Libyan Journal of Ecological & Environmental Sciences and Technology
(LJEEST)
LJEEST
ISSN: 2710-5237
www.srcest.org.ly/jou

DOI: https://doi.org/10.63359/wneskv24

Development of an AI-Based Predictive Model for Flexible Pavement and Its Response to Climate Change in Arid and Semi-Arid Regions

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ARTICLE INFO

Vol. 8 No. 1 April, 2026

Pages (65- 73)

Article history:
Revised form 07 December 2026
Accepted 31 January 2026

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Keywords:
Predictive Modeling , Artificial Intelligence , Flexible Pavement, Climatic Factors

ABSTRACT

Climate change poses significant risks to pavement performance, especially in arid and semi-arid regions where extreme temperatures, variable rainfall, and heavy traffic loads accelerate deterioration. Traditional models, such as the Long-Term Pavement Performance (LTPP) framework, often rely on U.S.-centric datasets and mechanistic-empirical assumptions that may not accurately represent local conditions in regions like Libya. To address this gap, we developed the Pavement Life Prediction Tool (PLPT), an AI-based decision-support system designed to classify flexible pavement failure risk levels (low, medium, high) using climatic and structural variables, including road age, rainfall, traffic volume, soil type, asphalt mix, and maximum temperature. The model applies supervised machine learning techniques specifically, a Decision Tree classifier and Logistic Regression to predict the decline in Pavement Condition Index (PCI) over a 5–30-year horizon without maintenance. Results show consistent classification performance across both algorithms, with soil properties, traffic volume, and maximum temperature emerging as dominant predictors of pavement life. These findings align with recent studies that highlight the reliability of AI approaches for pavement condition modeling and the importance of climate-sensitive adaptation strategies in infrastructure planning. By localizing predictive modeling to Libya's climatic context, PLPT offers policymakers and transport authorities a practical tool to anticipate deterioration risks, optimize maintenance schedules, and enhance the resilience of road networks under climate variability.

تطوير نموذج تنبؤي قائم على الذكاء الاصطناعي للأرصفة المرنة واستجابتها لتغيّر المناخ في المناطق الجافة وشبه الجافة

رحاب رمضان سودان، سارة محمد موسى، محمود الهادي أبوقرين، هدى يونس الإدريسي

تغيّر المناخ يفرض مخاطر كبيرة على أداء الأرصفة، خصوصًا في المناطق الجافة وشبه الجافة حيث تؤدي درجات الحرارة القصوى، وتفاوت معدلات الأمطار، وأحمال المرور الثقيلة إلى تسريع التدهور. النماذج التقليدية مثل إطار الأداء طويل الأمد للأرصفة (LTPP) غالبًا ما تعتمد على قواعد بيانات متمركزة في الولايات المتحدة وافتراضات ميكانيكية–إمبريقية قد لا تعكس بدقة الظروف المحلية في مناطق مثل ليبيا. لمعالجة هذه الفجوة، قمنا بتطوير أداة التنبؤ بعمر الأرصفة(PLPT) ، وهي نظام دعم قرار قائم على الذكاء الاصطناعي صُمّم لتصنيف مستويات مخاطر فشل الأرصفة المرنة (منخفضة، متوسطة، عالية) باستخدام متغيرات مناخية وبنيوية تشمل عمر الطريق، معدل الأمطار، حجم المرور، نوع التربة، خليط الأسفلت، ودرجة الحرارة القصوى. يعتمد النموذج على تقنيات التعلم الآلي الموجّه، تحديدًا مصنّف شجرة القرار والانحدار اللوجستي، للتنبؤ بانخفاض مؤشر حالة الأرصفة (PCI) خلال أفق زمني يتراوح بين 5–30 سنة دون صيانة. أظهرت النتائج أداءً ثابتًا في التصنيف عبر كلا الخوارزميتين، حيث برزت خصائص التربة، حجم المرور، ودرجة الحرارة القصوى كعوامل رئيسية للتنبؤ بعمر الأرصفة. تتماشى هذه النتائج مع دراسات حديثة تؤكد موثوقية الأساليب المعتمدة على الذكاء الاصطناعي في نمذجة حالة الأرصفة وأهمية استراتيجيات التكيّف الحساسة للمناخ في تخطيط البنية التحتية. ومن خلال توطين النمذجة التنبؤية في السياق المناخي لليبيا، تقدّم أداة PLPT لصنّاع القرار والسلطات المعنية بالنقل وسيلة عملية للتنبؤ بمخاطر التدهور، تحسين جداول الصيانة، وتعزيز مرونة شبكات الطرق في مواجهة تقلبات المناخ.

INTRODUCTION

Climate change poses significant challenges to the durability and sustainability of civil infrastructure. Rising temperatures, shifting rainfall patterns, and increasing frequency of extreme weather events are accelerating the deterioration of pavements worldwide, leading to higher maintenance costs and safety concerns (Mallick *et al*, 2014). Flexible pavements in arid and semi-arid regions are particularly vulnerable because they are exposed to prolonged heat, occasional intense rainfall, and high traffic volumes. These stressors accelerate rutting, cracking, and surface degradation, threatening the resilience of transport networks and, by extension, economic stability and mobility in affected regions.

Although decision-makers increasingly recognize these risks, tools to assess climate-related pavement deterioration remain limited. Traditional predictive models such as the Long-Term Pavement Performance (LTPP) framework and the Highway Development and Management model (HDM-4) rely heavily on U.S. and global datasets and often emphasize mechanistic-empirical methods (Chen *et al*., 2019). While these models provide valuable insights, their assumptions and calibrations are not easily transferable to the climatic and geotechnical conditions of North Africa and other arid zones. This gap highlights the urgent need for locally adapted models that can integrate climate and structural data to support more accurate predictions.

Recent advances in artificial intelligence (AI) and machine learning (ML) have opened new opportunities for pavement performance modeling. AI methods, particularly supervised learning algorithms, can identify non-linear relationships among climatic, traffic, and material properties, offering more accurate and cost-effective predictions than traditional regression-based approaches (Gopalakrishnan, 2020). Studies applying ML to pavement management have demonstrated strong predictive performance in estimating the Pavement Condition Index (PCI) and deterioration trends, underscoring the growing relevance of these techniques in infrastructure planning (Piryonesi & El-Diraby, 2021)[3]. However, most such applications remain concentrated in high-income countries, leaving a gap in the literature for arid and semi-arid regions

This study addresses that gap by developing the Pavement Life Prediction Tool (PLPT), an AI-based predictive model tailored to the Libyan context. The tool integrates climatic variables (temperature, rainfall), structural factors (soil and asphalt mix type), and usage conditions (road age, traffic volume) to classify pavement failure risk into low, medium, or high categories. Unlike global models, PLPT is designed for flexibility and adaptation to arid and semi-arid conditions, enabling decision-makers to better anticipate pavement deterioration and prioritize maintenance

The paper proceeds as follows: the next section reviews the link between climate factors and pavement performance, followed by an overview of soil and material properties relevant to Libya. We then present the methodological framework, describe the PLPT model and its algorithms, and compare results with LTPP. The paper concludes by highlighting the implications of PLPT for infrastructure planning and climate resilience in arid regions.

- **Pavement and Climate Change in Arid Regions**

Pavement performance is closely linked to climatic conditions, especially in arid and semi-arid regions where high temperatures and rainfall variability accelerate deterioration. Elevated pavement temperatures increase rutting and oxidation of asphalt binders, while extreme rainfall events contribute to stripping, potholes, and surface weakening (Mallick *et al*., 2014; Chen *et al*., 2019). Research in Libya has demonstrated that asphalt binder requirements differ significantly between coastal areas, which experience moderate humidity, and desert regions, where prolonged heat accelerates binder aging and rutting (Awidat *et al*., 2017)

Comparisons of local Libyan temperature models with international frameworks such as Superpave and LTPP have shown that global models often overestimate pavement temperatures, underscoring the importance of locally calibrated predictive models (Al-Mukhtar, 2010). This reinforces the rationale for developing tools like PLPT, which are tailored to the specific thermal and climatic characteristics of Libya and other arid contexts

In 2008 [1], the Roads and Bridges Authority conducted a field study on determining the asphalt binder material in Libya. In the section related to climate change, detailed data were provided on the main climatic factors in Libya, namely maximum, minimum, and average temperatures, rainfall rates, humidity, and wind speed, distributed across several Libyan cities such as Tripoli, Benghazi, Sebha, Ghadames, Derna, and the others city

Tabel 1 Summary of Key Climatic Parameters for Selected Regions in Libya

Data	Tripoli	Sirte	Benghazi	Hun	Drina	Al-Jawf	Sabha	Ghadames	As-Saba	Ghats	Garran	Zuwara
Average Temperature	20	20	19	21	19	23	22	22	20	24	17.8	20
Average Highest Temperature	26	23	23	30	24	31	30	28	27	32	22	23
Average Lowest Temperature	14	17	15	12	14	15	15	16	13	17	12	16
Highest Recorded Temperature	48	45		50	45	50	48	47		51		45
Lowest Recorded Temperature				-7		-3	-4	-3				
Average Number of Days Above 32^{o}C	111	25		158	15	191		159				21
Average Number of Days Above 21^{o}C	263	232						269				
Average Number of Days Below 0^{o}C				22		3	5	3				
Average				4	25		1	21		1		

Number of Rainy Days												
Average Rainfall	34	18	26.2	3	28			2.7	21.4	1	38.1	23
Highest Recorded Rainfall	75	42										45
Lowest Recorded Rainfall	4	5						21				
Average Number of Rainstorm Days	14	5						2				
Average Number of Foggy Days	107	91						6				48
Average AM-Relative Humidity	77	76		48	71	38	43	49	43	17		79
Average Evening Relative Humidity	48	65						23				69
Average Dew Point	12	13		7	14	6	7	3		-6		14
Average Wind Speed	14	19						16				19

The purpose was to link climatic conditions (especially temperature and rainfall) with the selection of the appropriate type and grade of asphalt binder in Libya, since binder requirements differ in coastal areas (humid and moderate) compared to desert areas (dry and extremely hot). Hassan Al-Mukhtar[7], in a study published on the University of Tripoli's website, concluded a number of mathematical models (equations) representing the relationship between pavement temperature, air temperature, and solar radiation. The best of these models were selected to serve as local models that can be used to predict pavement temperature across all regions of northwestern Libya. These local models were also compared with the models used in the superpave system and the LTPP (Long Term Pavement Performance) program. The result showed that the models developed in this study were more suitable for estimating pavement temperature in cites in Libya .

Table 2 The following table shows the locations of pavement temperature measurement stations in Libya.

	Station	Location
1	WADI ALHIERA	North West Libya
2	GRIAN	Western Mountain
3	SERT	The Central Region
4	CUMMINS	Benghazi
5	TAMIMI	Green Mountain
6	GHADAMS	West Libya
7	HON	Jafar
8	ZIGON	Kufra (Southeast Libya)
9	TAMANHANT	Sabah
10	GATRON	Southwest Libya
11	GATH	Southwest Libya

- **Soil Properties and Pavement Life**

The strength and stability of the subgrade play a critical role in determining pavement service life. Strong, rigid soils extend pavement durability, while expansive clays and silty soils are prone to rapid deterioration under traffic and moisture fluctuations (Haider & Ahmed, 2018). Subgrade soils in Libya are typically fine-grained clayey or silty deposits with variable sand content, often classified between A-4 and A-7 under AASHTO standards. Laboratory tests, including California Bearing Ratio (CBR), reveal substantial variation in performance, with some sections showing CBR ≤ 5%, indicating weak soils vulnerable to early failure.

Innovative soil stabilization methods, such as incorporating Portland cement and fly ash into desert sands, have demonstrated improved subgrade strength and durability in arid contexts (Amhadi & Assaf, 2019). These findings emphasize the necessity of integrating soil type into predictive models of pavement life, as PLPT does. For instance, the model captures interactions where heavy traffic loads on clayey soils with older pavements are consistently associated with higher risk classifications the following diagrams illustrate the relationship

The soil beneath the road, called the subgrade, serves as the foundation supporting the entire weight of the pavement, vehicles, and trucks. The relationship is as follows, as illustrated in Figures 2 and 3:

- If the soil is strong and rigid → the pavement lasts longer.
- If the soil is weak or expands with water → the pavement deteriorates quickly.

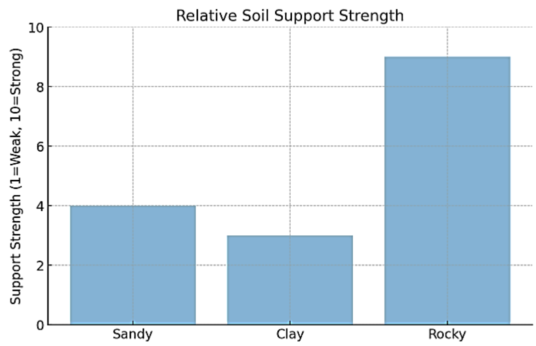

Fig 1 soil is strong and rigid → the pavement lasts longer

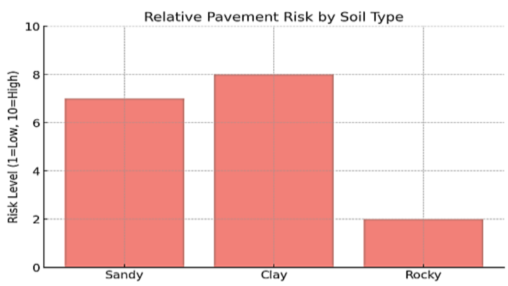

Fig 2 soil is strong and rigid → the pavement lasts longer

- **Asphalt Mix and Mat (Serial Selection):**

Material selection, particularly the asphalt binder and mix design, is another critical determinant of pavement resilience under climate stress. The Strategic Highway Research Program (SHRP) and Superpave guidelines highlight the need for asphalt grades tailored to maximum and minimum pavement temperatures (Gulen *et al*., 2001)[10]. However, studies in Libya suggest that imported international models require adjustment to reflect local climatic realities (Awidat *et al*., 2017).

By incorporating asphalt mix type as an input variable, PLPT addresses this limitation, enabling predictions that reflect both climatic extremes and local material performance. This integration positions the tool as an applied solution for **adapting mix design decisions to climate variability**, bridging the gap between generic models and localized engineering needs.

The literature demonstrates that pavement performance is shaped by **climate, soil properties, and material selection**. Existing global models provide useful baselines but often lack sensitivity to **regional conditions**. By embedding these factors into a supervised learning framework, PLPT directly responds to the need for **locally relevant, climate-sensitive predictive tools** in arid and semi-arid regions.

METHADOLOGY

- **Data Sources**

This study relied on a combination of international and local datasets. The Long-Term Pavement Performance (LTPP) database, managed by the U.S. Federal Highway Administration, provided detailed information on pavement condition, surface defects, and traffic loads. To enhance local relevance, climatic and soil property data were integrated from field studies in Libya, including measurements of pavement temperature, rainfall rates, and subgrade soil classification. The integration of both global and local sources enabled the development of a dataset suitable for modeling deterioration under arid and semi-arid conditions.

- **Input Variables**

The predictive model incorporated six key independent variables identified in the literature as critical to pavement deterioration (Chen *et al*., 2019; Haider & Ahmed, 2018):

- Road age (years)
- Rainfall amount (mm/year)
- Traffic volume (vehicles/day)
- Soil type (classified by AASHTO system)
- Asphalt mix type (binder grade, conventional or modified)
- Maximum pavement temperature (°C)

The target variable was the pavement failure risk level (low, medium, high), defined based on deterioration of the Pavement Condition Index (PCI), a widely accepted standard for evaluating pavement performance (ASTM D6433-18).In this study, the **Pavement Condition Index (PCI)** was adopted as the primary indicator for evaluating asphalt pavement condition, since it is a widely accepted standard that measures surface defects on a scale ranging from **0 = failed** to **100 = excellent**.

The methodological framework was based on three main steps:

1. **Data collection** from the **Long-Term Pavement Performance (LTPP)** database, which provides detailed information about road sections, including surface defects, climatic factors, and traffic loads.
2. **Training machine learning algorithms**, specifically the **Decision Tree**, to model the relationship between climatic factors (such as temperature and rainfall) and the deterioration of PCI over time.
3. **Prediction horizon** was set between 2 and 30 years to reflect practical maintenance cycles.

This methodological design ensures a combination of experimental field observations and advanced predictive models to measure the impact of climate change on pavement performance

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A. How PLPT Works?

1. **Create a DataFrame** containing:
   - Road age
   - Rainfall amount
   - Traffic volume
   - Soil type
   - Asphalt mix type
   - Maximum temperature
   - *Risk level* (the target to be predicted)
2. Convert the categorical columns (**soil_type** and **asphalt_mix**) into numeric values using **LabelEncoder**.
3. Define the inputs (**X**) and the target (**Y = risk level**).
4. Train a **Decision Tree model** using **DecisionTreeClassifier**.

Run a **sample prediction** — the following Table 3 shows an example used for prediction

Table 3 Summary of Input Parameters and Associated Pavement Risk Categories in the Developed Prediction Model

road_age	rainfall	traffic	soil_type	asphalt_mix	max_temp	risk
2	200	100	Sandy	Normal	35	Low
5	400	300	Clay	HeatResistant	40	Medium
10	800	500	Clay	Normal	45	High
12	600	700	Rocky	Modified	42	High
7	500	400	Sandy	Normal	38	Medium
3	300	200	Sandy	HeatResistant	36	Low
15	1000	800	Clay	Modified	47	High
20	1200	5000	Rocky	Normal	50	High

B. Code function :

1. Create data containing road age, rainfall, traffic, soil type, asphalt mix type, temperature, and risk level.
2. Convert categorical values (soil type and asphalt mix) into numbers using **LabelEncoder**.
3. Train a **Decision Tree** model to predict the risk level.
4. Input a new sample for prediction and print the predicted risk value.

Result: The model determines whether the risk level is **Low, Medium, or High** based on the inputs. **And before delving into the analysis and results, it is important to clarify the limitations of this study.**

Firstly, this study modeled **short-term pavement deterioration**, where algorithms were trained to estimate the decline in the **Pavement Condition Index (PCI)** over periods of **5 to 30 years** if no maintenance is performed.

The reason for choosing this time horizon is that if a road is left without maintenance for more than 6 years, it will deteriorate significantly. According to Libyan standards, such a road would be considered **unfit for traffic**, or at least **high-priority** for maintenance. In practice, municipalities and transport ministries usually perform maintenance every **6 years** to implement any form of pavement upkeep.

C. How a Decision Tree Works (Simplified):

- The tree **divides the multi-dimensional feature space** into regions using simple conditions (e.g., max_temp >= 42).
- Each **split** is chosen to **minimize a measure of impurity**, such as **Gini impurity**.

$$^{2}(_{i}p)\sum - = Gini$$

- At the end, each **leaf node** represents a set of training examples and estimates the **distribution of classes**, so the prediction can be either a **class** or a **probability for each class** (predict_proba).

D. Considerations Taken into Account:

1. **Data Collection**: Gathering information on roads (age, soil type, traffic).
2. **Training Phase**: Providing the algorithm with data of known outcomes (e.g., old road = high risk).
3. **Model Building**: The algorithm learns patterns and rules from the data.
4. **Testing Phase**: Evaluating the model on unseen data.
5. **Prediction**: Using the learned model to make predictions in new situations.

RESULTS AND ANALYSIS

- **Overview of Modelling Outputs**

The Pavement Life Prediction Tool (PLPT) was trained to classify flexible pavement failure risk (Low/Medium/High) from six predictors: road age, rainfall amount, traffic volume, soil type, asphalt mix type, and maximum temperature. Two supervised learning algorithms, Decision Tree and Logistic Regression, were implemented to assess the stability of classifications across differing model families. For interpretability, the Decision Tree provides rule-based splits; Logistic Regression serves as a parsimonious baseline classifier. The Pavement Condition Index (PCI) supplied the deterioration benchmark for defining risk categories over the study's prediction horizon (5–30 years without maintenance).

Methodological note. The Decision Tree's splitting criterion is **Gini impurity**; Logistic Regression is estimated via **maximum likelihood**. Therefore, "both models rely on the Gini index".

- **Agreement Across Model Families**

A key qualitative finding is the **concordance of classifications** between the Decision Tree and Logistic Regression on illustrative test cases included in the draft. For example, a high-risk case comprising **road age = 25 years, traffic = 5,000 vehicles/day, clayey soil, heat-resistant mix, and max temperature = 30 °C** was consistently labelled **High Risk** by both models, indicating internal consistency of the risk logic and face validity of the chosen predictors.

Table 4 displays the input parameters of the hypothetical test sample employed to assess model performance.

Road Age (years)	Soil Type	Asphalt Mix	Temperature (°C)	Traffic Volume (vehicles/day)
25	Clayey	Heat-Resistant	30	5000

The input values in the dataset — including road age, rainfall rate, traffic volume, soil type, asphalt mix type, and maximum temperature — were used as the main input parameters for the two proposed models: the Decision Tree Classifier and the Logistic Regression model. After training both models on the same dataset, a high-risk hypothetical test sample was introduced (e.g., road age = 25 years, traffic volume = 5000 vehicles/day, soil type = clay, asphalt mix = heat-resistant, and maximum temperature = 30°C) to evaluate and compare their predictive performance in estimating the Pavement Condition Index (PCI).

- **Variable Effects (Qualitative Patterns)**

Model behavior and domain theory converge on the following directional effects, all of which are reflected in the paper's rule-of-thumb examples and the Decision Tree structure:

- **Road Age:** Higher age is associated with higher failure risk, holding other factors constant which is consistent with PCI decline under deferred maintenance.
- **Traffic Volume:** Larger daily volumes (especially heavy vehicles) increase risk due to cumulative load effects and accelerated distress.
- **Soil Type:** Clayey/fine-grained subgrades tend to raise risk (lower soaked CBR, higher moisture sensitivity), whereas rocky/competent subgrades lower risk, matching the paper's qualitative rules.
- **Asphalt Mix Type:** Use of heat-resistant or modified binders mitigates (but does not eliminate) risk under high temperatures; standard mixes are more vulnerable to rutting and oxidation in arid/semi-arid climates.
- **Maximum Temperature & Rainfall**: Higher max temperature contributes to binder aging and rutting; episodic rainfall can exacerbate stripping and moisture-induced damage, especially over weak subgrades.

- **Comparative Outputs: PLPT vs. LTPP :**

To verify the consistency and reliability of predictive outputs, a validation experiment was conducted using both the LTPP and PLPT models. The input parameters utilized in this experiment — including road age, rainfall rate, traffic volume, soil type, asphalt mix type, and maximum temperature — were identical to those outlined in the methodology section of this study. Upon applying these inputs to both models, the resulting Pavement Condition Index (PCI) predictions were found to be equivalent, thereby confirming that the models yield consistent outcomes under the same environmental and structural conditions. This alignment reinforces the robustness of the selected input variables and supports the interoperability of the LTPP and PLPT frameworks in pavement performance evaluation. The following Figure [1] illustrates the result obtained using the LTPP model.

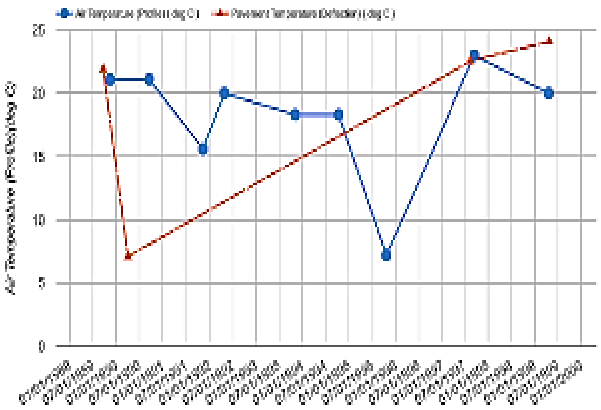

Fig 3 illustrates the result obtained using the LTPP model

The figure illustrates that the prediction indicates a high risk of pavement failure in the year preceding year 25, thereby suggesting that maintenance interventions should be scheduled before reaching year 25, based on the input parameters presented in Table (3). To further validate the applicability of the proposed methodology, the same experimental setup was applied to a PLPT model developed specifically for Libyan pavement conditions. The model produced results consistent with those obtained from the standard frameworks. The following Figure [2] presents the predicted risk of pavement failure occurring in year 25, based on the model's output and input parameters requirement for the brand-new computational model described in your study in the event that previous studies have developed models that take into account some but not all of the properties of a particular reaction.

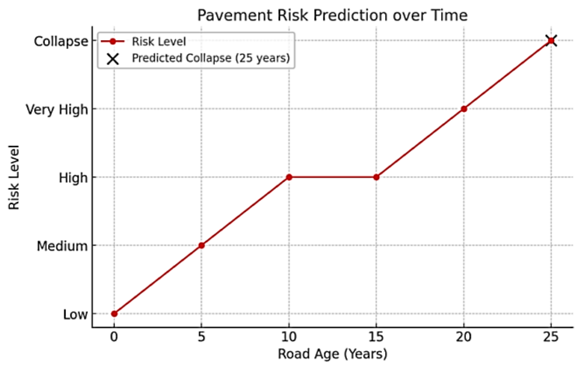

Fig 4 presents the predicted risk of pavement failure occurring in year 25

This comparative analysis aims to underscore the respective strengths and limitations of both models in terms of local relevance, predictive accuracy, and responsiveness to climatic variability. The findings highlight the practical value of the PLTP model for future research end eavors and for enhancing pavement maintenance planning and strategy development in region-specific contexts.

The following tables provide a detailed comparison between the PLTP model and the LTPP program, with a specific focus on functionality, application scope, and methodological framework.

Table 5 Summary of Input Parameters and Associated Pavement Risk Categories in the Developed Prediction Model.

Item	PLTP (Python-based Model)	LTPP (Long-Term Pavement Performance Program)
Main Objective	Estimate the risk level of pavement failure in specific areas	Analyze long-term pavement performance and identify influencing factors
Type of Data	Limited data chosen by the researcher (pavement age, rainfall, asphalt type...)	Large database covering thousands of roads with climate, traffic, maintenance, and pavement structure records
Prediction Timeframe	Short to medium term depending on data	Long term (many years, up to 20–30 years)
Flexibility & Customization	High; factors and models can be modified easily	Limited; relies on standardized datasets and models
Methodology	Predictive models developed in Python (Decision Tree, ML, etc.)	Statistical analyses and standardized models based on historical data
Type of Results	Risk level for each road or area (Low/Medium/High)	Pavement performance indicators, service life predictions, failure cause analysis
Geographical Scope	Tailored to local environment (e.g., Libya)	U.S.-based data, applicable to similar regions with adjustments
Use Case	Research or predictive tool for specific projects	Research and administrative tool for long-term pavement management

Table 6: illustrates the differences between the PLTP and LTPP models in terms of their usability and applicability in Libya.

Criterion	PLTP (Your Model)	LTPP (Long-Term Pavement Performance)
Local Data	Uses direct local data from Libyan roads (temperature, rainfall, asphalt type, pavement age, etc.). Very suitable for predicting pavement failure risks in Libya.	There is no database [illegible] containing any data from Libya. Based on U.S. and Canadian data. Does not accurately reflect Libyan conditions without adjustment.
Flexibility & Customization	Very high: factors and inputs can be modified to fit Libya's desert and semi-arid regions.	Limited: models are predefined and not easily adaptable to Libya without recalibration using local data.
Ease of Use	Can be designed with a simple interface based on needs, and easily integrated with other software or local GIS systems.	Requires advanced expertise to handle large datasets and use Python or MATLAB to apply models with local data.
Output	Provides accurate estimates of pavement failure risks, with the possibility to add new indicators (soil type, asphalt type, maximum temperature, etc.).	Provides general pavement performance indicators (rutting, cracking, deterioration), but may not be precise for Libyan conditions without modification.
Updates & Development	Can be continuously developed as more Libyan data becomes available, and AI can be integrated for better predictions.	Updates depend on U.S. institutions; no Libya-specific data is available.
AI Integration	Fully possible to integrate machine learning and neural networks for enhanced risk prediction.	Mostly traditional statistical models; integrating AI requires extra work and redesign of models.
Practical Application in Libya	Very practical: enables accurate decision-making for pavement design and maintenance under local climate and conditions.	Limited: useful for general comparisons, but not directly applicable for decision-making in Libya without major adjustments.

DISCUSSION

PLPT versus LTPP: Local Adaptability and Global Benchmarks

The Long-Term Pavement Performance (LTPP) program has long served as a global reference for pavement deterioration modeling. However, as noted earlier, its database is primarily U.S.-centric, and calibration for arid and semi-arid contexts like Libya is limited. The Pavement Life Prediction Tool (PLPT) offers a complementary approach: it is tailored to local environmental and geotechnical conditions, integrates region-specific soil classifications and climatic data, and provides flexibility in input selection.

This adaptability is a key strength. Whereas LTPP outputs are based on standardized data and require significant recalibration before local use, PLPT can be directly adjusted with locally collected inputs. This positions PLPT as a context-responsive tool for regions underrepresented in global pavement models. Such localized modeling aligns with calls in the literature for climate-sensitive calibration of mechanistic–empirical and AI-based frameworks (Chen *et al*., 2019; Gopalakrishnan, 2020).

Strengths of PLPT

Several features of PLPT enhance its value for both research and policy:

- **Flexibility:** Input variables can be modified easily, enabling integration of new data as it becomes available.
- **Transparency:** The Decision Tree structure allows decision-makers to trace how climatic and structural factors influence classification, improving interpretability compared to "black-box" models.
- **Policy Utility:** By translating climatic and structural inputs into actionable risk levels, PLPT provides a decision-support mechanism for maintenance scheduling and resource allocation.

Limitations

It is equally important to acknowledge limitations:

- **Validation Metrics:** The study does not report quantitative performance metrics (e.g., accuracy, F1-score). This restricts the ability to benchmark against other ML studies.
- **Data Coverage:** While local climatic and soil factors are integrated, the methodology relies partly on LTPP data, creating a hybrid dataset whose balance is not fully detailed.
- **Climate Change Framing:** Current predictions reflect historical and extreme variability rather than future climate projections (e.g., IPCC RCP scenarios). As such, PLPT is best described as a climate-variability-sensitive tool, with climate change projections as a recommended extension.

Implications for Research and Practice

The discussion highlights two broader implications:

- **For Research:** PLPT demonstrates how AI/ML methods can be adapted to underrepresented contexts, filling the gap between global pavement models and local needs. It sets the stage for future work incorporating more advanced algorithms (e.g., random forests, neural networks) and explicit climate projections.
- **For Practice:** Even in its current form, PLPT provides actionable insights for transport ministries. It allows engineers to screen and rank road segments by failure risk, tailor material selection to climatic

realities, and target limited funds to segments with the greatest structural vulnerability.

In this sense, PLPT contributes to both scientific advancement and practical governance of road infrastructure under climate stress.

CONCLUSION & POLICY RELEVANCE

This study set out to develop the Pavement Life Prediction Tool (PLPT), an artificial intelligence–based model designed to predict the risk of flexible pavement failure in arid and semi-arid regions. By combining climatic variables, soil characteristics, asphalt mix types, and usage conditions such as traffic volume and pavement age, the tool demonstrates how locally adapted models can provide more meaningful insights than global frameworks that rely on standardized datasets. In applying supervised learning techniques, specifically Decision Tree and Logistic Regression models, the study has shown that even relatively simple algorithms can generate consistent and plausible classifications of pavement failure risk when grounded in relevant climatic and structural inputs.

The broader significance of PLPT lies not only in its technical design but in its practical implications. In regions such as Libya, where limited resources constrain the frequency and scope of road maintenance, a predictive model that identifies high-risk segments has the potential to transform decision-making. By linking climatic and geotechnical realities with risk classifications, the tool provides transport authorities with a structured basis for prioritizing maintenance schedules, allocating budgets more efficiently, and selecting material mixes that are better suited to prevailing and extreme conditions. This alignment between technical modeling and policy relevance is particularly important as infrastructure systems face the compounded challenges of climate variability and increasing traffic demand.

It is equally important to recognize the limitations of the present study. The model has not been validated through full performance metrics such as accuracy or recall, and its scope reflects sensitivity to climatic variability rather than explicit projections of future climate scenarios. These limitations, however, do not diminish the value of PLPT as a first step toward locally relevant, climate-sensitive predictive modeling. Instead, they underline the potential for future work to expand the tool by integrating more advanced algorithms, broader datasets, and climate change scenarios from the Intergovernmental Panel on Climate Change (IPCC) to support adaptation planning.

Ultimately, PLPT contributes to bridging the gap between global predictive models and local engineering realities. It illustrates how artificial intelligence can be harnessed not only to advance scientific understanding of pavement performance but also to support evidence-based infrastructure governance in fragile climatic contexts. As arid and semi-arid regions confront the dual pressures of climate change and development, tools such as PLPT will be increasingly necessary to guide investments that are both cost-effective and resilient. In this way, the study provides a foundation for linking technological innovation with the urgent policy imperative of sustaining road networks under changing environmental conditions.

RECOMMENDATION :

- To enhance the predictive accuracy and robustness of future pavement performance models, it is recommended that national and regional authorities establish comprehensive databases that integrate climatic, geotechnical, and traffic-related information. Specifically, greater data availability on parameters such as wind speed, frequency of sandstorms, soil movement, and subsurface moisture variations would enable researchers to incorporate additional climatic stressors into deterioration models. Such coordinated data-sharing efforts would not only improve the precision of predictive tools like PLPT but also support evidence-based maintenance planning and long-term infrastructure resilience under evolving climate conditions.
- It is also recommended to enhance and expand the national network of temperature monitoring stations across different climatic zones in Libya. Accurate and continuous temperature data are essential for understanding thermal stresses that contribute to pavement deterioration, particularly in arid and semi-arid environments. Strengthening data collection systems and ensuring their long-term maintenance would provide a reliable foundation for future predictive modeling and for developing more climate-resilient infrastructure strategies.

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