Prediction of Remaining Service Life of Flexible Pavements Based on Structural and Functional Indices Using Machine Learning Approaches on Ekiti State Roads

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ORIGINAL RESEARCH

Abstract— Reliable estimation of the remaining service life (RSL) of flexible pavements is essential for effective maintenance planning and asset management. Some previous studies have relied primarily on regression-based models while others used single machine learning techniques. These models usually have problem of low accuracy, poor generalizability, and inadequate integration of structural and functional variables. To address these limitations, this study evaluates five predictive approaches: Multiple Linear Regression (MLR), Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machine (GBM) to predict RSL using Structural Number (SN), California Bearing Ratio (CBR), surface deflection, Pavement Condition Index (PCI), International Roughness Index (IRI), and Present Serviceability Index (PSI). The dataset comprised a stratified field survey of approximate 10 pavement sections from each of the road with 300 total datasets, collected from Ado–Iworoko Road, Ijan–Ilumoba Road, Ikere–Ise Road, Ifaki–Ido Road, Oye–Ikole Road, and Aramoko–Ijero Road in Ekiti State, Nigeria between April 2024 and September 2025. Model performance was evaluated with the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The findings reveal that regression model has R^2 = 0.67, ANN, RF, SVM and GBM have 0.78, 0.82, 0.75 and 0.85, respectively. The ensemble methods, particularly GBM, yielded the most accurate predictions, while regression remained valuable for interpretation. The feature importance analysis performed indicated SN and IRI as the strongest determinants of pavement performance among structural and functional variables respectively, while CBR and PCI contribute only moderately. This study help contributes to knowledge by confirming that ensemble learning provides an optimal reliable prediction compared to the traditional and single-model approaches, thereby supporting more efficient pavement management strategies.

Keywords— Functional indices, Machine learning, Pavement performance, Remaining service life, Structural indices

1 INTRODUCTION

The performance evaluation of flexible pavements is a fundamental element of pavement management systems, directly influencing the durability, safety, and cost efficiency of road infrastructure. The RSL is an important parameter used to determine the appropriate timing for maintenance and rehabilitation interventions of road pavements (AASHTO, 1993). The traditional empirical methods for estimating RSL often fail to capture the complex and nonlinear relationships between the structural and functional pavement characteristics (Huang, 2004). However, the development of data-driven approaches has led to the use of machine learning techniques, which are powerful tools for improving the accuracy of predictions in pavement engineering (Li & Mills, 2009).

Flexible pavement systems are exposed to continuous traffic loading and environmental stresses which lead to rapid deterioration and reduction of serviceability. An effective management of these assets requires reliable evaluation methods that combine both structural capacity and functional quality. Indicators such as SN, CBR, PCI, and IRI are used to measure the performance of pavement, while RSL help to determine how long a pavement section can continue to perform before intervention strategies are required (AASHTO, 1993; ASTM, 2018). Previous studies confirm that if structural indicators such as SN and CBR with functional indicators such as PCI and IRI are combined can help improve the accuracy of pavement performance prediction (Gharaibeh & Darter, 2003).

Traditional regression-based approaches have been widely used but often fail to capture nonlinear deterioration mechanisms (Nabipour *et al* 2019). Neural networks and other artificial intelligence techniques have also shown great proficiency in modelling pavement serviceability and structural response (Ceylan et al., 2005; Terzi, 2007). Ensemble techniques and deep learning have been included into pavement management systems. This is related to the recent advances in machine learning that have showed greater prediction capacity (Tamagusko et al., 2024). In addition, deep learning has been used to measure pavement distress by means of deep learning-based distress detection (Zheng et al., 2024). They proved that machine learning techniques need to be used in local settings like the Nigerian road networks, where data-driven techniques are not being applied.

However, a comprehensive review of previous research reveals a number of dataset limitations; many studies used localized data or extremely small samples which reduced generalizability. Regression-based methods would be oversimplified for nonlinear relations in many cases for prediction models and single ML models were not enough. Previous studies have only reported R2

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values of assessment measures, without providing other metrics like RMSE or MAE, which are essential to assess the reliability of the prediction. Geographically, most of the studies originated from North America, Europe, or Asia, with limited data from pavement systems in Africa. Finally, there are certain disadvantages of prior studies, such as the limited scope, the lack of feature importance analysis, and the insufficient combination of both structural and functional indicators.

The work bridges these gaps by using and comparing the predictions of MLR, ANN, RF, SVM and GBM on a dataset of 300 pavement sections collected from major roads in Ekiti State, Nigeria. Descriptive statistics are utilized in creating a baseline understanding of pavements performance metrics and then predictive modelling is employed in assessing accuracy and interpretability. This study uses feature significance analysis to give new insights on the relative influence of structural and functional markers. The results encourage better pavement management tactics by providing transportation authorities with tangible evidence that ensemble learning techniques can achieve greater predictive reliability.

2 REVIEW OF STUDIES

Some early researches were conducted using mechanistic empirical models and regression analysis. These models were interpretable, but did not describe sufficiently complex deteriorative processes. Then machine learning techniques like RF and SVM started to show that they can do better than regression by detecting nonlinear dependencies (Nabipour et al., 2019). ML applications have been more recently extended to pavement engineering. Kaur and Kumar (2025) used RF and recurrent neural networks for predicting the fatigue and rutting life with good accuracy. Hybrid smart models for pavement management were explored by Luja (2025), who found hybrid solutions to be critical to provide a trade-off between accuracy and interpretability. Lei et al. (2025) proposed a multi-model ensemble learning strategy to increase the generalizability of forecasts of pavement structural deterioration. Gupta and Kumar (2025) propose an ensemble learning method for predictive maintenance scheduling by using SHAP-based rating of treatments.

DL has improved further the detection of pavement distress. Zheng et al. (2024) researched the methods for CNN-based detection. The significance of feature-importance analysis and indices such as SN, IRI, and CBR for pavement durability have been highlighted by Ahmad et al. (2024) and Alnaqbi et al. (2024). Hybrid machine learning methods for service life prediction were proved to be effective by Azodinia et al. (2025).

To summarize, our results support the use of ensemble and deep learning methods instead of regression and emphasize the necessity of including both structural and functional factors. However, few studies have systematically applied similar approaches to African road networks. This study consequently filled this gap with data from the Ekiti State Road.

3 METHODOLOGY

3.1 DATA DESCRIPTION

The collection consists of 10 pavement sections of key roads in Ekiti State, Nigeria, namely: Ado–Iworoko Road, Ijan–Ilumoba Road, Ikere–Ise Road, Ifaki–Ido Road, Oye–Ikole Road, and Aramoko–Ijero Road. The results were acquired in field testing throughout 2024-2025 under different traffic and environmental conditions. The structural (SN, MSN, CBR, rebound deflection) and functional characteristics (PCI, IRI, PSI) were identified for each section. The sample was stratified to represent various types of roads and pavement conditions. Missing data for continuous variables were imputed using the mean and for categorical variables with the mode. The features were normalized to the same range.

3.1.1 STRUCTURAL NUMBER (SN)

The SN is a measure of the overall structural strength of the pavement system. It determines the strength of the pavement as a consequence of the thickness and quality of each of its layers. This measure combines material properties and moisture susceptibility to provide a good indication of structural adequacy. It is given by the following equation: (1)

$$SN = a_1D_1 + a_2D_2m_2 + a_3D_3m_3 \quad (1)$$

where $a_1, a_2, a_3$are layer coefficients, D_1, D_2, D_3 are layer thicknesses, and m_2, m_3 are drainage factors.

Table 1 is a summary of the AASHTO Layer coefficient chart used

Table 1. AASHTO Layer Coefficient Chart

Pavement Layer	Coefficient (a)
Asphalt Concrete (a_1)	0.40 – 0.44
Granular Base Course (a_2)	0.11 – 0.14
Lateritic Sub-base Course (a_3)	0.08 – 0.11

3.1.2 REBOUND DEFLECTION

Deflection measures pavement response under load. Higher deflection values indicate weaker structural support. Rebound deflection was measured on the field using the Benkelman Beam equipment. The corrected deflection was obtained by adjusting for temperature and seasonal effects with these formulars shown in Equation (2) and (3) respectively:

$$D_T = D_m \cdot [1 + k(T_m - T_r)], \quad (2)$$

$$D_S = D_T \cdot C_s \quad (3)$$

3.1.3 CALIFORNIA BEARING RATIO (CBR)

Unsoaked CBR values were obtained in the laboratory by compacting and soaking the soil specimens for 48 hours and applying load at 2.5 mm and 5.0 mm penetration. The higher value was reported using Equation (4).

$$CBR = \frac{\text{Test Load}}{\text{Standard Load}} \times 100 \quad (4)$$

3.1.4 MODIFIED STRUCTURAL NUMBER (MSN)

The traditional SN does not account for subgrade strength. So, in order to incorporate this, the CBR of the subgrade is introduced. The MSN is defined by AASHTO (1993) as shown in Equation (5).

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$MSN = SN + 3.51 \cdot \text{〖log〗}_{10}(CBR_s) - 0.85 \cdot [\text{〖log〗}_{10}(CBR_s)]^2 - 1.43$ (5)

where $CBR_s$is the subgrade CBR.

3.1.5 PAVEMENT CONDITION INDEX (PCI)

PCI was derived from distress surveys measured on the field. The PCI is the measurement of surface condition of the pavement by measuring different pavement types such as cracking, potholes, rutting, patching, raveling etc. and their severity (such as low, medium and high). Deduct values were calculated and corrected to get PCI using Equation 6:

$$PCI = 100 - CDV \quad (6)$$

Where CDV = Corrected Deduct Value

3.1.6 INTERNATIONAL ROUGHNESS INDEX (IRI)

IRI quantifies surface roughness and ride quality. It was measured using RoadLab Pro. smartphone sensors. Values expressed in m/km quantified ride quality, with lower values indicating smoother pavements while higher values indicate deteriorating surface conditions, which accelerate service life reduction. Table 2 presented the method of rating.

Table 2. IRI rating scale

IRI (m/km)	Pavement Condition	Remarks
> 2	Excellent/Very Good	Smooth pavement, high ride quality
2.0–4.0	Good/Fair	Acceptable ride quality, minor roughness
4.0 – 6.0	Poor	Noticeable roughness, reduced comfort
> 6.0	Very Poor/Failed	Severe roughness, poor serviceability

3.1.7 PRESENT SERVICEABILITY INDEX (PSI)

The PSI evaluates pavement functionality, which reflects user perception of pavement quality, focusing on ride quality and surface condition. It is derived from roughness and distress data, typically expressed by Equation (7) as:

$$\text{PSI} = 5.0 - 1.5\log(1 + \text{SV}) - 0.01(\text{C} + \text{P}) - 1.38(\text{RD})^2 \quad (7)$$

Where:

SV= Slope Variance (measure of surface roughness);

C = extent of cracking;

P = patched or pothole area and

Rd = rut depth (in inches).

Values range from 0 (failed pavement) to 5 (perfect condition). The higher the PSI, the smoother the pavement and the better its serviceability. Lower numbers mean deterioration and less comfort.

3.1.8 REMAINING SERVICE LIFE (RSL)

The RSL was estimated by comparing corrected rebound deflection values with the allowable design deflection. Standardized deflections (D_S) were related to the permissible deflection (D_{allow}) and design life (L_{design}) using Equation 8:

$$RSL = \left(\frac{D_{allow}}{D_S}\right)^2 L_{design} \quad (8)$$

3.2 MODEL DEVELOPMENT

Five predictive models and were designed to estimate RSL. They are:

1. Multiple Linear Regression (MLR): It establishes a direct linear relationship. Equation 9 shows the general formulation.

$$RSL = \beta_0 + \beta_1 SN + \beta_2 CBR + \beta_3 PCI + \beta_4 IRI + \beta_5 D_S + \epsilon \quad (9)$$

2. Random Forest (RF): This is an ensemble of decision trees; prediction is the average of outputs obtained by Equation (10)

$$\widehat{RSL} = \frac{1}{N}\sum_{i=1}^{N} T_i(X) \quad (10)$$

where $T_i(X)$is the prediction from tree i.

3. Support Vector Machine (SVM): It finds optimal hyperplane using kernel functions obtained by Equation (11)

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x) + b \quad (11)$$

4. Artificial Neural Network (ANN): This learns nonlinear patterns through weighted layers, obtained by Equation (12)

$$y = f(\sum w_i x_i + b) \quad (12)$$

with activation functions applied across hidden layers.

5. Gradient Boosting Machine (GBM): It builds models sequentially, minimizing residuals, obtained by Equation (13)

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \quad (13)$$

where $h_m(x)$ is the weak learner fitted to residuals.

3.3 MODEL IMPLEMENTATION

All the prediction models were implemented in a Jupyter Notebook environment using Python 3.11. The model was designed and assessed using scikit-learn, TensorFlow/Keras, and XGBoost tools. Data preparation was performed to ensure consistency across all variables, including normalization, outlier removal, and mean imputation of missing data. The hyperparameters were tuned using grid search cross-validation. Thus, for each model, a full search over a range of parameter values is performed to obtain the best configuration. The MLR model was trained on the scikit-learn package. In the Linear Regression class, transparency and interpretability are the gold criteria. The RF model was built with 500 trees, a maximum depth of 15, a minimum of 4 samples per node, and mean squared error as the splitting criterion. The SVM model was trained with a radial basis function (RBF) kernel, it enables nonlinear separation of the data points. The penalty (C) was set to 10, and gamma was set to 0.1. The ANN structure contains two hidden layers with 32 and 16 neurons respectively. The ReLU activation function was used for the hidden layers, and the sigmoid function for the output layer. The network was trained with Adam optimizer with a learning rate of 0.0005, a maximum of 3000 iterations, and a batch size of 32. For 200 epochs with early pauses to prevent over-fitting. The GBM model was developed using XGBoost with a learning rate of 0.03, 300 estimators, a maximum depth of 3, and a subsample ratio of 0.8 for improving generalization

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3.4 Model Validation

For model validation, three performance metrics were used to assess the accuracy of the models. The dataset was split into 80% for training and 20% for testing, with five-fold cross-validation applied to minimize bias and ensemble models (RF and GBM) were further analyzed for feature importance. The Model performance was evaluated used are as follows:

1. Coefficient of Determination (R^2)

R^2 measures how much of the variance in the dependent variable is explained by the model. This is obtained using Equation (14).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (14)$$

Where:

y_i: observed values

$\hat{y}_i$: predicted values

$\bar{y}$: mean of observed values

2. Root Mean Square Error (RMSE)

RMSE penalizes large errors more heavily by squaring deviations before averaging, obtained by Equation 15.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (15)$$

3. Mean Absolute Error (MAE)

MAE is the mean magnitude of mistakes regardless of direction and is given by Equation 16.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (16)$$

4 RESULTS AND DISCUSSION

4.1 DESCRIPTIVE STATISTICS

Table 3. Descriptive statistics of the dataset. Table 3 summarizes the pavement performance metrics. The mean value of SN (3.89) and SD (0.31) were very low, indicating structural sound homogeneity across the parts. The mean CBR was 37.31%, with greater dispersion (SD = 9.46) and heterogeneity in subgrade intensity. The IRI values ranged from 1.36 to 11.63 m/km, with an average of 3.68, indicating that most pavements were in fair to good condition, while other portions were quite rough. The average RSL was 9.96 years, but the wide range (3.23-15.12 years) underscores the need for forecasting to inform maintenance planning.

Table 3. Summary of Descriptive Statistics

Statistics	SN	CBR%	MSN	DEFLE-CTION	IRI	PCI	PSI	RSL
Mean	3.89	37.31	5.93	0.62	3.68	80.92	3.61	9.96
St. Error	0.02	0.54	0.02	0.01	0.09	0.51	0.02	0.25
Median	3.70	39.00	6.01	0.56	3.33	82.00	3.68	13.17
Mode	3.70	44.80	6.01	0.56	2.35	85.00	3.88	13.17
St. Dev.	0.31	9.46	0.40	0.10	1.51	8.94	0.34	4.45
Variance	0.10	89.57	0.16	0.01	2.28	79.97	0.12	19.77
Kurtosis	-0.79	-1.06	-0.75	-1.16	2.56	1.00	3.21	-1.39
Skewness	-0.44	-0.21	-0.34	0.70	1.34	-0.92	-1.47	-0.56
Range	1.01	37	1.66	0.29	10.27	53	2.18	11.89
Minimum	3.26	20	5.13	0.5	1.36	42	2.01	3.23
Maximum	4.27	57	6.79	0.79	11.63	95	4.19	15.12

4.2 REGRESSION EQUATION

From the result of the prediction of RSL of the pavement, the MLR fit is written as shown in Equation (17).

$$RSL = 12.84 - 0.72SN + 0.58MSN - 1.95Def + 0.04CBR - 0.21IRI + 0.63PSI + 0.37PCI \quad (17)$$

The signs and magnitudes of the coefficients provide valuable insight into how each variable influences pavement longevity. Variables with negative coefficients, SN, Deflection, and IRI, show that increases in these parameters correspond to a reduction in RSL, assuming other factors remain constant. This is consistent with technical assumptions that a higher SN value is often associated with pavements experiencing higher traffic demands and greater deflection, suggesting structural wear and loss of stiffness (AASHTO, 1993; Zhang et al., 2023). The higher the IRI, the greater the deterioration and the rougher the surface, which affects the service life (Paterson, 1987). Variables with a positive coefficient (e.g., MSN, CBR, PSI, PCI) contribute to higher RSL. Higher MSN and CBR values indicate greater capacity of the structural and subgrade layers to resist loads and to be durable (Huang, 2004). PSI and PCI represent surface quality and distress levels; their positive influence confirms that pavements in better functional and physical condition exhibit longer remaining service life (Shahin, 2005).

4.3 COMPARATIVE MODEL PERFORMANCE

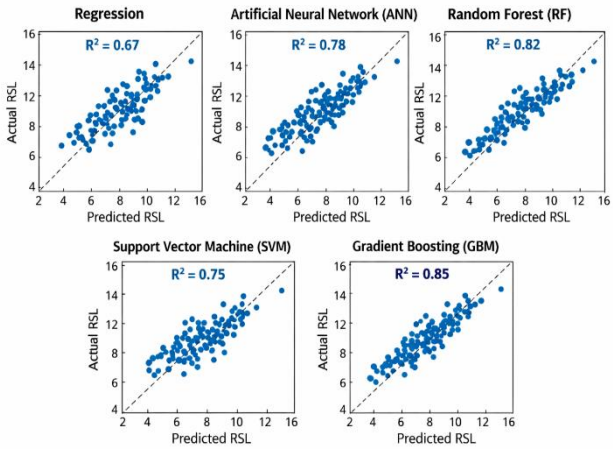

Fig. 1. Predicted versus actual RSL across the models

Figure 1 presents a comparative evaluation of forecasting models for pavement RSL. It demonstrates various strengths and weaknesses of the models. The regression model was able to predict RSL with a good accuracy (R2 = 0.67). This suggests that the model can learn the linear correlations between RSL and the input parameters, but not the nonlinear interactions. Table 4 Performance measures. The ANN improved the performance with R2=0.78 (16.4% improvement over MLR) and reduced RMSE and MAE by 13.3% and 13.4% respectively, indicating the ability of the ANN to learn challenging patterns. The RF model outperformed the other models with R2 = 0.82, which is 22.4% better R2 than MLR and around 20.9% and 24.4% lower in RMSE and MAE, respectively. The R2 obtained from the SVM was 0.75, which was 11.9% higher than that of the MLR and it caused a decrease of 6.7% and 6.1% in the RMSE and MAE, respectively. However, the robustness of SVM depends on the kernel selection. The GBM model was the best performing model (R2=0.85) and 26.9% better than the MLR model. RMSE is improved by 29.5%. MAE is

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enhanced by 32.9%. The results are statistically significant ($p<0.05$) and demonstrate the benefit of adopting non-linear models to mimic the complicated behaviour of pavements. The results are consistent with recent research results demonstrating the relative effectiveness of ensemble learning methods for predicting pavement service life, with the RF and GBM outperforming traditional regression methods (Nabipour et al., 2019; Azodinia et al., 2025).

Table 4. Model performance metric

Models	R^2	RMSE	MAE
Regression	0.67	0.105	0.082
ANN	0.78	0.091	0.071
RF	0.82	0.083	0.062
SVM	0.75	0.098	0.077
GBM	0.85	0.074	0.055

4.4 FEATURE IMPORTANCE

The feature importance analysis shown in Figure 2 shows that SN, IRI, and CBR were the most influential predictors of RSL. This result is consistent with evidence that both structural integrity (SN, CBR) and functional quality (IRI) are critical determinants of pavement longevity, with SN and IRI strongly correlated with deflection and long-term serviceability (Ahmad et al., 2024; Alnaqbi et al., 2024). The ensemble models outperformed regression models in capturing these intricate connections, yielding predictions that closely align with observed RSL values and reaffirming their applicability to pavement management.

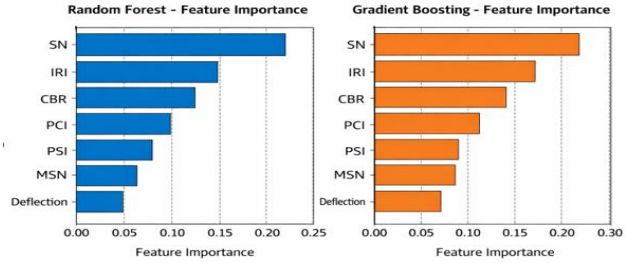

Fig. 2. Feature importance in RF and GBM models for RSL prediction

5 CONCLUSION

From the result of this study, the following conclusions were drawn:

1. SN consistently emerged as the most influential predictor, accounts for nearly 25% of predictive power, revealing its central role in pavement design and performance.
2. IRI contributes to roughly one-fifth (20%) of the predictive power, showing the necessity of monitoring surface roughness as a crucial signal of deterioration.
3. CBR provides approximate of 13% of explanatory strength, enhancing the influence of subgrade support.
4. PCI and PSI contribute moderately; they remain essential for capturing user-perceived quality and visible distress
5. GBM and RF performed reasonably well with R^2 values of 0.85 and 0.82 respectively.
6. Generally, the ML models outperformed the regression model.

6 RECOMMENDATION

1. The RSL prediction models will help highway agencies to schedule maintenance interventions at the right time by preventing untimely rehabilitation and will also help to prolong pavement life.
2. Integrating ensemble models into Pavement Management Systems (PMS) will enhance decision-making, and allow agencies to prioritize sections with the highest risk of failure.
3. This model could help agencies save an estimated 15–20% in lifecycle costs, by freeing resources for other infrastructure needs.
4. Machine learning-based RSL prediction provides evidence-based infrastructure planning, is in line with modern asset management frameworks, and ensures effective allocation of public funding.

Future work should explore hybrid modeling strategies that combine the regression with the predictive strength of ensemble methods to ensure that data-driven approaches remain both robust and practical for engineering applications.

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