement condition index. *Construction and Building Materials*, *306*, 124905. https://doi.org/10.1016/j.conbuildmat.2021.124905

Siddharth, L., & Luo, J. (2024). Retrieval augmented generation using engineering design knowledge. *Knowledge-Based Systems*, *303*, 112410. https://doi.org/10.1016/j.knosys.2024.112410

Wang, Z., Liu, Z., Lu, W., & Jia, L. (2025). Improving knowledge management in building engineering with hybrid retrieval-augmented generation framework. *Journal of Building Engineering*, *103*, 112189. https://doi.org/10.1016/j.jobe.2025.112189

Xiong, C., Zayed, T., & Abdelkader, E. M. (2024). A novel YOLOv8-GAM-Wise-IoU model for automated detection of bridge surface cracks. *Construction and Building Materials*, *414*, 135025. https://doi.org/10.1016/j.conbuildmat.2024.135025

Younos, M. A., Abd El-Hakim, R. T., El-Badawy, S. M., & Afify, H. A. (2020). Multi-input performance prediction models for flexible pavements using LTPP database. *Innovative Infrastructure Solutions*, *5*(1), 1–11. https://doi.org/10.1007/s41062-020-0275-3

Zhang, K., & Wang, Z. (2023). LTPP data-based investigation on asphalt pavement performance using geospatial hot spot analysis and decision tree models. *International Journal of Transportation Science and Technology*, *12*(2), 606–627. https://doi.org/10.1016/j.ijtst.2022.06.007