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Prediction of International Roughness Index of Flexible Pavement Using Machine Learning-Based Predictive Framework in Ekiti State

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Abstract
Accurate prediction of pavement roughness is essential for effective road design, maintenance planning, and long-term serviceability. The International Roughness Index (IRI) is a key indicator of ride quality, yet direct measurement can be resource-intensive. This study develops predictive models for IRI using commonly measured pavement indices: Present Serviceability Index (PSI), Pavement Condition Index (PCI), and Mean Texture Depth (MTD). Five modelling approaches were employed: Linear Regression, Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN), applied to 480 highway sections in Ekiti State, Nigeria. Comparative evaluation using R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) showed that all models provided reasonable predictive capability, with R^2 values ranging from 0.71 to 0.94 and RMSE values between 0.41 and 0.60. Ensemble methods GBM ($R^2 \approx 0.94$, RMSE = 0.41) and RF ($R^2 \approx 0.92$, RMSE = 0.45) consistently outperformed other models, effectively capturing nonlinear interactions among pavement indices. ANN and SVM offered moderate improvements over Linear Regression but were less accurate than ensemble methods. The findings highlight the applicability of machine learning for translating pavement condition indices into reliable IRI predictions, enabling data-driven decision-making. Integrating GBM and RF models into routine pavement evaluation frameworks can support timely maintenance interventions, optimize resource allocation, and improve road safety and ride quality. The study recommends regular model calibration with local pavement data to maintain accuracy and reinforce predictive reliability. Overall, ensemble learning approaches provide robust, cost-effective solutions for pavement roughness forecasting, demonstrating their potential to enhance sustainable infrastructure management in resource-constrained environments.

Keywords: *International roughness index, pavement condition, present serviceability index, surface texture, machine learning tools.*

1.0 Introduction

Effective monitoring of road conditions is a fundamental component of infrastructure management, as it supplies critical information for prioritizing maintenance interventions and optimizing resource allocation [1]. The main objective of assessing road conditions is to detect surface distresses and irregularities that could affect safety or reduce driving comfort [2]. Such evaluations provide insight into the serviceability of the road network, indicating the expected driving experience, potential hazards, and long-term vehicle wear [3]. Data obtained from these assessments form a core part of Road Asset Management Systems (RAMS) and guide the planning of maintenance and rehabilitation activities [4], [5]. Among the various indicators of pavement performance, surface roughness is particularly important because it reflects deviations that compromise ride quality, increase vehicle operating costs, and reduce driver comfort. Research conducted by the World Bank highlights roughness as a key factor in balancing pavement quality with user-related costs.

Road roughness is influenced by multiple factors, including traffic volume—especially heavy truck movements—environmental conditions, material properties, pavement thickness, drainage design, construction practices, and the frequency and quality of maintenance interventions. Historically, ride quality was quantified using the serviceability index introduced in the AASHTO tests of 1957. Today, functional performance is commonly assessed through indices such as the International Roughness Index (IRI), Pavement Serviceability Index (PSI), Pavement Condition Index (PCI), and Mean Texture Depth (MTD), which provide numerical measures of pavement surface performance.

This study investigates the application of machine learning (ML) techniques to model the relationship between IRI and other pavement performance indicators across 480 highway segments in Ekiti State, Southwestern Nigeria. The IRI serves as a standard measure for asphalt pavement smoothness, while PSI reflects overall functional performance. Implementing ML enables data-driven prediction of pavement behavior, reducing reliance on extensive and costly laboratory or field testing. Previous studies have demonstrated the effectiveness of ML in capturing complex patterns within civil engineering datasets [6]. Several ML algorithms, including Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF),

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and M5 Model Trees (M5P), have proven effective for estimating geotechnical and pavement performance indices. These methods are particularly valuable for modelling intricate relationships among variables when the underlying physical mechanisms are complex or difficult to express mathematically. By leveraging such approaches, engineers can efficiently characterize the interactions among pavement properties, offering an accurate, cost-effective alternative to exhaustive field testing while maintaining high predictive reliability.

2.0 Literature Review

The operational quality of highway pavements is a key factor in transportation infrastructure management, as it directly affects road user safety, driving comfort, and vehicle operating costs. In countries like Nigeria, where road transport is the predominant mode for moving both people and goods, pavements often degrade rapidly. Contributing factors include heavy traffic loads, insufficient maintenance, environmental influences, and aging structures, underscoring the importance of reliable methods for monitoring pavement conditions and forecasting their performance over time [6], [7]. To assess pavement condition, several performance indices have been developed, including the International Roughness Index (IRI), Present Serviceability Index (PSI), Pavement Condition Index (PCI), and Mean Texture Depth (MTD). Among these, the IRI is widely recognized as the international benchmark for quantifying pavement surface roughness and ride quality [8], [9].

These indices provide objective measures for evaluating pavement serviceability and informing maintenance and rehabilitation planning. Conventionally, pavement condition assessment has relied on field instruments such as road profilers, bump integrators, and visual inspection surveys. While these techniques yield valuable insights, they are often resource-intensive, requiring specialized equipment and trained personnel, which can limit their application in regions with constrained budgets [10], [11]. This limitation has motivated the development of alternative, computationally efficient methods that can complement or even replace traditional measurement approaches.

In recent years, machine learning (ML) techniques have gained traction for predicting pavement roughness and related performance parameters. For instance, Albatsh et al. [12] demonstrated the use of regression-based models to forecast roughness indices for flexible pavements. Chandra et al. [13] applied Artificial Neural Networks (ANNs) to develop predictive models for Indian highway pavements, reporting superior accuracy compared to conventional empirical models. Similarly, Gong et al. [14] employed Random Forest (RF) algorithms on sensor-based pavement data, highlighting the advantage of ensemble learning in capturing complex, nonlinear pavement behavior. Furthermore, Mubarak et al. [15] explored Support Vector Machines (SVMs) for modeling pavement deterioration trends, demonstrating their effectiveness in predicting performance over time.

Beyond pavement applications, machine learning has also been used extensively for estimating geotechnical soil properties**,** which are critical for both pavement and foundation design. Traditional laboratory testing to determine parameters such as Optimum Moisture Content (OMC)**,** Maximum Dry Density (MDD), and California Bearing Ratio (CBR) is often costly and time-consuming.

Consequently, researchers have increasingly explored data-driven approaches capable of estimating these properties from simpler soil index measurements [16]. For example, Akinwamide et al. [17] applied a suite of machine learning algorithms—including Multiple Linear Regression (MLR)**,** ANN, SVM, RF, and M5 model trees—to predict key geotechnical parameters from laboratory-tested soil indices. Using 480 soil samples from Ekiti State, Nigeria**,** their study showed that ML models could accurately estimate soil properties while substantially reducing the need for extensive laboratory testing.

Several international studies have further validated the effectiveness of ML in geotechnical engineering. Pham et al. [18] used support vector regression and neural networks to predict OMC and MDD from soil index parameters, achieving better performance than traditional empirical correlations. Ghasemi et al. [19] developed ANN models to estimate soil shear strength, highlighting their ability to capture nonlinear behavior. Bui et al. [20] applied a hybrid approach combining neural networks with metaheuristic optimization to improve predictions of CBR and other geotechnical properties. Similarly, Moayedi et al. [21] implemented ensemble methods such as RF and Gradient Boosting Machines (GBM) to model various soil indices, demonstrating their capacity to handle large and complex datasets.

Despite the widespread use of machine learning for geotechnical property estimation, research specifically addressing highway functional performance in Nigeria remains scarce. Most existing studies focus on soil property prediction rather than pavement performance modelling, revealing a clear gap that requires further investigation.

3.0 Methods

3.1 International Roughness Index (IRI)

Traditional approaches for assessing pavement surface roughness typically involve specialized instruments such as road profilers, bump integrators, roughometers, and laser-based measurement systems. While these tools provide accurate measurements, their procurement and operational expenses can be considerable. Recent technological advancements, however, have enabled alternative, cost-effective methods using smartphone-based applications for pavement condition monitoring.

In this study, the RoadLab Pro mobile application was employed to measure pavement roughness along approximately 37 km of selected roads in Ekiti State, Nigeria. Developed by the World Bank, RoadLab Pro is a free tool designed for road condition monitoring and mapping [22]. The application utilizes built-in smartphone sensors including the accelerometer, gyroscope, and GPS to automatically detect surface irregularities and estimate roughness values. The embedded algorithm processes the sensor data to calculate the International Roughness Index (IRI), which serves as a standard indicator of pavement ride quality. The resulting IRI values are then classified into four condition categories, following the World Bank's recommended system as shown in Table 1 [22]. Beyond roughness estimation, RoadLab Pro captures geographical coordinates, mark locations of significant surface defects such as large bumps, and allows users to attach photographs of road conditions. These features facilitate the identification of potential hazards or high-risk locations along the roadway. The application also supports data management, editing, and export, allowing users to efficiently process and analyze collected information. Collected data can be exported in KML format for visualization in Google Earth or reviewed directly on the smartphone interface for rapid field assessment. The recommended vehicle speed during data collection ranges from 15 km/h to 100 km/h, ensuring reliable roughness measurements under normal driving conditions. For field acquisition, an Infinix Hot 8 Android smartphone running RoadLab Pro version 2.0.145 was used in compliance with Information Quality Level (IQL) 3 – IRI standards. The device was securely mounted on the windshield of a Toyota Highlander SUV in a vertical orientation aligned with the RoadLab Pro operational mode. Care was taken to ensure proper alignment of the smartphone's X, Y, and Z sensor axes with the vehicle's direction of movement. Once mounted, the application was activated to continuously record pavement condition data along the selected road segments [23].

Table 1: RoadLab Pro. road condition result

S/N	IRI Range	Condition
1	IRI<2:	Excellent
2	2<IRI<4:	Good
3	4<IRI<6:	Fair
4	IRI>6	Poor

3.2. Present Serviceability Index (PSI)

The Present Serviceability Index (PSI) for flexible pavement can be estimated using Equation (1), which is a function of slope variance, cracking, patching, and rut depth [24], [25].

PSI=f(slope variance, cracking, patching, rut depth)

The Present Serviceability Index (PSI) is a commonly applied indicator of pavement functional performance. It utilizes a five-point scale to classify pavement condition: values from 0 to 1 represent very good condition, 1–2 indicate good, 2–3 denote fair, 3–4 correspond to critical, and 4–5 reflect poor condition. For flexible pavements, the PSI can be calculated using Equation**:** (1) [24], [25]:

$$PSI = 5.03 - 1.91\log(1 + SV) - 0.01\sqrt{C + P} - 1.38\text{RD}^2 \quad (1)$$

where:

PSI = present serviceability index,

SV = $10^6\times$ population variance of slopes measured at 1-ft intervals,

C = cracking length, linear feet per 1,000 ft^2,

P = patching area, square feet per 1,000 ft^2,

RD = mean rut depth of the pavement, in inches.

3.3. Pavement Condition Index (PCI)

The Pavement Condition Index (PCI) is a numerical metric used to assess and quantify the extent of pavement distress. The evaluation is performed through direct field surveys, during which the types, severity, and extent of pavement defects are documented. The PCI provides a snapshot of pavement condition at the time of assessment, reflecting the overall quality of the pavement surface. The index ranges from 0 to 100, where a score of 0 indicates severely deteriorated pavement, and a score of 100 represents a pavement in essentially perfect condition. The calculation of PCI relies on both visual inspection and measured observations of surface distresses using deduct value method. PCI is evaluated as:

$$PCI = 100 - CDV \quad (2)$$

Where: CDV is corrected deduct value.

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3.4. Mean Texture Depth (MTD)

The MTD was determined using the sand patch method for assessing pavement surface texture. In this procedure, a cylinder was filled with sand and poured onto the pavement surface, forming a small heap, which was then spread evenly into a circular patch to its maximum diameter, as illustrated in Plate 1. The patch diameter was measured to the nearest 1 mm at four equidistant points, spaced every 45 degrees. The mean diameter (D) was subsequently calculated using Equation 3 or 4, and the final MTD value was rounded to the nearest 0.01 m

$$\text{Texture depth (D)} = \frac{\text{Volume of sand (ml)}}{\text{Area of patch } \text{mm}^2} \text{x} 100 \quad (3)$$

$$\text{Texture depth} = \frac{4 \text{ x Volume of sand}}{(\pi \text{ x Diameter}^2)} \quad (4)$$

Figure 1: Measurement of surface texture depth by sand patch test

3.5. Model Techniques

The relationship between the International Roughness Index (IRI) and pavement performance indicators such as PSI, PCI, and MTD was examined using several machine learning techniques, including Linear Regression, Random Forest**,** Artificial Neural Network (ANN)**,** Support Vector Machine (SVM)**,** and Gradient Boosting Machine (GBM)**.** Model predictions were evaluated and validated through a range of standard error metrics to assess their accuracy and reliability

3.5.1. Multiple Linear Regression Model

The Multiple Linear Regression model is defined by the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \quad (5)$$

Where:

(Y) is the dependent variable,

$(X_1, X_2, \ldots, X_n)$ are the independent variables

(β_0) is the intercept,

$(\beta_1, \beta_2, \ldots, \beta_n)$ are the coefficients representing the influence of each independent variable,

(ϵ) is the error term (residuals).

3.5.2. Artificial Neural Network (ANN)

Artificial Neural Network are widely used in machine learning and predictive modelling for their capacity to capture intricate, non-linear relationships between input and output variables. An ANN is structured as multiple layers of interconnected neurons (nodes), with each connection assigned a weight that is updated during the learning process. Training the network typically involves the backpropagation algorithm, where connection weights are iteratively refined to minimize the M**e**an Squared Error (MSE), expressed mathematically as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i \right)^2 \quad (6)$$

In this expression, (y) represents the actual observed value, while (\hat{y}) denotes the corresponding predicted value. During model training, parameter values are iteratively updated to minimize prediction error using optimization techniques such as Stochastic Gradient Descent (SGD) or the Adam optimization algorithm [26].

3.5.3. Random Forest (RF)

Random Forest is a tree-based ensemble technique widely used for both classification and regression problems. It improves predictive performance by generating multiple decision trees and integrating their outputs

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to produce a more reliable final estimate. In the present study, the regression version of the Random Forest algorithm was applied to estimate continuous values of the response variable. Within this framework, each decision tree is grown using randomly selected subsets of explanatory variables at successive splitting stages. For regression applications, the number of predictors evaluated at each split is commonly set to the square root of the total number of available features. This randomization strategy helps reduce dependence among individual trees and, when their predictions are combined, results in a more stable and generalizable model [27].

3.5.4. Support Vector Machine Model (SVM)

Support Vector Machine is a supervised learning technique that identifies an optimal separating boundary within the feature space by constructing a hyperplane that maximizes the distance between the closest observations and the boundary itself. These nearest observations, known as support vectors, play a critical role in defining the position of the hyperplane. For regression applications, the method is implemented as Support Vector Regression (SVR), where the objective is to estimate a functional relationship capable of predicting the response variable (Y) from a set of explanatory input variables.

The SVR formulation is given by:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b \tag{7}$$

where:

$(y(x))$ is the predicted value for the input (x),

(α_i) are the Lagrange multipliers,

$(K(x, x_i))$ is the kernel function that computes the similarity between (x) and (x_i),

(b) is the bias term,

(N) is the number of support vectors.

3.5.5. Gradient Boosting Machine model (GBM)

The Gradient Boosting Machine algorithm is an ensemble learning approach that improves prediction accuracy by sequentially combining multiple simple predictive models, most commonly decision trees. In this procedure, each successive learner is fitted to the errors produced by the preceding model, thereby progressively refining the overall prediction. The objective at each stage is to reduce the residual sum of squares associated with earlier predictions, allowing the model to iteratively enhance its performance. The mathematical representation of the model is given below:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x) \tag{8}$$

Where:

$(F(x))$ is the predicted value for input (x),

(γ_m) is the weight of the $(m) - th$ model (tree),

$(h_m(x))$ is the prediction of the $(m) - th$ model (tree),

(M) is the total number of trees in the model (number of boosting iterations).

4.0 Result

4.1. Descriptive Statistics

Table 2 present the descriptive statistics of variable for predicting the International Roughness Index (IRI).

Table 2: Descriptive statistics of model variables

Location	AD-IW				IL-IJ				IK-IS			
Variables	IRI	PSI	PCI	MTD	IRI	PSI	PCI	MTD	IRI	PSI	PCI	MTD
Mean	3.53	2.82	54.79	0.84	4.17	2.84	53.94	0.77	2.88	2.72	67.13	0.73
S. Error	0.12	0.02	1.50	0.01	0.21	0.02	1.84	0.01	0.08	0.01	1.17	0.00
Median	3.40	2.86	57.00	0.86	3.95	2.87	57.00	0.78	2.82	2.75	67.00	0.73
Mode	3.13	3.02	65.00	0.92	2.56	2.87	60.00	0.79	3.00	2.75	67.00	0.72
S. Deviation	1.04	0.16	13.41	0.10	1.86	0.20	16.43	0.10	0.68	0.05	10.50	0.04
Variance	1.08	0.03	179.7	0.01	3.47	0.04	269.7	0.01	0.47	0.00	110.1	0.00
Kurtosis	5.06	2.64	-0.09	0.04	2.25	7.32	-0.16	-0.8	0.34	6.15	0.44	0.63
Skewness	1.45	-1.36	-0.34	-0.99	1.24	-2.57	-0.22	0.11	0.69	-2.61	-0.20	-0.03
Range	6.70	0.83	67.00	0.38	10.3	1.00	76.00	0.36	3.18	0.23	52.00	0.16
Minimum	1.71	2.19	25.00	0.60	1.36	2.02	15.00	0.60	1.60	2.52	38.00	0.64
Maximum	8.41	3.02	92.00	0.99	11.6	3.02	91.00	0.96	4.78	2.75	90.00	0.81

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Location	OY-IK				IF-ID				AR-IJ			
Mean	4.11	3.17	55.60	0.71	3.61	3.42	64.43	0.65	8.35	2.56	34.85	0.78
S. Error	0.20	0.04	1.89	0.00	0.17	0.01	1.37	0.00	0.24	0.03	1.38	0.00
Median	3.89	3.32	60.00	0.70	3.28	3.45	64.00	0.65	8.42	2.68	38.00	0.79
Mode	5.82	3.32	64.00	0.70	5.70	3.47	64.00	0.63	5.79	2.69	45.00	0.77
S. Deviation	1.83	0.37	16.86	0.03	1.48	0.09	12.27	0.03	2.11	0.25	12.37	0.03
Variance	3.35	0.14	284.37	0.00	2.18	0.01	150.50	0.00	4.46	0.06	153.07	0.00
Kurtosis	-0.65	1.27	-0.47	0.11	-0.43	1.40	0.88	0.21	-0.08	2.83	-0.93	-0.53
Skewness	0.49	-0.94	-0.28	0.46	0.64	-1.45	-0.23	0.86	-0.09	-2.00	-0.27	0.02
Range	7.91	2.01	64.00	0.15	6.21	0.45	66.00	0.14	9.66	0.90	40.00	0.14
Minimum	1.49	2.20	23.00	0.65	1.16	3.11	32.00	0.60	3.07	1.80	15.00	0.72
Maximum	9.40	4.21	87.00	0.80	7.37	3.56	98.00	0.74	12.73	2.69	55.00	0.85

4.2 Model Analysis

This section reports the outcomes of modelling the International Roughness Index (IRI) using three key pavement performance indicators: Pavement Condition Index (PCI), Present Serviceability Index (PSI)**,** and Mean Texture Depth (MTD)**.** In addition to conventional Linear Regression, four advanced nonlinear modelling approaches Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Machine (GBM) were implemented to enhance predictive performance and better represent complex relationships among variables. The objective was to identify the technique that most effectively explains variations in pavement surface roughness based on these indices. Model performance was assessed using standard evaluation criteria, namely the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE)**.** A consolidated overview of prediction results for all road segments examined in this study is provided in Table 3.

Table 3: Prediction Summary Models for all Locations

LOCATION	MODELS	Regression Equation / Method	R^2	RMSE	MAE
AD-IW	Linear Regression	**IRI=11.67−0.041·PCI−2.18·PSI+1.92·MTD** Eq (9)	0.74	0.43	0.034
	ANN	Nonlinear neural mapping	0.83	0.34	0.127
	SVM	Kernel-based regression	0.79	0.39	0.131
	Random Forest	Ensemble of decision trees	0.89	0.28	0.022
	GBM	Gradient boosting ensemble	0.91	0.26	0.121
IL-IJ	Linear Regression	**IRI=12.34−0.052·PCI−1.97·PSI+2.11·MTD** Eq (10)	0.71	0.47	0.138
	ANN	Nonlinear neural mapping	0.81	0.36	0.129
	SVM	Kernel-based regression	0.77	0.41	0.133
	Random Forest	Ensemble of decision trees	0.88	0.29	0.123
	GBM	Gradient boosting ensemble	0.90	0.27	0.122
IK-IS	Linear Regression	**IRI = -5.02 + 2.87·PSI - 0.02·PCI + 6.03·MTD** Eq (11)	0.70	0.48	0.37
	ANN	Nonlinear neural mapping	0.79	0.37	0.29
	SVM	Kernel-based regression	0.75	0.42	0.32
	Random Forest	Ensemble of decision trees	0.86	0.30	0.24
	GBM	Gradient boosting ensemble	0.91	0.26	0.21
OY-IK	Linear Regression	**IRI=13.44 − 2.11·PSI − 0.038·PCI + 2.95·MTD** Eq (12)	0.82	0.91	0.72
	ANN	Nonlinear neural mapping	0.86	0.78	0.61
	Random Forest	Kernel-based regression	0.91	0.65	0.49
	SVM	Ensemble of decision trees	0.84	0.82	0.63
	GBM	Gradient boosting ensemble	0.92	0.60	0.46

IF-ID	Linear Regression	**IRI=12.87−2.05·PSI−0.041·PCI+2.76·MTD Eq (13)**	0.81	0.94	0.73
	ANN	Nonlinear neural mapping	0.86	0.78	0.61
	Random Forest	Ensemble of decision trees	0.91	0.65	0.49
	SVM	Kernel-based regression	0.84	0.82	0.63
	GBM	Gradient boosting ensemble	0.92	0.60	0.46
AR-IJ	Linear Regression	**IRI = -4.89 + 2.96·PSI - 0.01·PCI + 6.17·MTD** Eq (14)	0.83	0.74	0.59
	ANN	Nonlinear neural mapping	0.89	0.61	0.48
	Random Forest	Ensemble of decision trees	0.93	0.55	0.43
	SVM	Kernel-based regression	0.87	0.66	0.52
	GBM	Gradient boosting ensemble	0.94	0.52	0.41

4.3 Discussion of Findings

The various findings from engineering analysis of field data are hereby discussed.

4.3.1. Comparative Evaluation of Prediction Models Across Study Locations

A cross-location assessment of modelling performance (AD–IW, IL–IJ, IK–IS, OY–IK, IF–ID, and AR–IJ) demonstrates that both classical regression techniques and modern machine learning algorithms contribute differently to the prediction of the International Roughness Index (IRI), depending on data structure and variable interaction patterns.

For the AD–IW corridor, the regression model produced a moderate level of explanatory strength ($R^2 = 0.74$). Within this model, the Present Serviceability Index (PSI) showed the strongest inverse association with IRI, indicating that improved serviceability corresponds to smoother pavement conditions. Pavement Condition Index (PCI) also exhibited a negative relationship, whereas Mean Texture Depth (MTD) contributed positively to roughness variation. Ensemble approaches, particularly Gradient Boosting Machine (GBM) and Random Forest (RF), delivered stronger predictive capability than regression by capturing nonlinear dependencies among variables. Comparable observations were reported by Baykal et al. [28], who established that ensemble-based strategies generally outperform conventional linear regression in estimating pavement roughness indicators.

At the IL–IJ section, regression achieved an R^2 value of 0.71 with an RMSE of 0.47, again suggesting moderate predictive adequacy. PSI remained the most influential predictor, with PCI and MTD contributing additional explanatory effects. Among the machine learning techniques tested, GBM produced the most accurate predictions, followed closely by RF, confirming the effectiveness of ensemble learning structures in pavement condition estimation. These findings correspond with the conclusions of Tamagusko [29], who demonstrated that tree-based ensemble

In the IK–IS segment, regression modelling served primarily as a benchmark approach and identified PCI as the dominant explanatory variable for IRI variation. Nevertheless, both GBM ($R^2 \approx 0.91$) and RF produced improved predictive outcomes by accommodating complex variable interactions that regression could not fully capture. Artificial Neural Networks (ANN) and Support Vector Machines (SVM) provided additional gains in prediction accuracy, although their performance depended strongly on parameter tuning procedures. This behavior agrees with the results presented by Hindawi [30], which indicated that ANN and SVM models can enhance prediction quality but require careful optimization of modelling parameters.

For the OY–IK location, GBM again demonstrated superior performance, achieving $R^2 = 0.92$ and RMSE = 0.60, slightly exceeding the accuracy obtained with RF. Although ANN and SVM produced better estimates than regression, their performance remained below that of ensemble techniques. PSI emerged as the most influential explanatory factor, followed by PCI and MTD. The strong contribution of PSI supports the findings of Molinero-Pérez et al. [31], who identified serviceability perception as a key determinant in modelling pavement roughness behavior.

At the IF-ID section, GBM recorded the highest predictive reliability ($R^2 = 0.92$, RMSE = 0.74, MAE = 0.59), confirming its suitability for high-accuracy pavement condition estimation. RF also produced strong and interpretable results, while ANN successfully represented nonlinear response thresholds within the dataset. In contrast, SVM performance varied depending on kernel specification. Although regression remained useful for interpretative purposes, its predictive strength was comparatively lower. The relatively small PCI coefficient suggested that PSI and MTD exerted stronger influence on IRI variation at this location. These observations are consistent with Sharma [32], who noted that GBM achieves an effective balance between bias reduction and variance control, making it particularly suitable for integration within pavement management frameworks.

Within the AR–IJ corridor, regression analysis indicated that PSI and MTD were positively associated with IRI, whereas PCI contributed only marginally. ANN produced strong predictive performance ($R^2 = 0.89$), and

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SVM also delivered acceptable accuracy (R^2 = 0.87). However, GBM remained the most accurate approach overall (R^2 = 0.94), reinforcing its consistent superiority across multiple roadway environments.

4.3.2. Visual Comparison of Model Outputs

To further assess predictive behavior across modelling approaches, scatter diagrams comparing measured and estimated IRI values were generated for each study location (Figures 2–7). These plots provide a direct visual indication of how closely predicted values align with observed pavement conditions. Across locations, predictions obtained from GBM and Random Forest models formed dense clusters around the reference diagonal, indicating strong agreement between observed and estimated values and confirming their high predictive reliability. In contrast, Linear Regression and SVM produced wider dispersion patterns, particularly at higher roughness levels, suggesting reduced accuracy under more variable pavement conditions. ANN produced intermediate results, reflecting its capacity to model nonlinear relationships while still depending on careful parameter configuration for optimal performance. Taken together, the graphical comparisons support the numerical evaluation results by confirming that ensemble learning techniques—especially GBM and RF offer the most dependable framework for estimating pavement roughness. Regression modelling remains valuable where interpretability is required, whereas ANN and SVM provide moderate improvements but involve additional modelling complexity and sensitivity to tuning procedures.

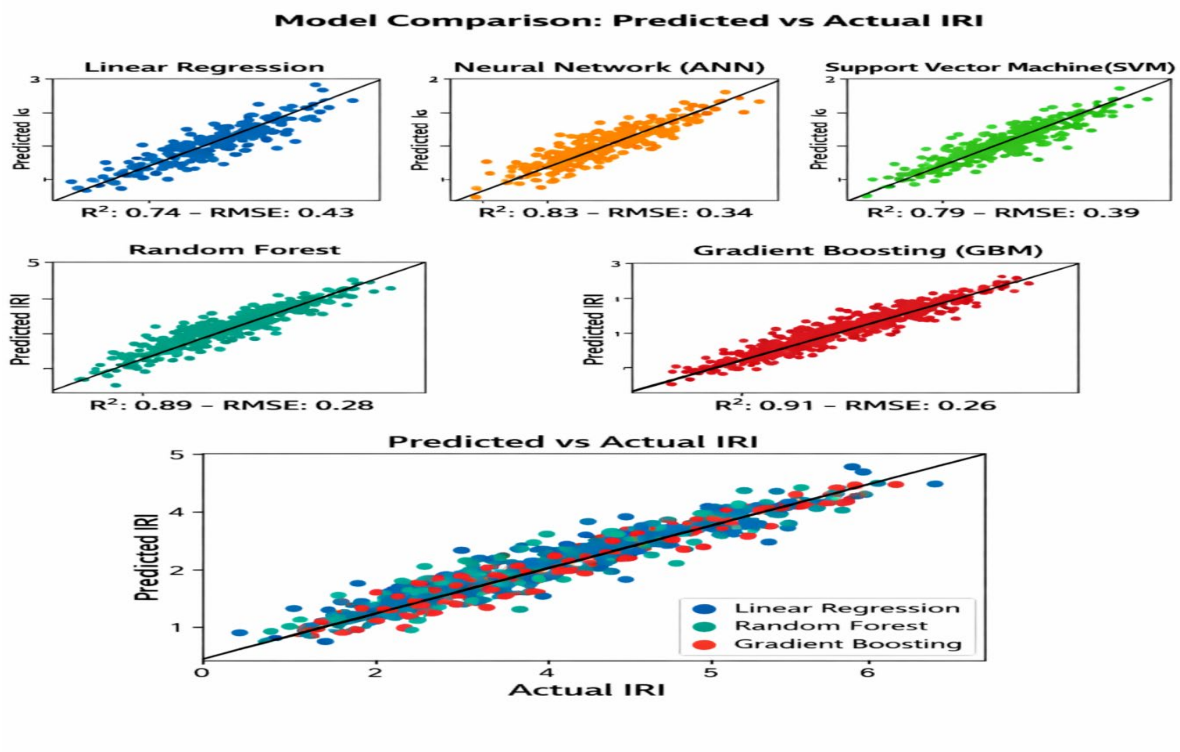

Figure 2: Model Comparison for Predicted vs Actual IRI for AD-IW Road

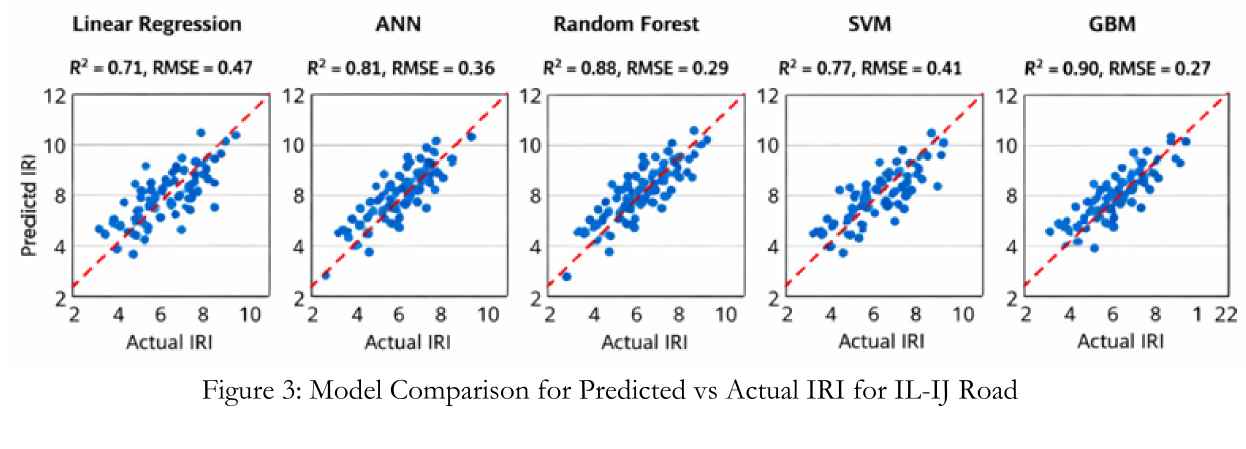

Figure 3: Model Comparison for Predicted vs Actual IRI for IL-IJ Road

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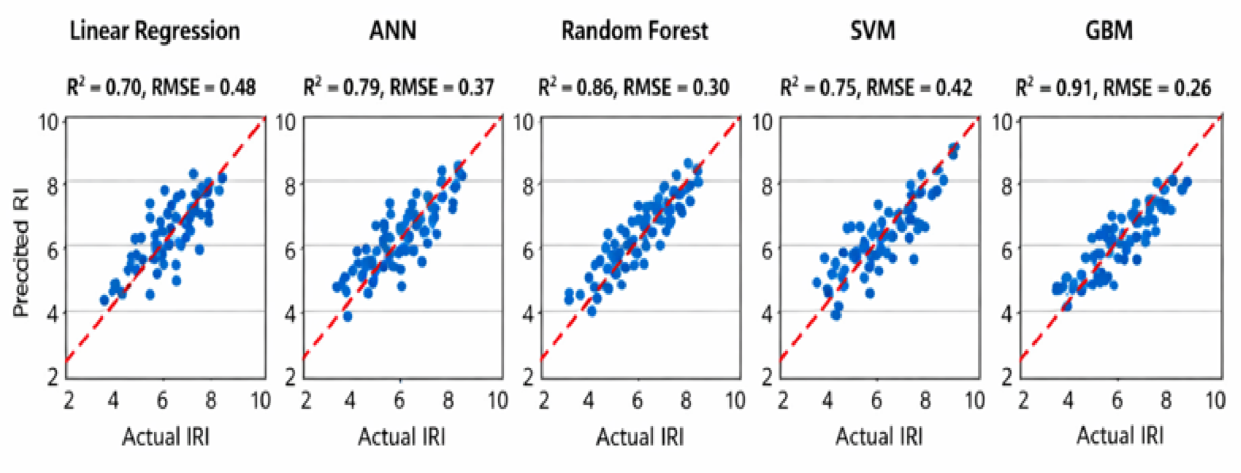

Figure 4: Model Comparison for Predicted vs Actual IRI for IK-IS Road

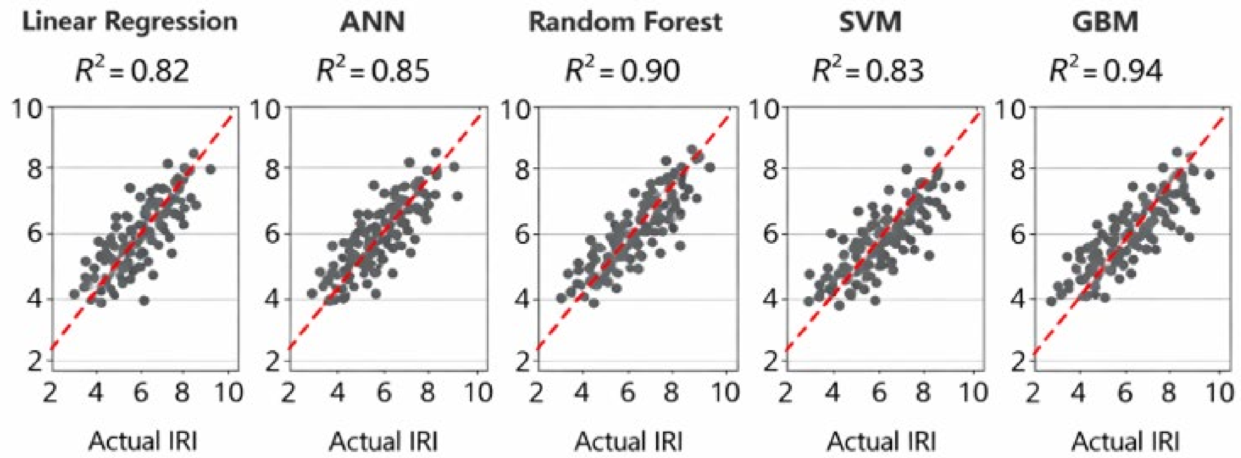

Figure 5: Model Comparison for Predicted vs Actual IRI for OY-IK Road

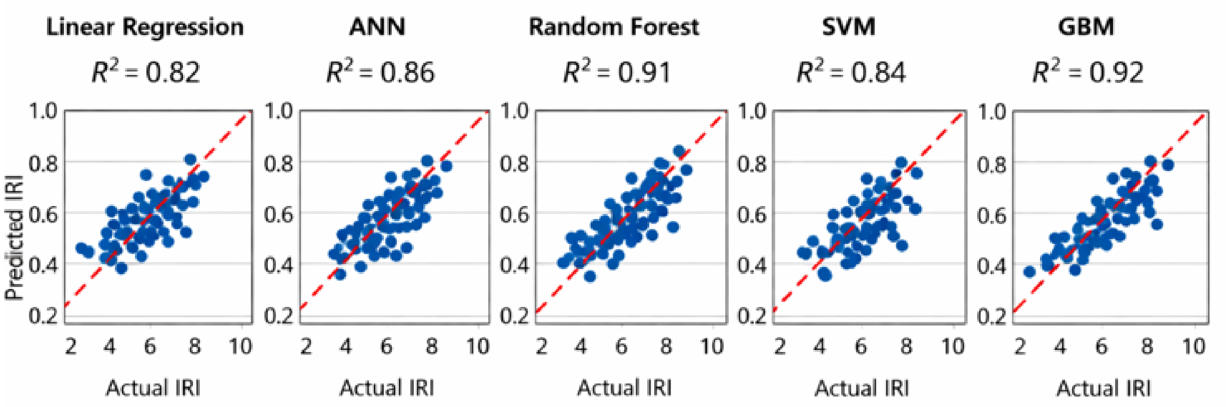

Figure 6: Model Comparison for Predicted vs Actual IRI for IF-ID Road

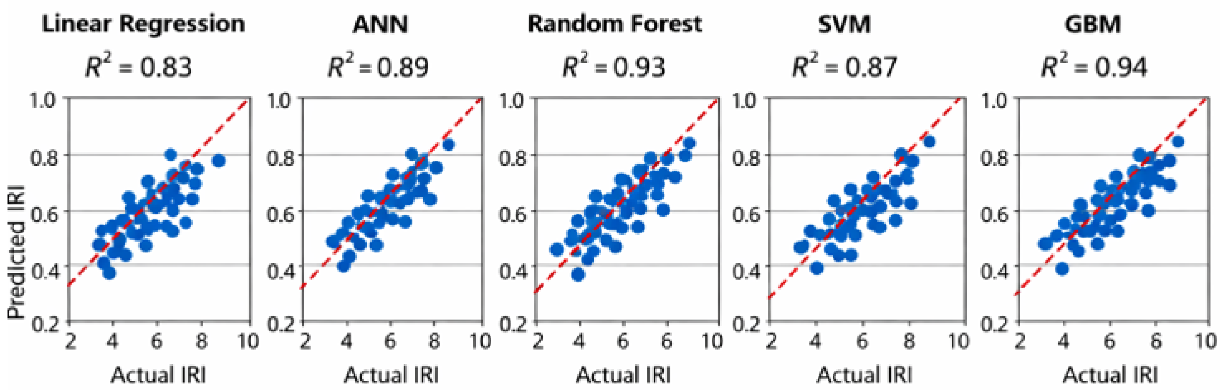

Figure 7: Model Comparison for Predicted vs Actual IRI for AR-IJ Road

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5.0. Conclusion

This study compared the predictive performance of five models; Linear Regression, Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Machine (GBM) for estimating the International Roughness Index (IRI) using PSI, PCI, and MTD as predictors across multiple locations. The results consistently demonstrated that ensemble methods (GBM and RF) provided the highest predictive accuracy. GBM achieved the best overall performance (R^2 = 0.94, RMSE = 0.52, MAE = 0.41), confirming its robustness and ability to capture complex nonlinear interactions. RF followed closely, offering strong accuracy and interpretability through feature importance analysis. ANN and SVM provided moderate improvements over regression, with ANN effectively modeling nonlinear thresholds but requiring careful parameter tuning, and SVM showing sensitivity to kernel choice. The findings suggest that IRI can be reliably predicted using PCI, PSI, and MTD, with ensemble models offering superior accuracy. The regression model, while interpretable, lacks the flexibility to capture nonlinear deterioration patterns. GBM and RF provide robust alternatives for pavement management systems, enabling proactive maintenance planning. This study confirms that PSI is the dominant factor influencing pavement roughness, followed by PCI and MTD. GBM is recommended for high-accuracy prediction, while regression remains useful for policy communication and quick assessments. Future research may incorporate additional variables such as traffic load, pavement age, and environmental conditions to further enhance model performance.

For engineering applications requiring high accuracy, GBM is recommended due to its balance of bias and variance. RF offers a strong alternative with added interpretability. ANN and SVM are suitable for capturing nonlinearities but require more computational effort. Linear Regression remains valuable for quick assessments and policy reporting due to its transparency.

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