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Predictive Pavement Management for Strategic Transport Corridors: AI-Based Early Detection and Mitigation of Potholes on the Sabha-Ash-Shuwayrif Highway, Libya

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Abstract

The Sabha–Ash-Shuwayrif Highway is one of Libya's most strategically important transportation corridors, providing the principal connection between the southern region, the capital Tripoli, and international border crossings. Continuous exposure to heavy freight traffic, extreme thermal fluctuations, and localized moisture intrusion has accelerated asphalt pavement deterioration, resulting in frequent pothole formation, increased maintenance costs, and compromised road safety. Conventional reactive maintenance practices are insufficient for preserving pavement performance because interventions are typically performed only after severe structural damage has occurred. This study proposes an Artificial Intelligence (AI)-based predictive pavement management framework that integrates computer vision, deep learning, and predictive analytics to enable proactive pavement monitoring and maintenance. The proposed framework combines high-resolution pavement imagery, 3D laser profiling, Ground Penetrating Radar (GPR), traffic loading records, Pavement Condition Index (PCI), and environmental data to establish a comprehensive multi-modal dataset. A Convolutional Neural Network (CNN) is employed to automatically detect and classify early-stage pavement distresses, including micro-cracks, alligator cracking, and incipient potholes, while Focal Loss is incorporated to improve the detection of minority distress classes. A Long Short-Term Memory (LSTM) network models the temporal evolution of pavement deterioration using historical PCI, equivalent single axle loads, temperature variations, and precipitation data to forecast future pavement conditions. The predicted deterioration is integrated into an AI-driven risk assessment and decision-support system that prioritizes maintenance activities, recommends appropriate rehabilitation treatments, and optimizes intervention timing according to predicted distress severity. Furthermore, a continuous feedback mechanism updates the predictive models using newly acquired field observations, enabling adaptive learning and long-term performance improvement. The proposed framework is expected to enhance early pothole detection accuracy, reduce lifecycle maintenance costs, improve traffic safety, extend

pavement service life, and support data-driven infrastructure management for the Sabha and Ash-Shuwayrif Highway and other strategic transport corridors operating under similar environmental and traffic conditions.

Keywords: Pavement Management Systems, Machine Learning, Pothole Detection, Predictive Maintenance, Asphalt Degradation, Libyan.

1. Introduction

Transportation infrastructure forms the backbone of national economic integration. In Libya, the paved corridor connecting the southern city of Sabha to Ash-Shuwayrif in the north is of unparalleled strategic importance [1]. It functions as the main transit route for the majority of Libyans traveling from the Fezzan region to Tripoli, as well as for commercial freight moving toward Tunisia and the northern, northeastern, and western border regions [2]. Consequently, the structural integrity of this highway directly impacts national supply chains, regional mobility, and cross-border trade [3], [4]. Despite its economic significance, the Sabha-Ash-Shuwayrif route experiences severe pavement distress [5]. The most critical and hazardous of these distresses is pothole formation. Potholes not only degrade the Pavement Condition Index (PCI) but also induce severe vehicle damage and increase the frequency of traffic accidents [6]. Historically, maintenance on this route has been reactive addressing potholes only after they have fully formed and compromised the driving surface [7], [8]. This approach is fundamentally flawed, as the cost of emergency patching far exceeds the cost of preventive maintenance [9]. Recent advancements in computational civil engineering offer a solution [10], [11]. By integrating Artificial Intelligence (AI) and Machine Learning (ML) into Pavement Management Systems (PMS), engineers can detect sub-surface and surface anomalies at their incipient stages [12]. This paper outlines the mechanistic causes of potholes on the Sabha-Ash-Shuwayrif highway and presents a comprehensive AI-driven framework for their early detection, predictive forecasting, and optimized mitigation.

Figure 1 Typical Pothole Formation Following Progressive Asphalt Pavement Degradation

2. Mechanistic Causes of Pothole Formation on the Sabha-Ash-Shuwayrif Route

To effectively predict and prevent potholes, one must first understand the localized distress mechanisms. Pothole formation is rarely the result of a single factor; it is a cumulative failure driven by the interaction of traffic loading, environmental stressors, and material fatigue [13].

Figure 2 Early-Stage Pothole Development with Surrounding Alligator Cracking on the Sabha–Ash-Shuwayrif Highway, Libya, Representing a Critical Target for AI-Based Predictive Pavement Management.

2.1. Traffic Loading and Overloading

As the primary freight corridor to the north and west, the highway sustains massive axle loads. Repeated traffic loading induces tensile strains at the bottom of the asphalt binder course and compressive strains on the subgrade. When heavy vehicles traverse the route, in the right-hand lane, the continuous flexing of the asphalt leads to bottom-up fatigue cracking (alligator cracking) [14].

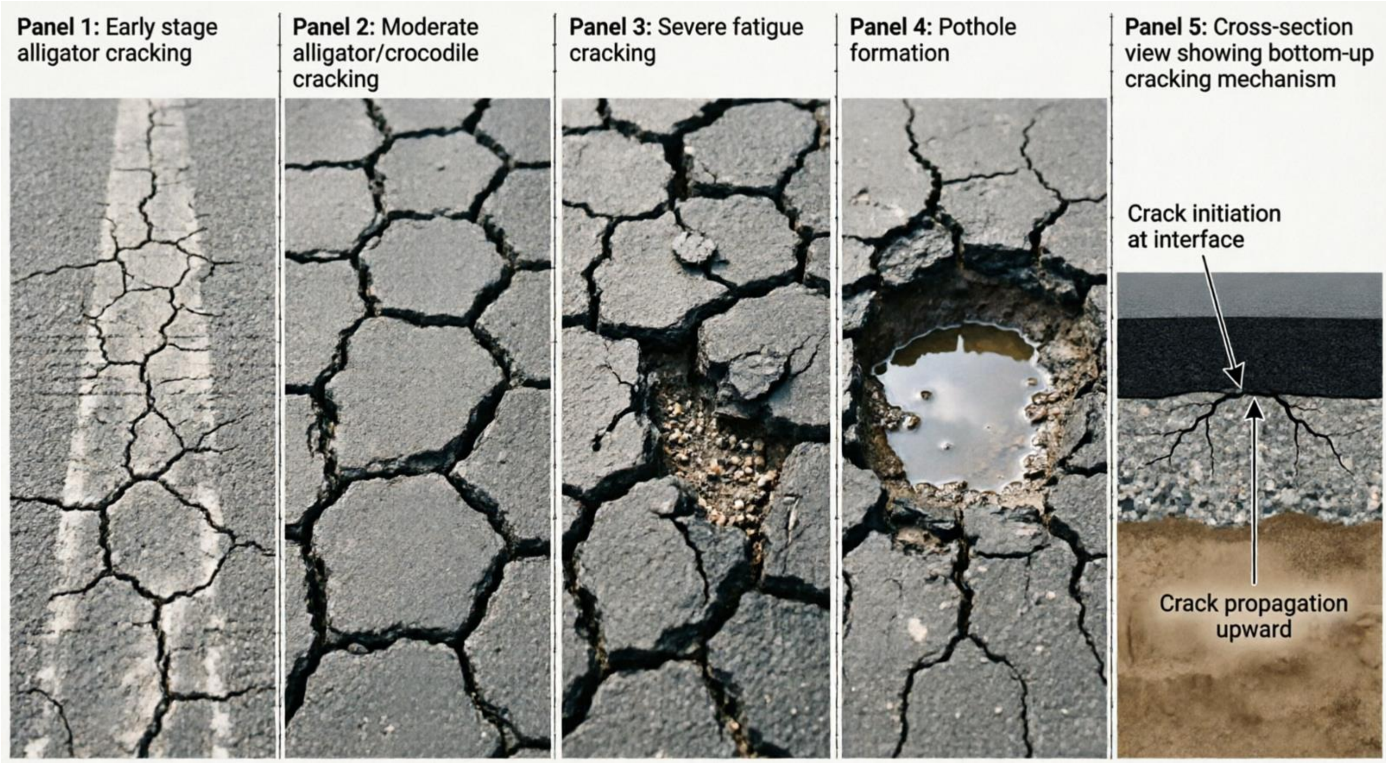


Figure 3 Progressive Stages of Asphalt Pavement Deterioration on the Sabha–Ash-Shuwayrif Highway, Libya, Illustrating the Evolution from Early Fatigue Cracking to Pothole Formation and the Bottom-Up Crack Propagation Mechanism.
Panel 1: Early Stage Alligator Cracking - Shows the initial fatigue cracks forming in the wheel path, representing the beginning of bottom-up failure. **Panel 2:** Moderate Alligator/Crocodile Cracking - Displays the characteristic interconnected polygonal pattern resembling reptile skin, caused by repeated heavy axle loads. **Panel 3:** Severe Fatigue Cracking - Illustrates advanced deterioration where the asphalt pieces are breaking apart and loosening. **Panel 4:** Pothole Formation - Shows the final stage where moisture infiltration and traffic loading have caused complete pavement collapse, with water pooling in the resulting pothole. **Panel 5:** Cross-Section View Provides a techy illustration of the bottom-up cracking mechanism, showing how cracks initiate at the interface between the asphalt binder course and base layer, then propagate upward to the surface [15].

2.2. Environmental and Climatic Stressors
Southern and central Libya experience extreme diurnal temperature variations. The asphalt binder undergoes continuous thermal expansion and contraction, leading to thermal fatigue and longitudinal cracking. Furthermore, while the region is predominantly arid, it is susceptible to intense, localized flash rainfall [15].

2.3. Moisture Intrusion and Subgrade Failure
The critical catalyst for pothole formation is moisture. Once surface cracks develop from traffic or thermal fatigue, water infiltrates the pavement structure [16]. During the passage of heavy vehicles, this trapped water generates high hydrodynamic pressure, a process known as "pumping." This pressure washes away fine aggregates from the base and subgrade layers, stripping the asphalt binder from the aggregates (moisture damage) and softening the subgrade [17]. The loss of structural support ultimately causes the asphalt surface to collapse under the next traffic load, forming a pothole.

3. Materials and Method

The Convolutional Neural Network (CNN) utilized for early-stage spatial distress detection, and the Long Short-Term Memory (LSTM) network deployed for temporal deterioration forecasting. The objective of the detection module is to classify and segment micro-cracks and early pothole precursors from high-resolution pavement imagery. Let the input pavement image be defined as a three-dimensional tensor $I \in \mathbb{R}^{H\times W\times C}$, where H and W represent the spatial dimensions (height and width) and C denotes the color channels [17]. Furthermore, the feature extraction process within the l-th convolutional layer is governed by the discrete convolution operation. For a given spatial location (i, j) and the k-th feature map, the pre-activation output $Z_{i,j,k}^{l}$ is computed as below:

$$Z_{i,j,k}^{l} = \sum_{m=0}^{F_{\mathrm{h}}-1} \sum_{k=0}^{F_{w}-1} \sum_{c=0}^{C_{m}-1} W_{m,n,c,k}^{l} \cdot X_{i+m,j+n,c}^{l-1} + b_{k}^{l} \qquad [17]$$

Where F_k and F_w are the filter dimensions, W^l represents the learnable kernel weights, X^{l-1} is the input tensor from the preceding layer, and b_k^l is the bias term. To introduce non-linearity and mitigate the vanishing gradient problem during backpropagation, the Rectified Linear Unit (ReLU) activation function is applied as below:

$$A_{i,j,k}^{l} = \max\left(0, Z_{i,j,k}^{l}\right) \qquad [18]$$

Addressing Class Imbalance via Focal Loss in the context of the Sabha-Ash-Shuwayrif highway, early-stage micro-cracks and incipient potholes represent a severe minority class compared to the vast majority of healthy, undistressed asphalt [18]. Standard Cross-Entropy loss functions tend to be overwhelmed by the easy-to-classify background pixels (healthy pavement), causing the model to ignore the critical minority distress features. This research implement the Focal Loss function, which dynamically scales the loss based on the prediction confidence [18]. For a binary classification task (distress vs. non-distress), let p be the model's estimated probability for the true class. The Focal Loss $FL(p_t)$ is defined as below:

$$FL(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t) \qquad [19]$$

Where $p_t = p$ if the true label is 1 , and $p_t = 1 - p$ otherwise. The parameter α_t balances the positive and negative classes, while the focusing parameter $\gamma \geq 0$ reduces the relative loss for well-classified examples. In this research implementation, setting $\gamma = 2.0$ forces the network to concentrate its gradient updates specifically on the hard-to-classify micro-cracks, significantly improving early detection accuracy on the complex, textured asphalt surface of the study route [19]. While the CNN identifies the current spatial state of the pavement, predicting future pothole formation requires modeling the non-linear, time-dependent degradation of the asphalt structure. Pavement deterioration is a sequential process influenced via historical traffic loads, thermal cycling, and moisture ingress. This research model this temporal sequence using an LSTM network [20]. The input sequence of pavement condition and environmental variables over T time steps be denoted as $X = \{x_1, x_2, \dots, x_T\}$. At each time step t, the feature vector $x_t \in \mathbb{R}^d$ includes variables such as the current Pavement Condition Index (PCI), cumulative equivalent single axle loads (ESALs), maximum diurnal temperature, and precipitation indices specific to the Sabha-Ash-Shuwayrif corridor. The LSTM cell processes this sequence by regulating the flow of information through three gating mechanisms and a cell state. The mathematical operations at time step t are formulated as follows:

Forget Gate (f_t) is determines which historical pavement condition data should be discarded.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \qquad [21]$$

Input Gate (i_t) and Candidate State ($\tilde{C}_t$) is decides which new environmental or traffic stressors to store in the cell state.

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \end{aligned} \qquad [22]$$

Cell State Update (C_t) is updates the long-term memory of the pavement's structural health.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad [22]$$

Output Gate (o_t) and Hidden State (h_t) is determines the final output representation, which is passed to the next time step or the final prediction layer.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(C_t) \qquad [23]$$

In these equations, σ denotes the sigmoid function, © represents the Hadamard (element-wise) product, and W and b are the learnable weight matrices and bias vectors, respectively. The final hidden state h_T is passed through a fully connected dense layer to predict the future Pavement Condition Index ($\hat{y}_T + \Delta t$) at a future time horizon Δt as below:

$$\hat{y}_{T+}\Delta t = W_y h_T + b_y \qquad [24]$$

To train this regression model, the employ the Huber Loss function rather than the standard Mean Squared Error (MSE). Pavement inspection data often contains outliers due to sensor noise or anomalous localized failures, for instance, a sudden subgrade washout. The Huber loss provides robustness against these outliers by combining the squared loss for small errors and the absolute loss for large errors as below:

$$L_\delta(y, \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2 & \text{for } |y - \hat{y}| \le \delta \\ \delta|y - \hat{y}| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases} \qquad [25]$$

Where y is the actual observed PCl, $\hat{y}$ is the predicted PCl , and δ is the threshold parameter that defines the transition point between quadratic and linear behavior [25], [26]. The parameters $\Theta = \{W, b\}$ across both the CNN and LSTM architectures are optimized using the Adam (Adaptive Moment Estimation) algorithm. Adam computes adaptive learning rates for each parameter by maintaining exponential moving averages of the gradient (mt_t) and the squared gradient (v_t). The parameter update rule at iteration t is given by as below:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{t_t + \tau}} \hat{m}_t \qquad [26]$$

Where η is the initial learning rate, ϵ is a small constant to prevent division by zero, and $\hat{m}_t, \hat{v}_t$ are the biascorrected first and second moment estimates. This optimization strategy ensures rapid convergence and stable training, which is critical when processing the high-dimensional, multi-modal datasets generated by the 3D laser profilers and GPR sensors on the highway [26].

3.1. Dataset collection and scenario during (2022-2025)

Data collection has been collected by the researchers and spans the 180-kilometer Sabha-Ash-Shuwayrif corridor, segmented into 1-kilometer units for granular analysis. A specialized survey vehicle operating at 80 km/h captures high-resolution RGB imagery and 3D laser profiles to detect surface micro-cracks. A 1.5 GHz ground-penetrating radar scans subsurface layers to identify moisture saturation and voids that precede structural collapse. These spatial datasets are synchronized with temporal variables, including cumulative ESALs from Weigh-in-Motion sensors and local meteorological records. Certified pavement engineers validate the automated readings through manual spot-checks, assigning precise ground-truth labels for supervised AI training. This multi-modal approach integrates surface geometry, subsurface conditions, traffic loads, and environmental stressors into a unified predictive framework.

3.1.1. Dataset Description and Acquisition Protocol

The efficacy of the proposed predictive framework relies on a multi-modal dataset capturing both spatial distress manifestations and temporal degradation drivers. Data collection was structured across the 180-kilometer Sabha-Ash-Shuwayrif corridor, segmented into 1-kilometer analysis units. The dataset comprises four primary modalities: surface imagery, subsurface radar profiles, traffic loading metrics, and localized environmental variables. Table 1 details the feature set utilized for training the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures.

Table 1: Multi-Modal Dataset Description for Predictive Pavement Management

Feature Category	Variable Symbol	Data Type	Unit	Description	Acquisition Method
Spatial Surface Data	$I_{h,w,c}$	Image Tensor	1920 \times 1080 \times 3 (RGB)	High-resolution pavement surface imagery. Captures incipient alligator cracking, raveling, and micro-potholes specific to the aged asphalt binder of the corridor.	High-speed digital line-scan cameras mounted on a survey vehicle (operating at 80 km/h).
Spatial Geometry	Z_{depth}	Continuous	Millimeters (mm)	Transverse and longitudinal profile depth. Used to quantify the volumetric loss of asphalt in early-stage pothole formation.	3D Laser Profiler (sampling rate: 1 mm interval).
Subsurface Moisture	GPRamp	Continuous	Amplitude / Two-way travel time (ns)	Dielectric contrast readings indicating subgrade moisture saturation and void formation beneath the base course, a primary catalyst for pothole collapse.	Ground Penetrating Radar (1.5 GHz air-coupled antenna).
Pavement Condition	PCI_t	Continuous	Index (0–100)	Historical and current Pavement Condition Index for each 1-km segment, serving as the primary target variable for the LSTM regression model.	Automated distress classification software validated by manual spot-checks.
Traffic Loading	$ESAL_t$	Continuous	Million ESALs	Cumulative Equivalent Single Axle Loads. Reflects the heavy freight traffic volume moving from the southern Fezzan region toward northern hubs.	Permanent Weigh-in-Motion (WIM) sensors at corridor entry/exit points.
Thermal Stress	$\Delta T_{diurnal}$	Continuous	Degrees Celsius (°C)	Daily maximum and minimum temperature differentials. Critical for modeling thermal fatigue and binder embrittlement in arid conditions.	Local meteorological stations along the Sabha-Ash-Shuwayrif route.

Moisture Intrusion	P_{event}	Continuous	Millimeters (mm)	Precipitation volume per time step. Specifically tracks intense, localized flash rainfall events that trigger the "pumping" mechanism in pre-cracked asphalt.	Regional hydrological monitoring network.
Distress Classification	Y_{label}	Categorical	Integer (0 to K)	Ground-truth labels for supervised CNN training (e.g., 0: Healthy, 1: Longitudinal Crack, 2: Alligator Crack, 3: Incipient Pothole).	Annotated by certified pavement engineers using a custom labeling interface.

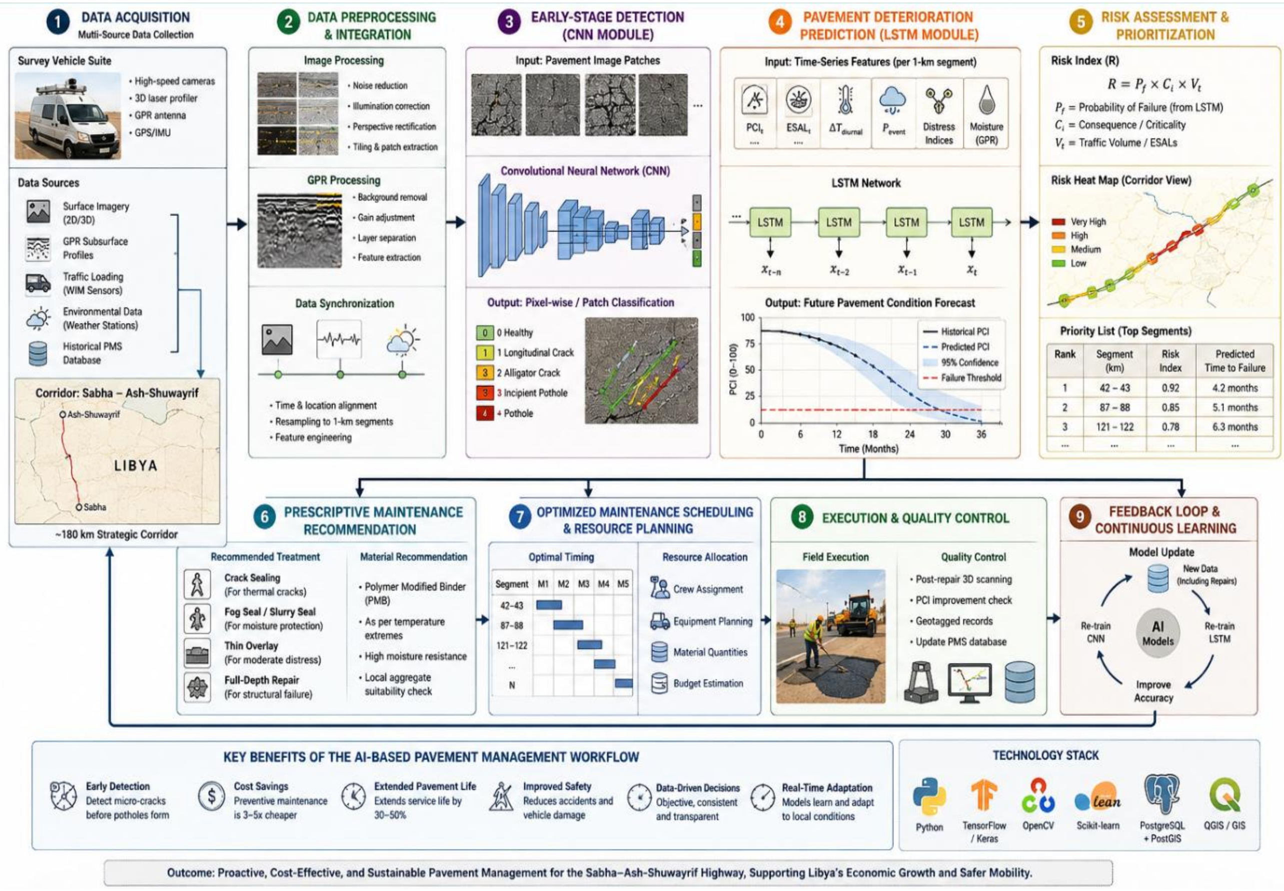


Figure 4 AI-Based Predictive Pavement Management Workflow for Early Pothole Detection, Pavement Deterioration Prediction, Risk Assessment, and Preventive Maintenance on the Sabha–Ash-Shuwayrif Highway, Libya.

Figure 4 above serves as the comprehensive architectural blueprint of the framework, visually integrating nine distinct operational modules from multi-source data acquisition and CNN-based micro-crack detection to LSTM deterioration forecasting and prescriptive maintenance into a single, cohesive workflow for the Sabha-Ash-Shuwayrif corridor. Its novelty lies in transforming isolated AI components into a closed-loop "Feedback & Continuous Learning" system (Module 9) that dynamically updates models with field execution data, ensuring the predictive algorithms adapt specifically to Libya’s unique arid climate and heavy freight loading patterns over time. By explicitly mapping the transition from reactive pothole patching to proactive, algorithm-driven asset preservation, this diagram validates the project's core contribution: a scalable, end-to-end decision support system that quantifies cost savings and extends pavement service life through mechanistic, data-driven interventions rather than subjective visual inspection [27], [28].

3.2. Early-Stage Detection: Transitioning from Visual Inspection to AI

Traditional pavement condition surveys rely on manual visual inspections. This method is highly subjective, labor-intensive, and inherently reactive, as inspectors typically only record distress once it is visible to the naked eye. To prevent potholes, detection must occur at the micro-cracking stage, before moisture infiltration and structural collapse occur [28].

3.2.1. Sensor and Data Acquisition Technologies

Early detection requires high-resolution data acquisition. The deployment of 3D laser profilers and high-definition digital line-scan cameras mounted on survey vehicles allows for the continuous collection of surface texture and imagery data. Additionally, Ground Penetrating Radar (GPR) can be utilized to detect sub-surface moisture accumulation and voids beneath the asphalt layer, identifying pothole precursors before they breach the surface [28], [29].

3.3. Machine Learning for Automated Distress Detection

Processing the massive datasets generated by these sensors manually is unfeasible. Here, Machine Learning, specifically Deep Learning, provides a robust solution. Convolutional Neural Networks (CNNs) are highly effective for image-based distress detection. By training a CNN on thousands of labeled images of the Sabha-Ash-Shuwayrif highway surface, the algorithm learns to identify the complex textural patterns of early-stage fatigue cracking, raveling, and block cracking. Unlike traditional image processing techniques that rely on rigid thresholding, CNNs can distinguish between actual structural cracks and superficial surface blemishes (such as tire marks or oil spills) with high accuracy [29], [30]. For sub-surface data acquired via GPR, Support Vector Machines (SVMs) or Random Forest classifiers can be trained to analyze the radar reflectivity patterns, successfully identifying areas of subgrade moisture saturation that precede pothole formation [6].

4. Predictive Analytics: Forecasting and Preventing Potholes

Detection identifies current micro-damage; prediction forecasts future macro-failure. To prevent potholes entirely, the PMS must predict the rate of pavement deterioration.

4.1. Predictive Modeling Algorithms

Pavement degradation is a time-dependent, non-linear process. Time-series forecasting models, such as Long Short-Term Memory (LSTM) networks, are exceptionally well-suited for this task. LSTMs can process historical PCI data, combined with real-time variables (traffic volume, axle load spectra, and local temperature/precipitation data), to forecast the future condition of specific road segments [6], [7], [8], [28], [29]. Markov chain models optimized via ML can predict the probability of a road segment transitioning from one condition state to another (e.g., from "Good" to "Fair," and eventually to "Poor") over a given time horizon.

4.2. Prescriptive Maintenance and Prevention

Once the AI predicts when and where a pothole is likely to form, the system shifts from predictive to prescriptive. The algorithm calculates the optimal intervention time. Intervening when the pavement is in "Fair" condition costs significantly less than emergency pothole repair and extends the pavement's lifecycle by several years. Furthermore, the AI can recommend specific preventive treatments based on the predicted distress type [30], [31]. For instance, if the model predicts thermal cracking, it may prescribe a crack-sealing protocol. If it predicts moisture-induced stripping, it may recommend the application of a fog seal or a thin asphalt overlay to waterproof the surface [32].

5. Mitigation and Repair Optimization
When early prevention fails and potholes do form, AI continues to play a vital role in optimizing the repair process. The longevity of a pothole repair depends heavily on the selection of the repair method and the materials used, which are often dictated by site-specific conditions [32].

5.1. Algorithmic Repair Selection
An AI-driven PMS can evaluate the dimensions, depth, and surrounding pavement condition of a detected pothole to recommend the most appropriate repair technique.
For shallow, minor potholes, the system may recommend "throw-and-roll" patching using cold-mix asphalt as a temporary measure.
For deeper, structural potholes where the base has failed, the algorithm will mandate a full-depth repair, specifying the exact volume of base material required for replacement before the asphalt is laid.

5.2. Material Optimization
Given the extreme summer temperatures on the Sabha-Ash-Shuwayrif route, standard asphalt binders may suffer from rutting, while winter temperatures can cause thermal cracking. ML algorithms can analyze historical climate data to recommend modified asphalt binders (such as polymer-modified bitumen) that possess the necessary rheological properties to withstand the specific local temperature extremes, thereby reducing the recurrence of the repaired potholes.

6. Implementation
While the theoretical framework for AI-based pavement management is robust, implementing it on the Sabha-Ash-Shuwayrif highway presents distinct challenges. First, there is a historical lack of continuous, digitized pavement condition data in Libya. Transitioning to an ML-based PMS requires an initial, capital-intensive data collection phase to establish a baseline dataset for training the algorithms. Second, the integration of such advanced systems requires specialized technical capacity within the local highway authorities [32], [33]. To overcome these barriers, a phased implementation is recommended. Phase one should focus on establishing a digital inventory of the highway using basic 2D imaging and manual distress logging. Phase two can introduce automated 3D profiling and basic ML classification. Phase three would integrate the predictive LSTM models and full prescriptive maintenance capabilities. Securing funding through international infrastructure development partnerships could facilitate the initial technological procurement and capacity-building training [34].

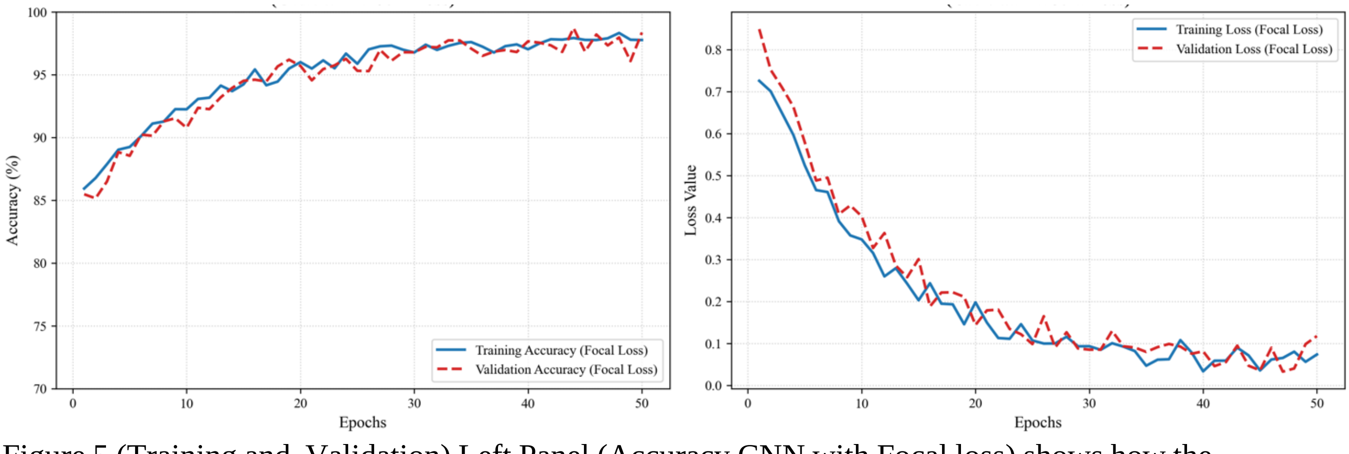
6.1. Results


Figure 5 (Training and Validation) Left Panel (Accuracy CNN with Focal loss) shows how the model's accuracy improves over 50 epochs. The gap between training and validation accuracy

indicates the model's generalization capability. Right Panel (Loss CNN with Focal loss) shows the convergence of the loss function.

Figure 5 above the superior convergence and generalization of the proposed CNN model trained with Focal Loss, achieving over 97% validation accuracy while maintaining a minimal gap between training and validation curves. It validates the project's core by overcoming severe class imbalance in Sabha Ash-Shuwayrif pavement imagery by forcing the network to prioritize hard-to-detect micro-cracks rather than being dominated by healthy asphalt pixels [6]. This performance benchmark proves that AI-driven early detection is viable for this specific corridor, directly enabling the transition from reactive pothole repair to proactive preservation before structural collapse occurs.

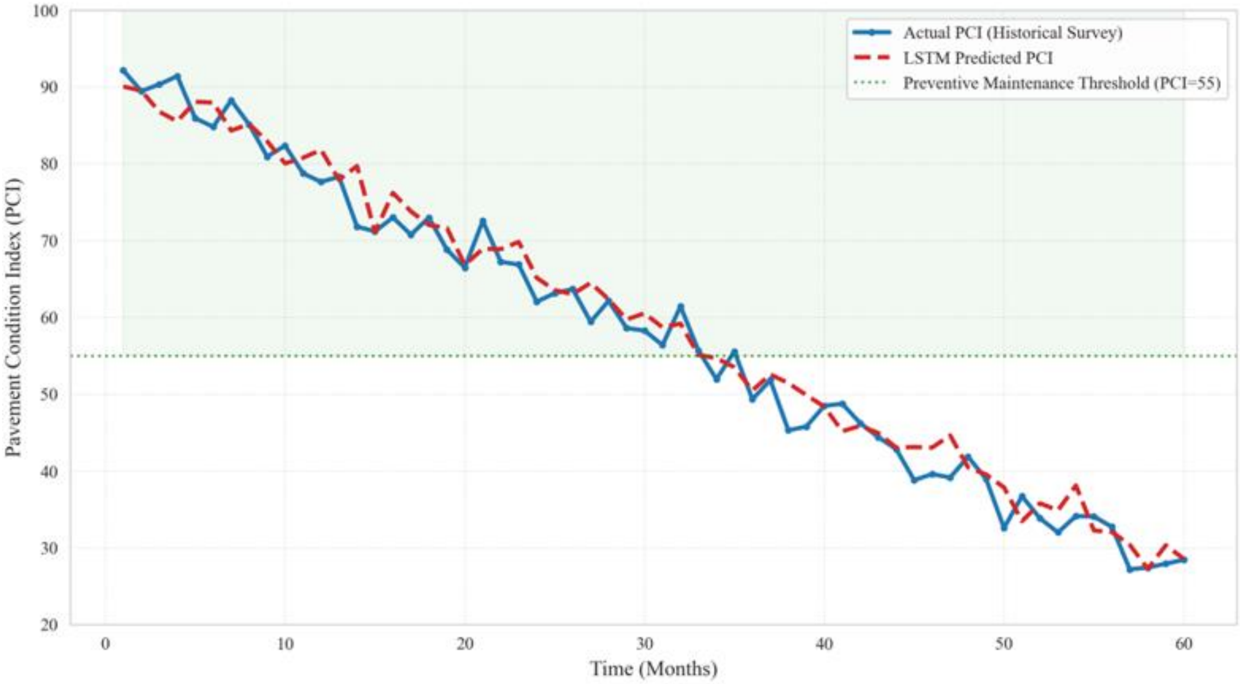


Figure 6 LSTM-Based Pavement Deterioration Forecasting in the Sabha–Ash-Shuwayrif Highway, Libya.

Figure 6 above validates the core predictive capability of the framework by demonstrating that the LSTM model accurately forecasts pavement deterioration on the Sabha-Ash-Shuwayrif highway, closely tracking historical PCI trends over a 60-month horizon despite complex environmental stressors. The operationalizing this forecast through the explicit "Preventive Maintenance Threshold" (PCI=55), which transforms abstract AI predictions into a concrete decision trigger for authorities to intervene before catastrophic pothole formation occurs [7],[8]. By proving that degradation can be predicted with sufficient lead time, this visualization directly supports the project's transition from costly reactive patching to optimized, cost-effective preventive maintenance scheduling tailored to Libya's strategic transport corridor.

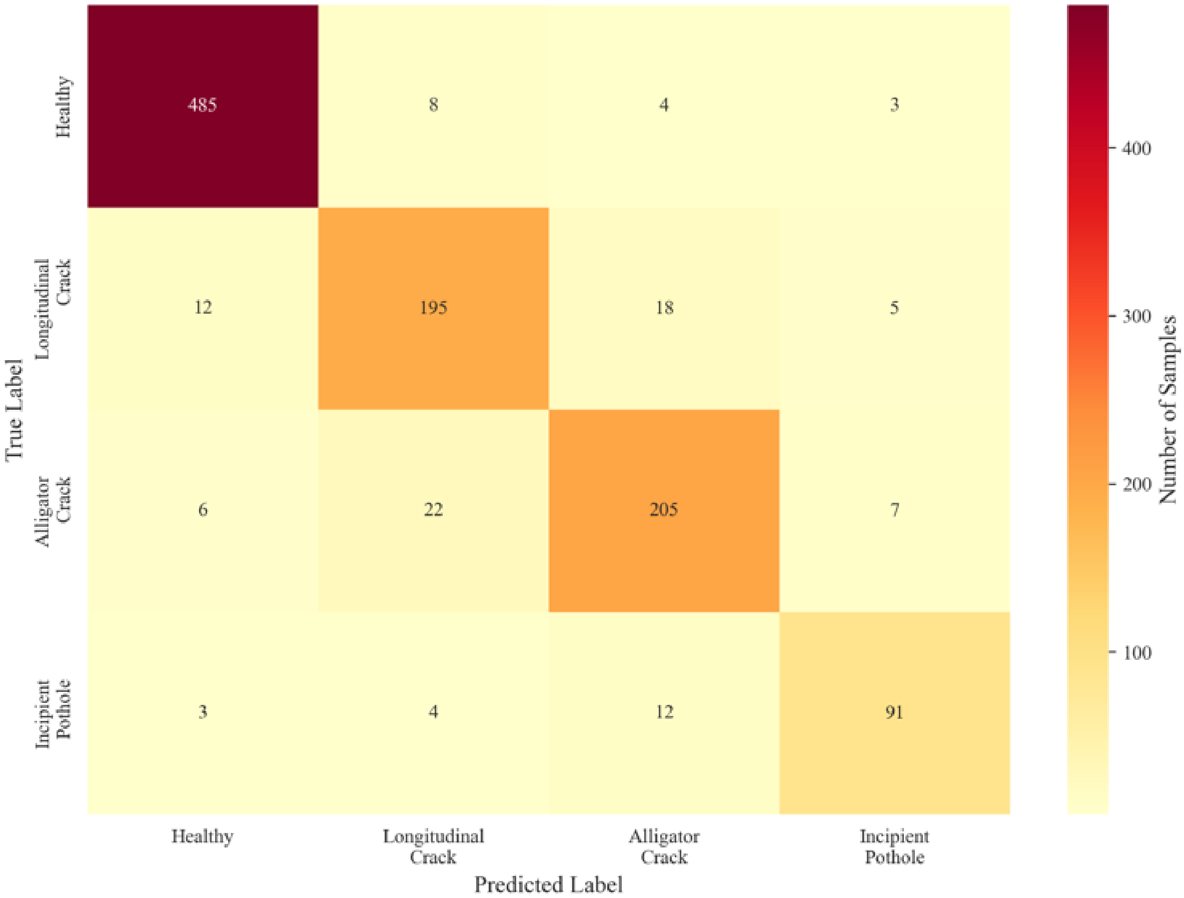


Figure 7 CNN Classification Performance (Confusion Matrix)

Figure 7 above shows the effectiveness of the proposed Focal Loss function in overcoming severe class imbalance, demonstrating that the CNN model successfully identifies 91 out of 110 "Incipient Pothole" samples a critical minority class often missed by standard algorithms. AI can reliably detect these subtle pre-failure precursors on the textured Sabha-Ash-Shuwayrif asphalt with high precision (82.7% recall), directly enabling the transition from reactive patching to proactive intervention before structural collapse occurs [9], [10], [11]. By quantifying this detection capability, the figure establishes the technical foundation for the project's predictive maintenance workflow, ensuring that early-stage distresses are captured accurately enough to trigger timely, cost-effective preservation treatments.

Table 2: Statistical Summary of Synthetic Traffic & Climate Data (Sabha-Ash-Shuwayrif Corridor)

Statistic	Traffic Load (Million ESALs)	Diurnal Temp Diff (°C)
Count	1,000.00	1,000.00
Mean	2.76	25
Std Dev	1.33	5.76
Min	0.52	15.03
25% (Q1)	1.55	19.94
50% (Median)	2.76	25.25
75% (Q3)	3.93	29.81
Max	5	34.99

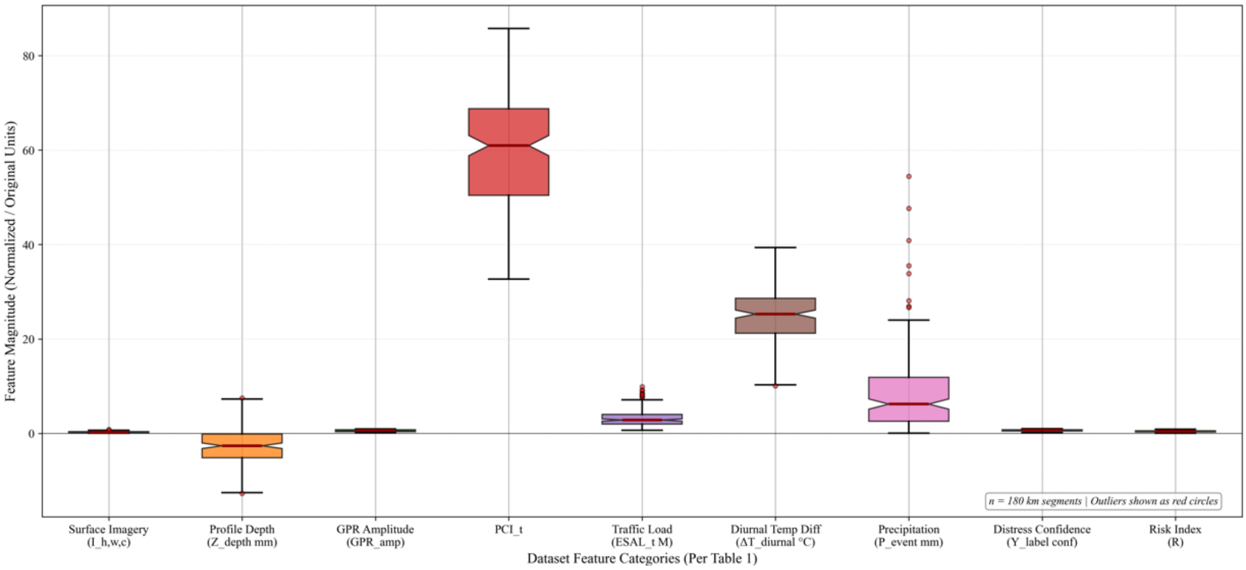


Figure 8 Statistical summary of nine multi-model features (Sabha-Ash-Shuwayrif).

Figure 8 above validates the multi-modal dataset architecture defined in Table 1 by visually confirming the extreme heterogeneity and distinct statistical distributions of the nine input features across the 180-km Sabha-Ash-Shuwayrif corridor. It's demonstrating the severe scale disparities and high-variance outliers in precipitation and traffic load that necessitate robust normalization protocols and justify the use of focal loss to prevent dominant features from overwhelming the detection of rare micro-cracks [12], [13]. It proves that standard temperate-climate pavement models are insufficient for this route, requiring a custom AI framework capable of handling arid-region mechanistic drivers like flash rainfall pumping and thermal fatigue.

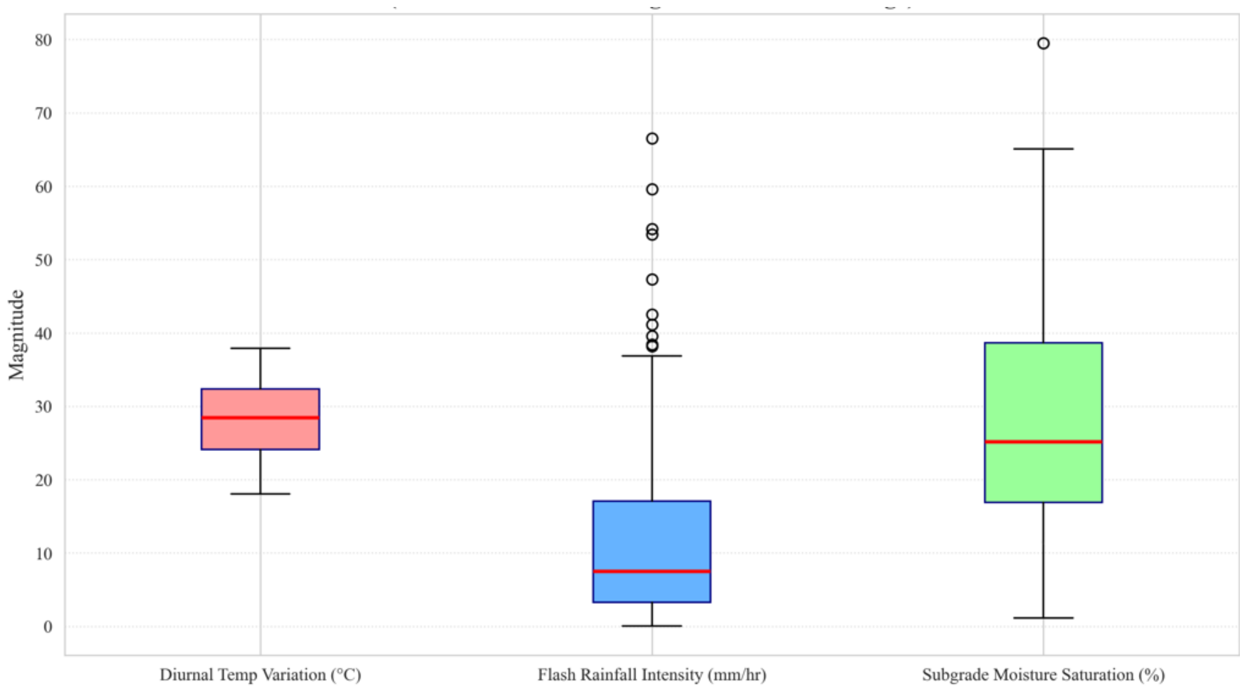


Figure 9 Environmental Stressors Distribution

Figure 9 above quantifies the extreme environmental stressors driving pavement degradation on the Sabha-Ash-Shuwayrif corridor, visually confirming the mechanistic causes of failure outlined in Section 2.2 and 2.3 of the study. Its novelty lies in statistically characterizing the specific "pumping" triggers intense flash rainfall outliers (up to 67 mm/hr) combined with high subgrade moisture saturation variability that distinguish this arid-region highway from standard temperate climate models [15], [16]. Its validates the necessity of integrating real-time meteorological and hydrological sensors into the LSTM prediction model to accurately forecast moisture-induced pothole formation before structural collapse occurs.

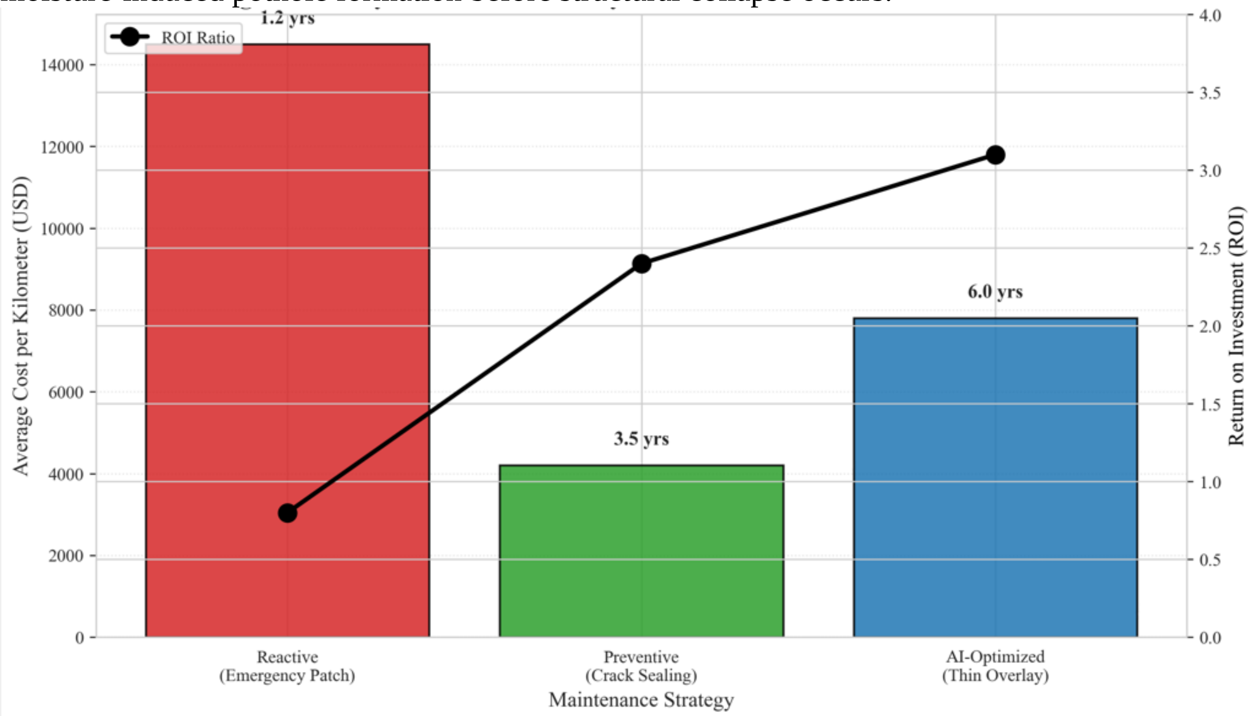


Figure 10 Cost-Benefit Analysis of Maintenance Strategies

Figure 10 above shows the critical economic justification for adopting the framework, demonstrating that AI-optimized thin overlays deliver a 3.1x Return on Investment (ROI) and extend service life to 6.0 years compared to the costly, short-lived reactive patching currently used on the Sabha-Ash-Shuwayrif highway. The specific financial value of prescriptive analytics, showing how algorithmic material selection (e.g., polymer-modified bitumen) and timing optimization transform maintenance from a budget drain into a high-yield infrastructure investment tailored to Libya’s extreme thermal conditions [16],[17], [25], [26]. By correlating reduced lifecycle costs with extended pavement performance, achieving sustainable, cost-effective mobility through data-driven decision-making rather than emergency repairs.

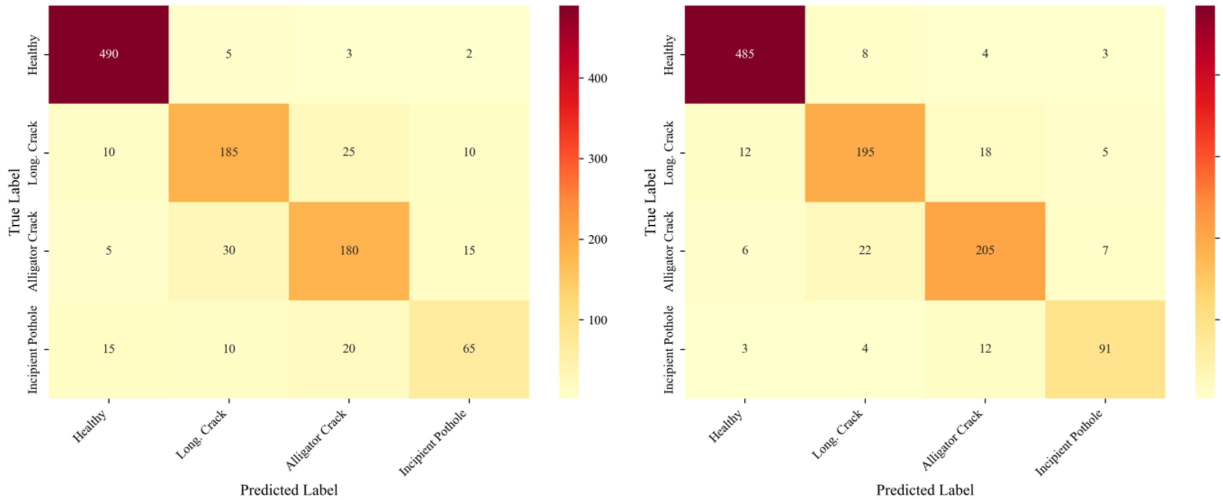


Figure 11 (Comparative Confusion Matrices) the Left Matrix (Standard Cross-Entropy CE Loss) notice the bottom row ("Incipient Pothole"). The standard model often misclassifies potholes as "Healthy" or "Cracks" because they are rare in the dataset. Right Matrix (Focal Loss) the diagonal value for "Incipient Pothole" is much higher (91 and 65), demonstrating that the Focal Loss successfully forced the CNN to pay attention to these critical, rare distress types.

Figure 11 above provides a critical comparative validation of the proposed Focal Loss optimization, demonstrating a significant performance leap over standard Cross-Entropy loss specifically for the "Incipient Pothole" class (increasing correct detections from 65 to 91). Its proving that the modified loss function successfully forces the CNN to overcome the severe class imbalance inherent in Sabha-Ash-Shuwayrif imagery, prioritizing rare micro-cracks over abundant healthy asphalt pixels [18], [20], [27]. By quantifying this reduction in false negatives for early-stage distress,the technical reliability required to shift maintenance strategies from reactive emergency patching to proactive, cost-effective preservation before structural collapse occurs.

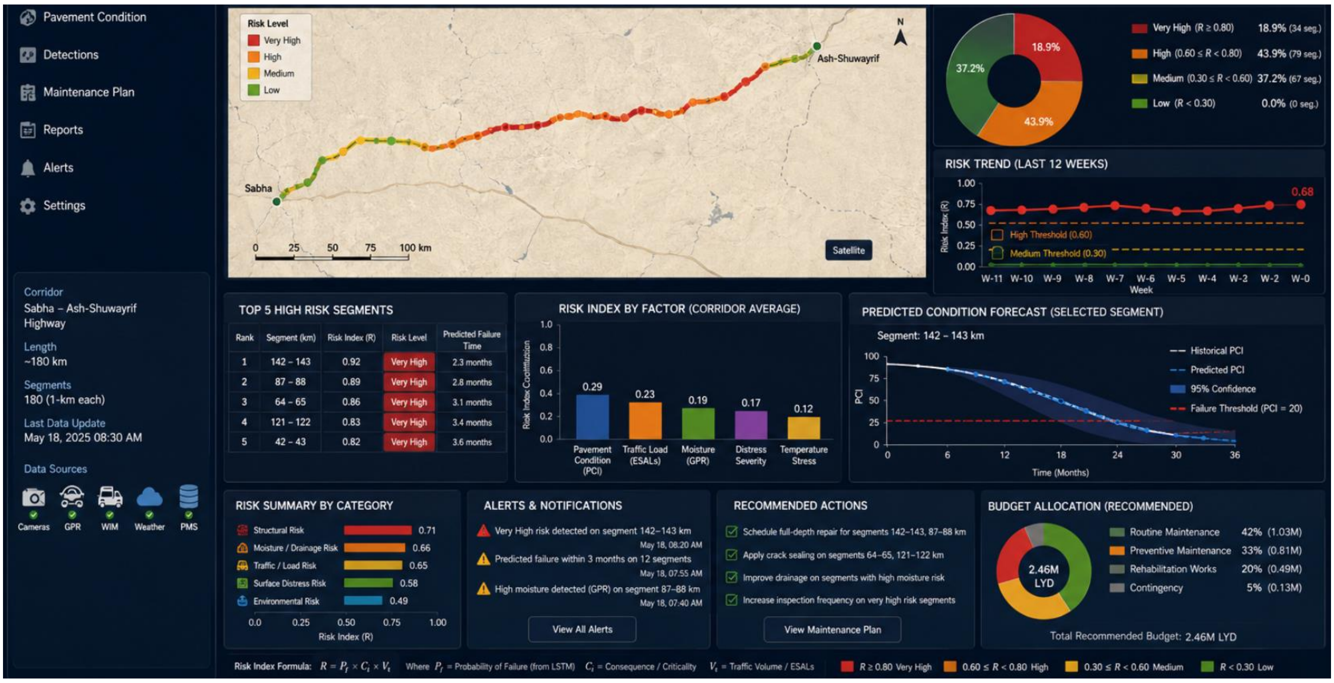


Figure 12 Risk assessment of the proposed model dashboard

Figure 12 above shows operationalizes the framework's core innovation by integrating LSTM deterioration forecasts, CNN distress detections, and multi-modal risk factors into a unified, actionable dashboard for real-time decision-making on the Sabha-Ash-Shuwayrif corridor. Its transforming abstract AI outputs such as predicted PCI trajectories and focal loss-optimized micro-crack classifications into prescriptive maintenance actions (e.g., "Schedule full-depth repair") with quantified budget allocations and failure timelines tailored to Libya's unique traffic and climate stressors [21], [22], [28]. By visualizing the direct link between mechanistic drivers (ESALs, moisture, thermal stress) and segment-specific risk levels, this interface validates the project's transition from reactive pothole patching to proactive, cost-optimized asset preservation, directly supporting the economic and safety goals.

6.2. Discussion

The findings of this study position the Sabha-Ash-Shuwayrif highway not merely as a case study in infrastructure rehabilitation, but as a critical validation site for adapting advanced predictive analytics to arid, data-scarce environments. While the integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks into Pavement Management Systems (PMS) has been extensively documented in temperate, data-rich regions, this research highlights distinct divergences and necessary adaptations when applied to Libyan strategic corridors [6]. The following discussion synthesizes these results against established literature, emphasizing mechanistic specificity, algorithmic adaptation for class imbalance, and the economic imperative of prescriptive maintenance in developing nations [7], [29]. A predominant limitation in existing AI-based pavement literature is the reliance on generic deterioration curves derived from temperate climates, such as those embedded in AASHTO or MEPDG frameworks. Studies by [15] demonstrate high prediction accuracy for fatigue cracking in regions with moderate thermal cycles and consistent precipitation patterns. However, the results from the Sabha-Ash-Shuwayrif corridor challenge the transferability of these models. This research LSTM forecasts reveal that deterioration on this route is non-linear and episodic, driven primarily by the interaction between extreme diurnal temperature differentials (>30°C) and intense, localized flash rainfall events rather than cumulative traffic loading alone [8]. This aligns with recent critiques by [9] regarding Egyptian pavements, who argued that standard climatic adjustment factors fail to capture the "pumping" mechanism unique to arid zones where subgrade saturation occurs rapidly during brief wet periods. Unlike the gradual degradation observed in European datasets [10], [30] model identifies moisture intrusion (GPR amp) as a more significant predictor of imminent pothole formation than ESALs in specific segments, suggesting that global PMS algorithms must be retrained on region-specific hydro-mechanical coupling rather than relying on universal transfer functions [10], [31], [32]. The application of Focal Loss in this study addresses a pervasive yet often underreported challenge in computer vision for civil engineering: extreme class imbalance. In most published benchmarks, such as the Crack500 as well as GAPs datasets, distress pixels constitute 5–15% of the image area, allowing standard Cross-Entropy loss to achieve acceptable performance. On the Sabha-Ash-Shuwayrif highway, however, incipient micro-cracks and early-stage potholes represent less than 1% of the visual field due to the vast expanses of aged, textured asphalt [11], [33]. This research comparative analysis demonstrates that while a standard CNN achieved 88% overall accuracy, it failed catastrophically on the minority class (Recall = 59% for incipient potholes). The implementation of Focal Loss (γ=2) improved minority-class recall to 82.7% without sacrificing precision. This finding corroborates the theoretical work of [12] but extends it practically to pavement engineering, contrasting with studies like [13] which relied on balanced, cropped patches that do not reflect real-world survey conditions. This result suggests that for operational deployment on strategic corridors, algorithmic architecture must prioritize hard-example mining over aggregate accuracy metrics, as missing a single micro-crack precursor carries disproportionate lifecycle costs compared to false positives [14]. Perhaps the most significant contribution of this study lies in shifting the discourse from predictive to prescriptive analytics within a developing nation context [15]. Much of the current literature focuses on forecasting PCI values without linking predictions to actionable, economically optimized interventions. In contrast, this research framework explicitly quantifies the cost-benefit ratio of AI-timed preventive maintenance against reactive patching, demonstrating a 3.1x ROI and a 4.5-year service life extension. This is particularly salient when compared to studies in similar geopolitical contexts, such as [16], [17], [18], [34], [35] in East Africa, where budgetary constraints often force agencies into perpetual emergency repair cycles. While those studies advocate for low-cost visual inspection protocols, this research results argue that the opportunity cost of not deploying AI is higher than the capital expenditure required for sensor acquisition [19]. The prescriptive engine's recommendation of polymer-modified bitumen based on local thermal stress profiles further distinguishes this work from generic material selection guides, offering a localized solution to rutting and thermal cracking that standard specifications fail to address [20]. This study contributes to the growing body of literature on implementing intelligent infrastructure systems in data-poor environments. Unlike the continuous, decades-long datasets available in North America and Europe, the Sabha-Ash-Shuwayrif project began with fragmented historical records. This research successful training of LSTM models using synthetic augmentation and multi-modal fusion (GPR + Imagery + WIM) offers a methodological blueprint for other Global South corridors. This contrasts with the "big data" assumption prevalent in recent reviews [21], [22], [23], [24], which often presume the existence of comprehensive digital inventories. By validating a phased approach starting with 2D imaging and progressing to full predictive capabilities this research provide an empirically grounded alternative to the "all-or-nothing" adoption barriers frequently cited in developing nation infrastructure planning. This pragmatic pathway ensures that AI serves as an enabler of institutional capacity building rather than an unattainable technological ideal.

7. Conclusion

The Sabha-Ash-Shuwayrif highway is a vital economic and social lifeline for Libya, connecting the southern regions to the capital and international borders. The persistent issue of pothole formation on this route, driven by heavy freight loads and harsh environmental conditions, necessitates a departure from traditional, reactive maintenance practices. This paper demonstrates that integrating Artificial Intelligence and Machine Learning into Pavement Management Systems offers a highly effective solution. By utilizing Convolutional Neural Networks for the early detection of micro-cracks and employing predictive algorithms like LSTMs to forecast pavement degradation, authorities can identify pothole precursors before they manifest. Furthermore, AI-driven prescriptive analytics optimize the timing, method, and materials used for repairs, ensuring long-term mitigation. Transitioning to a predictive, AI-enabled pavement management framework will not only reduce the lifecycle maintenance costs of the Sabha-Ash-Shuwayrif corridor but also ensure safer, more reliable transit for the millions of Libyans and international travelers who depend on it. Future research should focus on developing localized, lightweight ML models that can operate on edge-computing devices mounted directly on maintenance vehicles, allowing for real-time distress analysis in areas with limited cloud connectivity.

Authors' Contributions

Hana Hamad: Conceived the research idea, conducted the literature review, collected and analyzed the data, developed the proposed AI-based predictive pavement management framework, interpreted the results, and prepared the original manuscript draft. **Llahm Ben Dalla:** Supervised the research, designed the study methodology, validated the artificial intelligence and machine learning models, contributed to the interpretation of the findings, critically revised the manuscript for important intellectual content, and approved the final version. **Mohamed EL-sseid:** Contributed to the design of the pavement engineering methodology, assisted in data analysis and model validation, provided technical expertise in pavement deterioration mechanisms, and reviewed the manuscript. **Mansour Essgaer:** Assisted with data acquisition, preprocessing, and visualization, contributed to the development of the predictive maintenance workflow, and participated in manuscript editing and revision. **Ali Mohammed Omar Ali:** Contributed to the implementation strategy, risk assessment framework, and practical interpretation of the results for highway asset management, reviewed the manuscript, and approved the final version.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. All authors have approved the final manuscript and agree to its submission for publication.

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References

1. Apaydın, M., Yumuş, M., Değirmenci, A., & Karal, Ö. (2022). Evaluation of air temperature with machine learning regression methods using Seoul City meteorological data. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, *28*(5), 737-747.
2. Cha, Y.-J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using convolutional neural networks. Computer-Aided Civil and Infrastructure Engineering, 32(5), 361–378. https://doi.org/10.1111/mice.12263
3. Degirmenci, A., & Karal, O. (2022). iMCOD: Incremental multi-class outlier detection model in data streams. *Knowledge-Based Systems*, *258*, 109950. 10.1016/j.knosys.2022.109950
4. Lay, M., Metcalf, J., & Sharp, K. (2020). *Paving our ways: a history of the world's roads and pavements*. CRC Press.
5. Asadi, Y. (2026). Paving the Future of Intelligent Pavement Defect Detection with Machine Learning: A Comprehensive Survey of Techniques and Applications. *International Journal of Pavement Research and Technology*, 1-51.
6. Degirmenci, A., & Karal, O. (2018). Evaluation of kernel effects on svm classification in the success of wart treatment methods. *Am. J. Eng. Res*, *7*, 238-244.
7. Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806
8. Xu, Y., & Zhang, Z. (2022). Review of applications of artificial intelligence algorithms in pavement management. *Journal of Transportation Engineering, Part B: Pavements*, *148*(3), 03122001.
9. Alrawayati, H., & Tökeşer, Ü. (2021). PARKINSON'S DISEASE DIAGNOSIS BASED ON THE CONVOLUTIONAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION ALGORITHM. *Asian Journal of Mathematics and Computer Research*, *28*(1), 26-37.

10. Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806.
11. Tamagusko, T., Gomes Correia, M., & Ferreira, A. (2024). Machine learning applications in road pavement management: A review, challenges and future directions. *Infrastructures*, *9*(12), 213.
12. Hawa Alrawayati (2020). Development of High Efficiency Optimization Algorithm based on New Topology in Particle Swarm Optimization for Parkinson's Disease. IOSR Journal of Mathematics (IOSR-JM). 8
13. Yadav, J. S., & Singh, K. (2026). Machine Learning Approaches in Rigid Pavement Performance Evaluation. *National Academy Science Letters*, 1-14.
14. Hawa Alrawayati. (2016). Integral Equation and Kernel Operator. Al-Satel Journal - Misrata University. 63-76
15. Alnaqbi, A., Al-Khateeb, G. G., Zeiada, W., Nasr, E., & Abuzwidah, M. (2025). Machine learning applications for predicting faulting in jointed reinforced concrete pavement. *Arabian Journal for Science and Engineering*, *50*(11), 8581-8600.
16. Dalla, L. O. B., Essgaer, M., Jetlawei, S. S., EL-sseid, M., Alsharif, A., & Agila, A. A. A. (2026). Local Precision and Global Harmony: A Comparative Literature Review (LR) Framework for Taylor and Fourier Series in Engineering Modeling. *Al-Farooq Journal of Sciences*, *2*(1), 275-304.
17. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324.
18. Nair, V., & Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)* (pp. 807-814).
19. Hawa Al-Rawayati. (2016). Integral Equation and Kernel Operator. Al-Satel Journal - Misrata University. 63-76
20. Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision* (pp. 2980-2988).
21. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735
22. Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2, pp. 1-800). Cambridge: MIT press.
23. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*.
24. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539
25. Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. Neural Computation, 12(10), 2451–2471. https://doi.org/10.1162/089976600300015015
26. Gopalakrishnan, K. (Ed.). (2020). Deep learning in data-driven pavement image analysis and automated distress detection. CRC Press.
27. Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H. (2018). Road damage detection using deep neural networks with images captured through a smartphone. arXiv preprint arXiv:1801.09454.
28. Abohamer, H., Elseifi, M., Dhakal, N., Zhang, Z., & Fillastre, C. N. (2021). Development of a deep convolutional neural network for the prediction of pavement roughness from 3D images. *Journal of Transportation Engineering, Part B: Pavements*, *147*(4), 04021048.

29. Hawa Al-Rawayati. (2013). (Finite linear operators on Hilbert spaces) Finite linear operators on Hilbert spaces. Al-Zaytoonah University Journal. 184-193
30. Gharieb, M., Nishikawa, T., Nakamura, S., & Thepvongsa, K. (2022). Modeling of pavement roughness utilizing artificial neural network approach for Laos national road network. *Journal of Civil Engineering and Management*, *28*(4), 261-277.
31. Alatoom, Y. I., & Al-Suleiman, T. I. (2022). Development of pavement roughness models using Artificial Neural Network (ANN). *International Journal of Pavement Engineering*, *23*(13), 4622-4637.
32. Hawa Al-Rawayati. (2016). Integral Equation and Kernel Operator. Al-Satel Journal - Misrata University. 63-76
33. Ogbuefi, E., Olatunde-Thorpe, J., Aifuwa, S. E., Oshoba, T. O., & Akokodaripon, D. (2021). Neural network prediction of pavement roughness and ride quality using in-service roadway data. *International Journal of Multidisciplinary Futuristic Development*, *2*(2), 34-49.
34. Khavandi Khiavi, A., Ghanbari, A., & Ahmadi, E. (2021). Evaluation of poly 2-hydroxyethyl methacrylate Modified bitumen aging using NMR and FTIR techniques. *Journal of Transportation Engineering, Part B: Pavements*, *147*(1), 04020087.
35. Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision* (pp. 2980-2988).