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Machine Learning Modelling of IRI in Continuously Reinforced Concrete Pavements Using LTPP Data: Comparative Evaluation of Advanced Algorithms

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Abstract

Accurately predicting International Roughness Index (IRI) is essential for effective pavement maintenance and long-term network sustainability. This study evaluates several advanced machine learning models for IRI prediction in Continuously Reinforced Concrete Pavement (CRCP) using a comprehensive dataset from Long-Term Pavement Performance (LTPP) program. Support Vector Machines, Artificial Neural Networks, Regression Trees, Ensemble Trees, and Gaussian Process Regression (GPR) were developed and assessed using Root Mean Square Error (RMSE) and R-squared (R^2). The Matern 5/2 GPR model achieved the best performance, with R^2 = 0.97 and RMSE = 0.0776. Feature importance analysis using Random Forest identified initial IRI, construction number, layer thicknesses and temperature as the strongest predictors. Sensitivity analysis confirmed the influence of age, climate, and traffic on IRI. Using only the top ten variables produced nearly identical accuracy, improving computational efficiency. Overall, the study demonstrates the strong potential of ML for reliable and sustainable IRI prediction in rigid pavements.

INTRODUCTION

Continuously Reinforced Concrete Pavement (CRCP) is an important part of modern transportation infrastructure because of its outstanding durability and capacity to maintain a smooth riding surface over long periods of time [1-3]. Unlike traditional jointed concrete pavements, CRCP eliminates the need for transverse joints, which greatly reduces joint deterioration, increases structural integrity, and reduces maintenance requirements [4-5]. CRCP is widely employed on highways and high-volume roads where long-term performance and minimal disturbance are required [6-7].

The International Roughness Index (IRI) is a critical parameter for quantifying pavement surface smoothness, representing the longitudinal road profile and its impact on ride quality [8]. Lower IRI values are associated with enhanced driving comfort, reduced vehicle wear, and fewer traffic accidents [9]. Moreover, smooth pavements contribute to improved fuel efficiency and environmental benefits [10-13]. Therefore, accurate IRI prediction is indispensable for efficient Pavement Management Systems (PMS), allowing agencies to prioritize cost-effective maintenance and rehabilitation strategies [14-15]. Reliable IRI forecasts enable proactive maintenance planning, prolonging pavement life and optimizing user satisfaction [16-17].

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Traditionally, IRI has been estimated using empirical or regression-based models correlating IRI with factors such as pavement age, traffic, and climate [18-19]. While useful for general trend analysis, these models often fail to capture the complex nonlinear relationships influencing pavement roughness [20-22]. Additionally, traditional models tend to be reactive, relying on historical data that may not accurately reflect future pavement behavior [23]. Pavement roughness is affected by a multitude of interrelated variables, including structural attributes (e.g., material types and layer thicknesses) [24-29], environmental factors (e.g., temperature, precipitation, freeze-thaw cycles) [30-33], and traffic loading conditions [34-36]. These complexities necessitate more sophisticated, data-driven modeling approaches.

Machine Learning (ML) methods offer a powerful alternative, enabling the analysis of large datasets and detection of hidden patterns in data [37-40]. By leveraging multiple input sources and adaptive learning capabilities, ML techniques can enhance prediction accuracy and reliability for pavement performance forecasting [41-42]. As a subfield of artificial intelligence, ML allows systems to learn from data without explicitly programmed rules [43-44]. In recent years, ML has seen increasing adoption in civil engineering, especially in the domain of pavement analysis and management [45]. These techniques can model complex interactions and outperform traditional methods in predicting IRI by integrating structural, climatic, and traffic parameters [46]. Additionally, their ability to continuously adapt and learn improves long-term predictive performance.

Several advanced machine learning models, including Support Vector Machines (SVM), Decision Trees, Artificial Neural Networks (ANN), and ensemble approaches, have shown promising results in pavement roughness modeling [47-49]. These models excel in detecting small correlations and nonlinear patterns, resulting in more precise and timely maintenance interventions [50]. The Federal Highway Administration (FHWA) launched the Long-Term Pavement Performance (LTPP) program, which provides a comprehensive database of pavement condition, traffic, and environmental data across North America [51]. This freely available resource aids in the construction of robust pavement performance models [52]. While ML-based IRI prediction has been extensively studied for flexible pavements, there is a limited body of research on rigid pavements, specifically CRCP [53].

This study addresses this gap by developing and evaluating a range of advanced machine learning models for predicting the IRI in CRCP using data from the LTPP program. The investigated techniques include ensemble trees, regression decision trees, SVM, ANN, GPR, and kernel-based methods, all trained using comprehensive structural, climatic, and traffic-related input variables. Beyond model development, the study contributes to the pavement performance literature by adopting a controlled CRCP-specific framework that relies exclusively on untreated LTPP sections, thereby isolating natural roughness progression without maintenance interference. A unified and fair benchmarking strategy is applied across all models using identical preprocessing, feature sets, and evaluation metrics. The results demonstrate that Gaussian Process Regression, particularly the Matern 5/2 kernel, consistently outperforms commonly used tree-based and neural models for CRCP IRI prediction. Furthermore, the findings show that reducing the input space to the top ten influential variables preserves predictive accuracy while improving computational efficiency, providing practical insights for pavement management and sustainable infrastructure decision-making.

Research Aims

The goal of this study is to build and evaluate advanced machine learning models that use data from the LTPP database to reliably estimate the IRI in CRCP. The machine learning algorithms used include regression decision trees, SVM, ensemble trees (boosted and bagged), GPR, ANN, and kernel approaches. To fulfill this general purpose, the study aims to accomplish the following specific objectives:

1. Conduct a detailed examination of the LTPP dataset, providing an in-depth overview of the dataset's structure, attributes, and key variables related to IRI prediction in CRCP.
2. Perform comprehensive statistical analyses to understand the distribution patterns, variability, and main characteristics of the variables influencing IRI in CRCP.
3. Identify the critical factors within the LTPP dataset that significantly contribute to the prediction of IRI. Apply appropriate statistical methods to highlight the most influential variables affecting pavement surface roughness.
4. Implement a variety of predictive machine learning models, including Regression Trees, SVM, Ensemble Trees, GPR, ANN, and Kernel-based techniques. These models will be developed in two phases: one utilizing the full set of input features and the other using only the top ten variables identified through feature importance analysis.
5. Assess the predictive accuracy of each machine learning model using performance metrics such as Mean Squared Error (MSE), R-Squared (R^2), and other relevant indicators. Perform a comprehensive comparison of the models

based on these evaluation results to determine the most effective method for forecasting IRI in CRCP, considering the strengths and limitations of each approach.
6. Conduct sensitivity analysis on the best-performing model to evaluate how changes in the input variables influence prediction outcomes. This step aims to assess the robustness and reliability of the selected model across various conditions.

METHODS

Data Collection and Preprocessing

The LTPP database provided the dataset for this study. Although the LTPP program contains thousands of pavement sections, only 33 CRCP sections were selected because they met strict criteria essential for reliable IRI prediction. Specifically, we included only sections that had no recorded maintenance or rehabilitation activities throughout their monitoring period. This ensured that the observed changes in IRI reflected true pavement performance rather than the effects of repairs. From these sections, a comprehensive set of structural, climatic, and traffic-related variables was extracted as input features, while the IRI served as the target variable.

Although the number of analyzed CRCP sections is limited, the modeling strategy in this study prioritizes internal validity and controlled performance evaluation rather than broad population-level generalization. By restricting the dataset to pavement sections with no maintenance or rehabilitation activities, the analysis isolates intrinsic pavement deterioration mechanisms and minimizes confounding effects commonly present in heterogeneous datasets. This controlled-sample approach enhances the reliability of model comparison and performance interpretation, while acknowledging that the results represent high-confidence insights into untreated CRCP roughness evolution rather than universal models applicable to all rigid pavement networks.

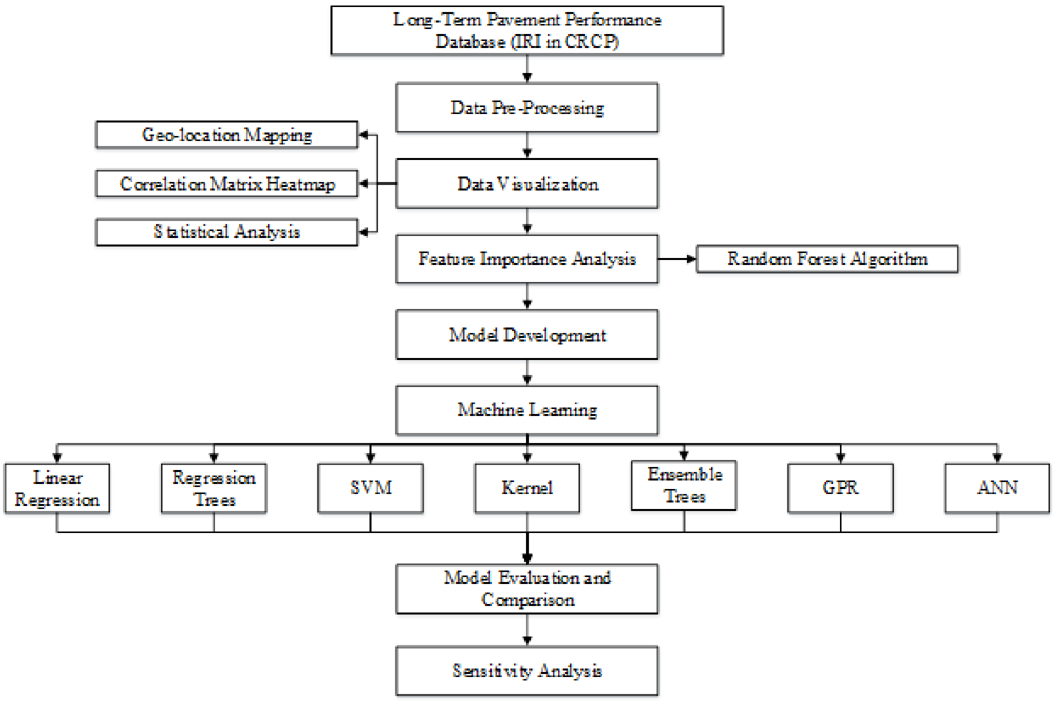


Figure 1. Overall Methodology Framework

Several data preparation steps were performed to ensure the dataset was suitable for reliable modeling. First, a detailed data cleaning process was conducted, during which all variables were checked for missing or incomplete records. Any observations with missing structural, climatic, or traffic data were removed to maintain consistency across the dataset. Next, filtering criteria were applied to include only CRCP sections with complete monitoring histories and no recorded maintenance or rehabilitation activities, ensuring that IRI progression reflected natural pavement deterioration. Outlier detection was performed using a two-stage procedure. First, univariate statistical screening was applied using the interquartile range (IQR) method, where observations outside Q1 − 1.5×IQR and Q3 + 1.5×IQR were flagged as potential outliers. Second, these flagged observations were evaluated using engineering plausibility checks based on known CRCP design limits, climatic bounds, and traffic ranges reported in LTPP documentation. Observations deemed physically unrealistic were removed. Missing data were handled using complete-case filtering, whereby observations with missing structural, climatic, or traffic variables were excluded. The same cleaned and standardized dataset was used consistently across all machine learning models to ensure fair comparison. Figure 1 presents the full methodology framework, including data collection, cleaning, preprocessing, feature selection, and model development steps.

Model Development and Evaluation Framework

Several machine learning (ML) models were employed to predict IRI in CRCP, including:
1. Regression Decision Trees
2. SVM
3. Ensemble Trees (Boosted and Bagged)
4. GPR
5. ANN
6. Kernel Methods

Each model was trained using supervised learning, where IRI values served as the dependent variable. Hyperparameter tuning was carried out using grid search and cross-validation to optimize performance.

Figure 2 presents the mapping of selected pavement sections, showing their geographical distribution across different environmental zones.

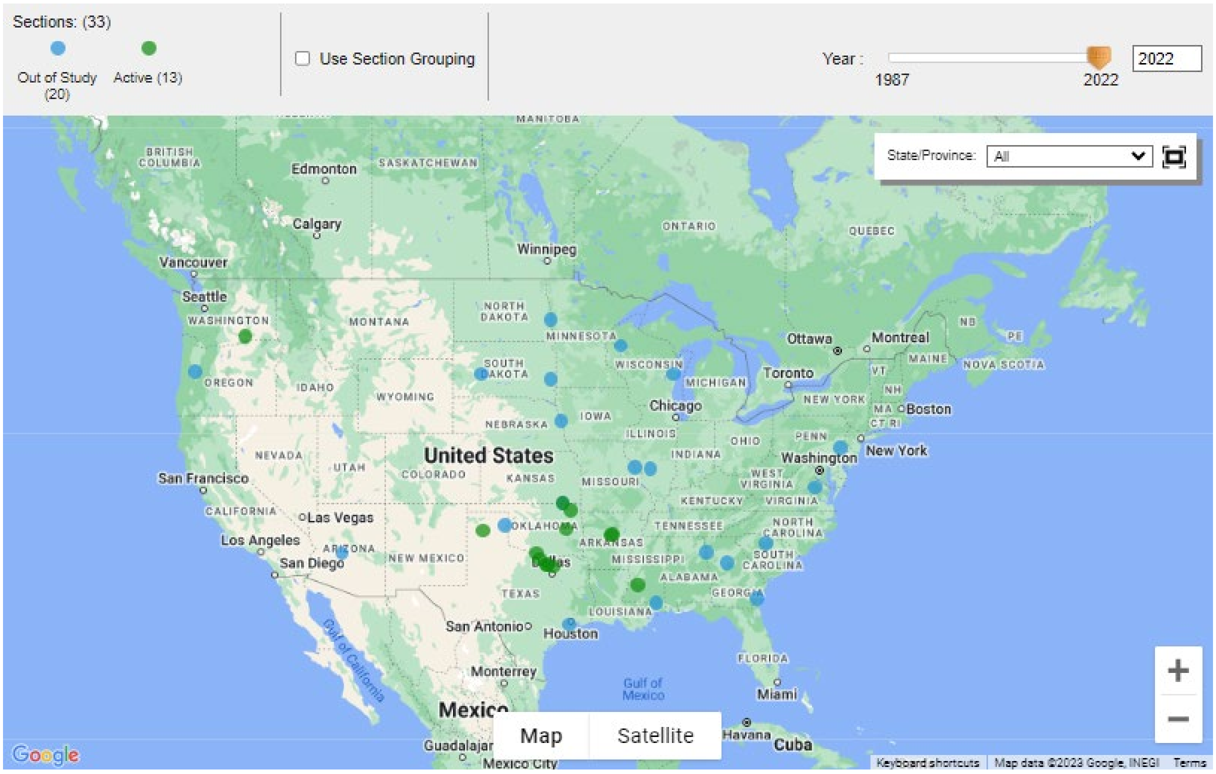


Figure 2. Geographic Distribution of the Selected CRCP Sections used in the Study

To assess model performance, the following evaluation metrics were utilized:
1. Root Mean Square Error (RMSE): Measures the average deviation of predictions from actual values.
2. R^2: Indicates how well the independent variables explain the variation in IRI.
3. MSE: Evaluates the average squared error of predictions.
4. Mean Absolute Error (MAE): Provides an absolute measure of prediction accuracy.

Table 1 summarizes the input variables, categorized into structural, climatic, traffic, and performance attributes.

Table 2 provides descriptive statistics of the dataset, including key variables such as pavement age, layer thicknesses, climate parameters, and traffic characteristics. Figure 3 shows the histogram of the output which is the IRI (m/km).

Table 1. Description and Classification of Input Variables used for IRI prediction in CRCP

Category	Variable Description	Type
Structural	Pavement Age (years since construction)	Numerical
	Construction Identifier Number	Numerical
	Material Type of the Second Layer	Categorical
	Thickness of the Second Layer (mm)	Numerical
	Material Type of the Third Layer	Categorical
	Thickness of the Third Layer (mm)	Numerical
	Material Type of the Fourth Layer	Categorical
	Thickness of the Fourth Layer (mm)	Numerical
	Total Pavement Thickness (mm)	Numerical
Climatic	Classification of Climate Zone	Categorical
	Mean Annual Precipitation (mm)	Numerical
	Mean Annual Temperature (°C)	Numerical
	Annual Freeze Index (°C-days)	Numerical
	Minimum Relative Humidity (%)	Numerical
	Maximum Relative Humidity (%)	Numerical
Traffic	Number of Traffic Lanes	Categorical
	Cumulative Equivalent Single Axle Loads (KESALs)	Numerical
	Mean Annual Daily Traffic Volume (AADT)	Numerical
	Mean Annual Daily Truck Traffic Volume (AADTT)	Numerical
Pavement Condition	Initial International Roughness Index (m/km)	Numerical
	Measured International Roughness Index (m/km)	Numerical

Table 2. Descriptive Statistics of the Quantitative Variables Extracted from The LTPP Database

Variable	Mean	SD	Minimum	Q1	Median	Q3	Maximum	IQR	Skewness
Age, years	20.48	10.53	1.00	13.00	20.00	28.00	47.00	15.00	0.19
L2 Thickness, mm	170.47	73.28	71.00	112.00	152.00	198.00	366.00	86.00	1.15
L3 Thickness, mm	162.41	77.52	41.00	102.00	147.00	226.00	325.00	124.00	0.22
L4 Thickness, mm	130.40	119.28	0.00	0.00	201.00	229.00	295.00	229.00	-0.09
Total Thickness, mm	463.28	113.24	264.00	376.00	462.00	549.00	694.00	173.00	0.39
Annual Average Precipitation, mm	1006.30	401.60	77.10	716.60	1033.50	1268.50	2209.20	551.90	0.03
Annual Average Temperature oC	15.00	4.08	3.80	12.30	15.60	18.00	22.80	5.70	-0.50
Annual Average Freeze Index C-Days	137.00	269.40	0.00	7.20	28.00	104.00	1621.00	96.80	3.15
Min Humidity, %	16.25	7.09	2.00	12.00	16.00	20.00	43.00	8.00	0.74
Max Humidity, %	116.70	4.93	103.00	114.00	117.00	120.00	131.00	6.00	0.04
AADT	7859.00	6912.00	784.00	3120.00	4959.00	12085.00	48640.00	8965.00	2.15
AADTT	1219.60	1057.30	104.00	534.30	890.00	1551.80	5809.00	1017.50	2.11
KESAL	598.90	674.30	22.00	136.00	353.00	765.00	3644.00	629.00	2.21
initial IRI, m/km	1.32	0.40	0.58	1.02	1.24	1.67	2.31	0.65	0.52
IRI, m/km	1.39	0.43	0.58	1.08	1.29	1.67	2.62	0.59	0.66

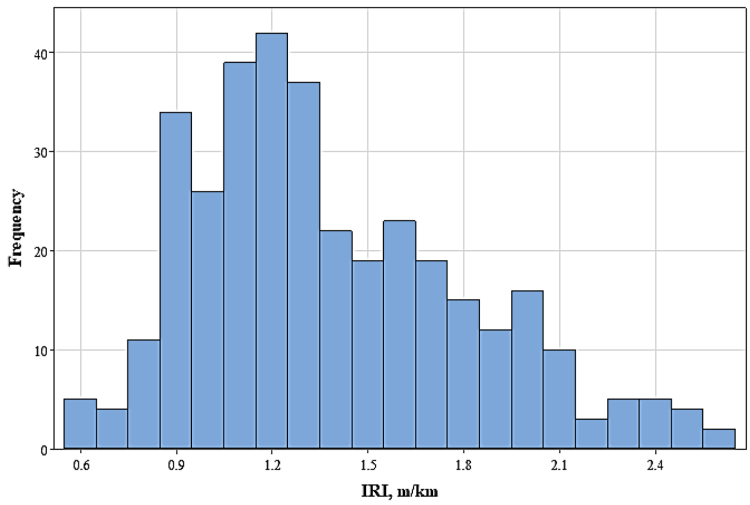


Figure 3. Histogram Showing the Distribution of IRI Values for the Analyzed CRCP Sections

Feature Importance Analysis

Figure 4 displays the heatmap of the correlation matrix, which illustrates the relationships between the various variables in the dataset. A gradient of hues from yellow to pink, where pink indicates strong negative correlations and yellow indicates strong positive correlations, is used in the heatmap to show the direction and strength of correlations. The significant positive correlation (0.922) between "L4 Thickness" and "Construction Number" suggests that L4 layers are frequently thicker in more recent construction projects. Similarly, a strong positive correlation (0.864) between "AADTT" and "KESAL" implies that increased truck traffic is associated with higher cumulative axle loads. A moderately negative correlation (-0.374) is observed between variables such as "Climate Zone" and "Max Humidity" to demonstrate the inverse association between climatic zones and maximum humidity levels. Given that starting roughness is a reliable indicator of future pavement roughness, the correlation between "initial IRI" and "IRI" is very high (0.946). For the development of precise prediction models, this detailed correlation study offers important insights into the relationships between various pavement properties and environmental conditions.

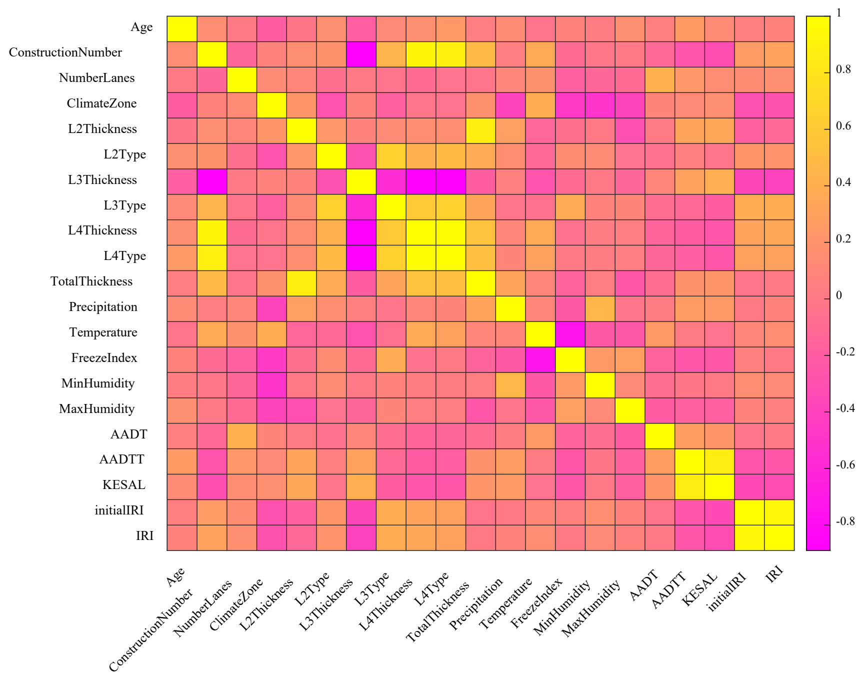


Figure 4. Correlation Matrix Heatmap Illustrating the Relationships between Structural, Climatic, Traffic, and Pavement Condition Variables

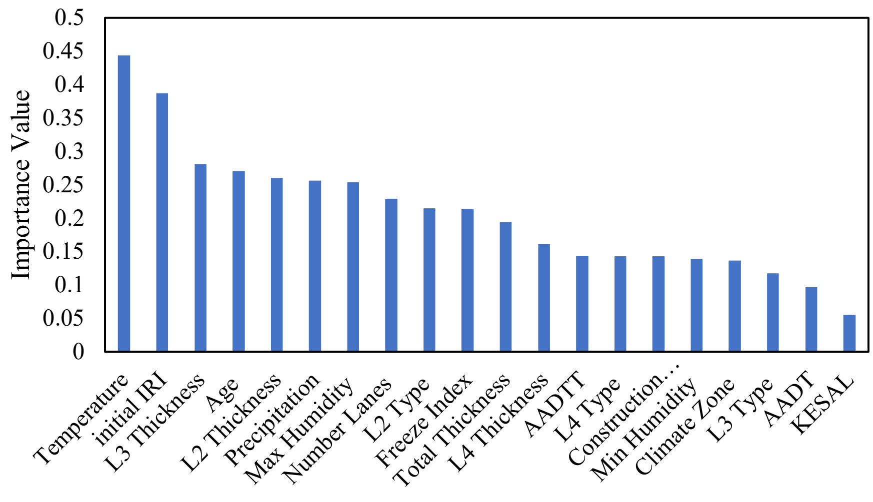


Figure 5. Random Forest–based Feature Importance Ranking for the Input Variables Affecting IRI Prediction in CRCP

Random Forest (RF) was chosen to calculate feature importance because it is a robust, ensemble-based method capable of capturing nonlinear interactions between structural, climatic, and traffic variables—all of which are predicted in IRI prediction. RF generates dependable permutation-based significance scores and is commonly utilized in pavement performance studies to identify dominating factors. Before extracting significance values, the RF model was fine-tuned by increasing the number of trees and maximum tree depth to ensure stable and unbiased results. The resulting feature importance rankings, given in Figure 5, suggest that temperature, initial IRI, pavement thickness, age, and annual precipitation are the most important variables influencing IRI in CRCP.

RESULTS AND DISCUSSION

The performance assessment of many machine learning (ML) models used to forecast the IRI in stiff pavements is shown in Table 3. Key metrics including RMSE, R^2, MSE, MAE, and Training Time are included in the results. These metrics offer a thorough evaluation of the predictive power and computational efficiency of each model. The ability of linear regression and its robust form to capture the link between input factors and IRI was investigated. With an R^2 of 0.95 and an RMSE of 0.0976, the basic linear regression model demonstrated a reasonably good fit. With an RMSE of 0.1054 and R^2 of 0.94, the robust linear regression model—which is intended to deal with outliers—performed somewhat worse. Both models were limited in their ability to handle the intricate nonlinear interactions seen in pavement roughness data, despite their computational efficiency. Three granularity levels (Fine, Medium, and Coarse) were used to evaluate regression tree models. With a rapid training time of 1.57 seconds and an RMSE of 0.0861 and R^2 of 0.96, the fine regression tree fared the best, ranking among the most accurate models. With an RMSE of 0.1443 and R^2 of 0.89, the coarse regression tree performed the worst as tree complexity declined, suggesting that less detailed trees were useless for this prediction job. A variety of kernels, including linear, quadratic, cubic, and Gaussian, were used to test support vector regression (SVR). With an RMSE of 0.0882 and R^2 of 0.96, the Quadratic SVM model outperformed the others, proving that it could capture the nonlinear nature of IRI. The Medium Gaussian SVM model struck a balance between accuracy and efficiency, with an RMSE of 0.0946 and R^2 of 0.95, making it a strong contender for IRI prediction. The Boosted Trees and Bagged Trees models were examined to determine their effectiveness in aggregating multiple decision trees for improved accuracy; the Bagged Trees model slightly underperformed with an RMSE of 0.1066 and R^2 of 0.94, while the Fine Gaussian SVM model performed the worst, with an RMSE of 0.2832 and R^2 of 0.57, demonstrating poor generalization to the dataset. These models were computationally costly in comparison to alternative approaches because of their significantly long training times (16.57 seconds for Boosted Trees and 12.36 seconds for Bagged Trees), even though their accuracy was moderate. GPR showed the highest prediction accuracy of all the models. With an RMSE of 0.0776 and R^2 of 0.97, the Matern 5/2 GPR model produced the best results, demonstrating its proficiency in handling intricate, nonlinear pavement roughness patterns. With RMSE values ranging from 0.0782 to 0.0809 and R^2 values between 0.96 and 0.97, other GPR models, such as the Exponential, Squared Exponential, and Rational Quadratic models, also showed strong performance. Nevertheless, GPR models were more computationally expensive; the Matern 5/2 GPR model took the longest to train (18.53 seconds), out of all the GPR models. Different architectures of ANNs, such as Narrow, Medium, Wide, Bilayered, and Trilayered Networks, were tested. With an RMSE of 0.0970 and R^2 of 0.95, the Narrow Neural Network (10 neurons) had the best accuracy and processing efficiency balance. However, increasing the network complexity does not always result in higher performance. With an RMSE of 0.1260 and R^2 of 0.91 for the Medium Neural Network (25 neurons) and an RMSE of 0.1120 and R^2 of 0.93 for the Wide Neural Network (100 neurons), it was clear that increasing the number of neurons did not always increase accuracy. Despite having the longest training time (34.42 seconds), the Tri-layered Neural Network had the weakest performance (RMSE = 0.1446, R^2 = 0.89). Additionally studied were regression models based on kernels, such as the SVM Kernel and the Least Squares Regression Kernel. In contrast to other machine learning models, their performance was noticeably worse. The least successful methods for IRI prediction were the SVM Kernel model (RMSE of 0.2250 and R^2 of 0.73) and the Least Squares Regression Kernel model (RMSE of 0.2584 and R^2 of 0.64). In terms of IRI prediction, GPR models—specifically, the Matern 5/2 variant—performed the best overall. In real-world applications, the Fine Regression Tree and Quadratic SVM models were competitively accurate and computationally more efficient, making them good substitutes.

Table 4 shows how well machine learning (ML) models perform when trained with just the ten most crucial features rather than the entire dataset. Whether lowering the number of input variables preserves model accuracy while increasing computational efficiency can be determined with the aid of this feature selection technique. When compared to employing all features, the Linear Regression model performed worse when applied to the smaller feature set. With an RMSE of 0.1349 and an R^2 of 0.90, the linear model demonstrated a moderate level of accuracy. With an RMSE of 0.1450 and R^2 of 0.89, the Ro-bust Linear Regression model—which was created to lessen the impact of outliers—performed somewhat worse. The intricate correlations found in pavement roughness data are difficult for linear regression models to capture, despite their continued computational efficiency (training times of

Table 3. Performance Comparison of Machine Learning Models for IRI Prediction using All Input Features

Model Category	Model Type / Configuration	RMSE	R^2 Score	MSE	MAE	Training Duration (s)
Linear Models	Simple Linear Regression	0.0976	0.95	0.0095	0.0717	10.68
	Robust Linear Regression	0.1054	0.94	0.0111	0.074	5.24
Decision Tree Models	Fine Tree	0.0861	0.96	0.0074	0.0599	1.57
	Medium Tree	0.1023	0.94	0.0105	0.0721	2.19
	Coarse Tree	0.1443	0.89	0.0208	0.1107	2.03
Support Vector Machine	Linear Kernel	0.1019	0.94	0.0104	0.072	2.22
	Quadratic Kernel	0.0882	0.96	0.0078	0.065	3.52
	Cubic Kernel	0.1103	0.93	0.0122	0.0739	3.32
	Fine Gaussian Kernel	0.2832	0.57	0.0802	0.2042	1.36
	Medium Gaussian Kernel	0.0946	0.95	0.009	0.0691	2.28
	Coarse Gaussian Kernel	0.1595	0.86	0.0254	0.108	1.09
Ensemble Techniques	Boosted Decision Trees	0.0999	0.95	0.01	0.0777	16.57
	Bagged Decision Trees	0.1066	0.94	0.0114	0.0747	12.36
Gaussian Process Models	Squared Exponential Kernel	0.0799	0.97	0.0064	0.0592	7.5
	Matern 5/2 Kernel	0.0776	0.97	0.006	0.0572	18.53
	Exponential Kernel	0.0809	0.96	0.0065	0.0596	17.56
	Rational Quadratic Kernel	0.0782	0.97	0.0061	0.0576	15.69
Neural Networks	Narrow Neural Network (10 Neurons)	0.097	0.95	0.0094	0.069	22.8
	Medium Neural Network (25 Neurons)	0.126	0.91	0.0159	0.0925	20.99
	Wide Neural Network (100 Neurons)	0.112	0.93	0.0125	0.0826	33.25
	Two-Layer Neural Network	0.1086	0.94	0.0118	0.0793	29.91
	Three-Layer Neural Network	0.1446	0.89	0.0209	0.0827	34.42
Kernel-Based Methods	Support Vector Kernel Regression	0.225	0.73	0.0506	0.1484	32.23
	Least Squares Regression with Kernel Function	0.2584	0.64	0.0667	0.1895	30.43

10.69 and 3.25 seconds, respectively). Even with just 10 features, regression trees—specifically the Fine Regression Tree—performed well, with an RMSE of 0.0985 and R^2 of 0.95 in a short training period of 1.48 seconds. However, accuracy decreased when tree complexity was reduced. The Coarse Regression Tree did the poorest (RMSE = 0.1439, R^2 = 0.89), while the Medium Regression Tree had an RMSE of 0.1052 and R^2 of 0.94. These findings demonstrate how crucial it is to preserve intricate tree topologies in order to increase forecast accuracy. The performance of SVM models varied according to the type of kernel. With an RMSE of 0.0921 and R^2 of 0.95, the Quadratic SVM model performed the best, proving that it can manage nonlinear interactions. With an R^2 of 0.95 and an RMSE of 0.0966, the Cubic SVM model likewise demonstrated strong performance. A linear decision boundary is insufficient for modeling IRI changes, as evidenced by the Linear SVM model's lower effectiveness (RMSE = 0.1411, R^2 = 0.89). Results from SVM models based on Gaussian were not always reliable. The Fine Gaussian SVM model demonstrated noticeably worse performance (RMSE = 0.2964, R^2 = 0.53) than the Medium Gaussian SVM model (RMSE = 0.1001, R^2 = 0.95), indicating the latter's inability to effectively capture pavement roughness trends. Strong prediction accuracy was maintained by ensemble learning models, which combine several decision trees to increase robustness. The Bagged Trees model came in second with an RMSE of 0.1109 and R^2 of 0.93, while the Boosted Trees model obtained an RMSE of 0.1038 and R^2 of 0.94. Despite providing accurate predictions, these models required somewhat long training times (5.95 seconds for Boosted Trees and 4.49 seconds for Bagged Trees). Even with the smaller feature set, GPR continued to be the most accurate method. With an RMSE of 0.0800 and R^2 of 0.97, the Matern 5/2 GPR model produced the best results, demonstrating its exceptional capacity to represent nonlinear patterns in pavement roughness. Excellent results were also obtained by the Squared Exponential, Exponential, and Rational Quadratic GPR models, with R^2 values of 0.96 to 0.97 and RMSE values ranging from 0.0812 to 0.0861. Although these models took longer to train (5.46 to 7.34 seconds), they had the best accuracy. With accuracy varied according to network architecture, ANNs performed similarly to other sophisticated machine learning models. The most effective ANN architecture was the Narrow Neural Network (10 neurons), which had an RMSE of 0.0911 and an R^2 of 0.96. Additionally, the Bilayered Neural Network performed well (RMSE = 0.0945, R^2 = 0.95). Nevertheless, improved accuracy was not always the result of greater network complexity. R^2 values decreased to 0.93 and 0.94 for the Medium, Wide, and Trilayered Neural Networks, while their RMSE values ranged from 0.1074 to 0.1178. As the capacity of the network rose, training times climbed dramatically, rising from 14.36 to 13.59 seconds. Out of all the investigated methods, kernel-based regression models had the weakest performance. The Least Squares Regression Kernel model had an RMSE of 0.3261 and R^2 of 0.43, whereas the SVM Kernel model had an RMSE of 0.3433 and R^2 of 0.36. These findings suggest that the dataset's nonlinear interactions were not adequately captured by kernel-based regression techniques. The accuracy of most models was slightly reduced as compared to Table 3 (all characteristics used) due to the reduction to the top-10 significant features. For high-performing models like GPR and SVM, the change was negligible, indicating that feature selection can increase computational efficiency without appreciably sacrificing prediction accuracy. The most effective models for predicting IRI using just the top ten significant features were GPR models, especially Matern 5/2. Reliable results were also obtained by the Fine Regression Tree and Quadratic SVM models, which made them suitable options for pavement management systems.

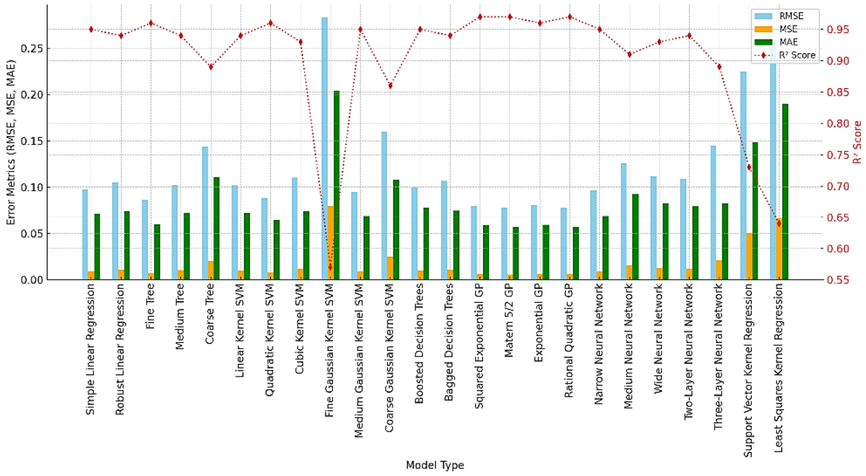


Figure 6. Performance Comparison of Machine Learning Models for IRI Prediction using All Input Features

Table 4. Performance Comparison of Machine Learning Models for IRI Prediction using the Top Ten Most Influential Features

Model Category	Model Configuration	RMSE	R² Score	MSE	MAE	Training Duration (s)
Linear Models	Basic Linear Regression	0.1349	0.9	0.0182	0.0946	10.69
	Robust Linear Regression	0.145	0.89	0.021	0.0864	3.25
Decision Tree Models	Fine Decision Tree	0.0985	0.95	0.0097	0.0682	1.48
	Medium Decision Tree	0.1052	0.94	0.0111	0.0741	3.07
	Coarse Decision Tree	0.1439	0.89	0.0207	0.108	1.69
Support Vector Machine	Linear SVM	0.1411	0.89	0.0199	0.0859	3.26
	Quadratic SVM	0.0921	0.95	0.0085	0.0668	1.56
	Cubic SVM	0.0966	0.95	0.0093	0.0699	3.55
	Fine Gaussian SVM	0.2964	0.53	0.0879	0.209	2.97
	Medium Gaussian SVM	0.1001	0.95	0.01	0.0698	2.41
	Coarse Gaussian SVM	0.1456	0.89	0.0212	0.0929	3.67
Ensemble Techniques	Boosted Tree Ensemble	0.1038	0.94	0.0108	0.0798	5.95
	Bagged Tree Ensemble	0.1109	0.93	0.0123	0.0751	4.49
Gaussian Process Regression	Squared Exponential Kernel	0.0812	0.96	0.0066	0.0595	7.34
	Matern 5/2 Kernel	0.08	0.97	0.0064	0.0584	5.46
	Exponential Kernel	0.0861	0.96	0.0074	0.0602	6.26
	Rational Quadratic Kernel	0.0812	0.96	0.0066	0.0591	7.21
Artificial Neural Networks	Narrow Network (10 Neurons)	0.0911	0.96	0.0083	0.0642	14.36
	Medium Network (25 Neurons)	0.1178	0.93	0.0139	0.0866	8.44
	Wide Network (100 Neurons)	0.1074	0.94	0.0115	0.0806	14
	Two-Layer Neural Network	0.0945	0.95	0.0089	0.0676	11.94
	Three-Layer Neural Network	0.1119	0.93	0.0125	0.0783	13.59
Kernel-Based Methods	SVM with Kernel Function	0.3433	0.36	0.1179	0.2412	8.59
	Least Squares Regression with Kernel	0.3261	0.43	0.1063	0.237	8.49

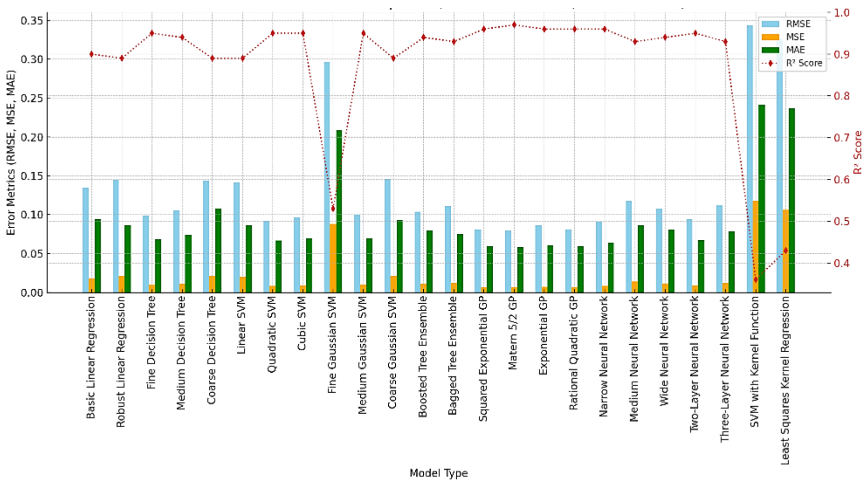
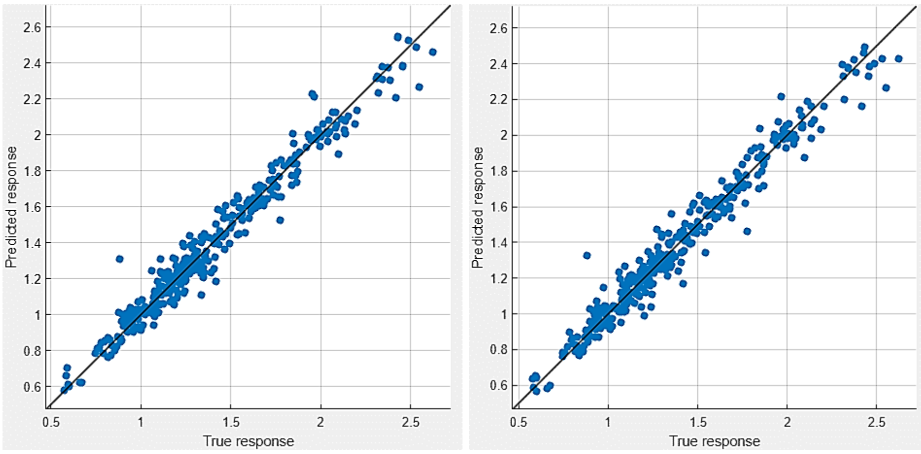


Figure 7. Performance Comparison of Machine Learning Models for IRI Prediction using the Top Ten Most Influential Features

The observed and anticipated IRI values for the best-performing models are shown in Figure 8. While panel (b) presents the results using the top ten features, panel (a) presents the results using all features. The models' great prediction accuracy is demonstrated by the two scatter plots, which show a high degree of correlation between the measured and anticipated IRI values. The 45-degree line, which represents perfect forecasts, is almost matched by the data points in Figure 8(a). This alignment shows that the model with all attributes predicts the IRI values very well over a wide range of data. The consistency and clustering around the line show that the model has significant generalization to the da-ta. Similarly, the model's performance is shown in Figure 8(b) using just the 10 most important characteristics. Despite the decrease in the number of attributes, the data points still exhibit a strong correlation with the 45-degree line. This suggests that the top 10 features account for the majority of the variability in IRI, allowing the model to maintain high accuracy even when employing a relatively limited set of predictors. Overall, the scatter plots demonstrate that both the complete and reduced feature sets perform well and that the machine learning models are effective in accurately predicting IRI for CRCP.



(a) (b)

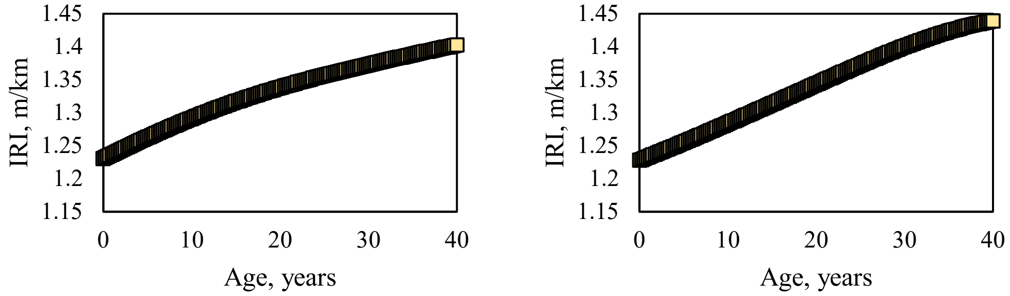
Figure 8. Comparison between Measured and Predicted IRI Values for the Best-Performing Machine Learning Models using (a) All Input Features, and (b) The Top Ten Selected Features

Sensitivity Analysis

Figures 9(a), 10(a), 11(a), 12(a), and 13(a) present the sensitivity analysis results for the best-performing machine learning model when considering all available features. This analysis was conducted on key influencing variables such as pavement age, temperature, freeze index, precipitation, and initial IRI to examine their individual impact on the predicted IRI. Each variable was varied independently, while all other factors were kept at their mean values to isolate its effect. Figure 9(a) highlights the influence of pavement age on IRI, demonstrating that as pavement ages, IRI increases, indicating a natural progression toward rougher surfaces over time. Figure 10(a) explores the relationship between temperature fluctuations and IRI, revealing a nonlinear trend where temperature variations lead to an increase in IRI. This underscores the impact of thermal expansion and contraction on pavement smoothness. Figure 11(a) examines the effect of freeze-thaw cycles on pavement roughness. A higher freeze index, representing frequent freeze-thaw occurrences, correlates with increased IRI, reinforcing the significant role of cyclical freezing and thawing in pavement deterioration. Similarly, Figure 12(a) shows how annual precipitation affects IRI, indicating that higher rainfall levels lead to increased pavement roughness, likely due to moisture infiltration and subsequent damage.

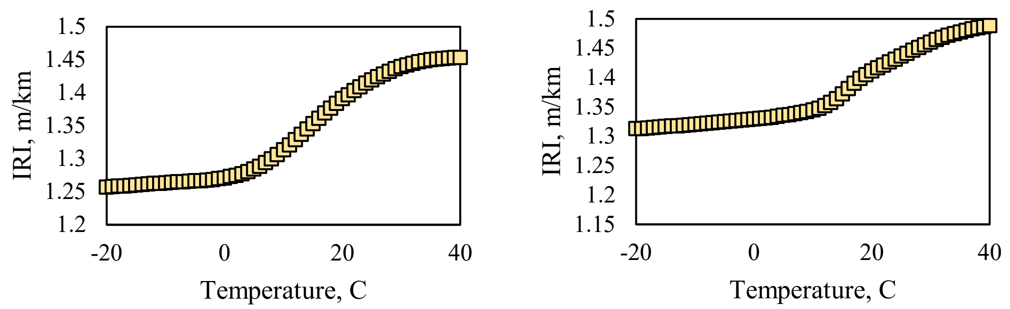
The final variable, initial IRI, is assessed in Figure 13(a), which confirms that higher initial roughness values result in higher predicted IRI values over time. This finding underscores the critical role of initial pavement conditions in determining long-term performance, emphasizing the necessity of early intervention in pavement maintenance. Overall, the sensitivity analysis reaffirms that age, temperature, freeze index, precipitation, and initial IRI are fundamental factors affecting pavement roughness. These results highlight the importance of incorporating these variables into predictive models for improved IRI forecasting and optimized maintenance planning. Figures 9(b), 10(b), 11(b), 12(b), and 13(b) display the sensitivity analysis results when using only the top 10 most influential features. Similar to the previous analysis, this approach aimed to isolate the impact of each key variable on IRI predictions while keeping all other factors at their mean values. The findings in Figures 9(b) and 10(b) align closely with those in Figures 9(a) and 10(a), reinforcing the strong relationship between pavement age and roughness. As seen in Figure 9(b), the sensitivity analysis confirms that IRI increases with pavement age, following the same trend observed in Figure 9(a). Similarly, Figure 10(b) shows a nonlinear temperature-IRI relationship, mirroring the findings in Figure 10(a). This further supports the significance of temperature fluctuations in influencing pavement smoothness due to thermal expansion and contraction.

The impact of the freeze index on IRI is evident in Figure 11(b), which, like Figure 11(a), shows that higher freeze index values correspond to increased IRI. This suggests that freeze-thaw cycles are a key contributor to pavement degradation. The relationship between precipitation and IRI, presented in Figure 12(b), exhibits a pattern similar to Figure 12(a), reinforcing that higher precipitation levels lead to rougher pavement surfaces due to moisture-induced deterioration. Lastly, Figure 13(b) confirms that initial IRI has a lasting impact on future pavement roughness, just as shown in Figure 13(a). A higher initial roughness leads to a greater predicted IRI over time, emphasizing the necessity of maintaining low initial roughness levels for long-term pavement performance. When comparing the sensitivity analysis results obtained using all features (Figures 9(a)-13(a)) versus the top 10 most important features (Figures 9(b)-13(b)), a consistent trend is observed across both approaches. This similarity suggests that the top 10 features successfully capture the majority of the variability in IRI, allowing for accurate predictions while reducing the complexity of the model. The consistency between both analyses validates the effectiveness of feature selection, demonstrating that models can maintain high predictive accuracy while focusing on only the most significant variables. This streamlined approach simplifies computations, enhances efficiency, and ensures robust performance in pavement roughness prediction models.



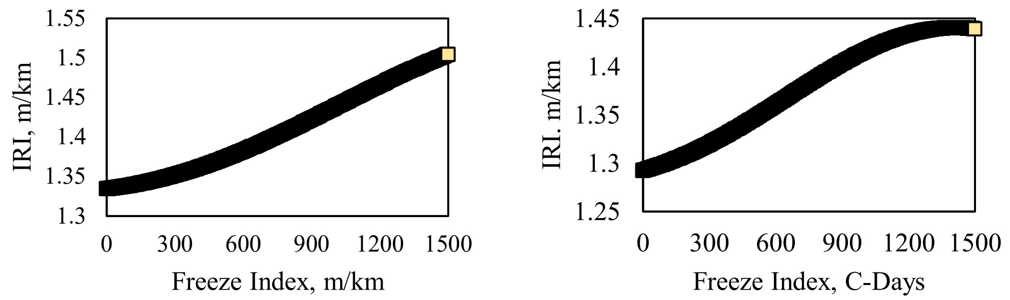
(a) (b)

Figure 9. Sensitivity Analysis Results Illustrating the Effect of Pavement Age on Predicted IRI using (a) All Features, and (b) The Selected Top Ten Features



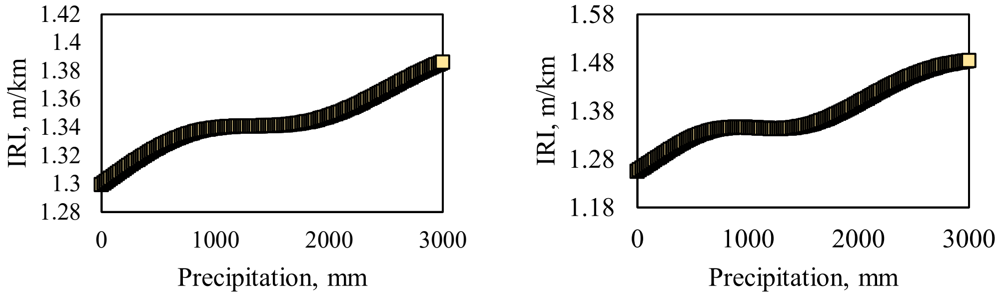
(a) (b)

Figure 10. Sensitivity Analysis Results Illustrating the Effect of Annual Average Temperature on Predicted IRI using (a) All Features, and (b) The Selected Top Ten Features



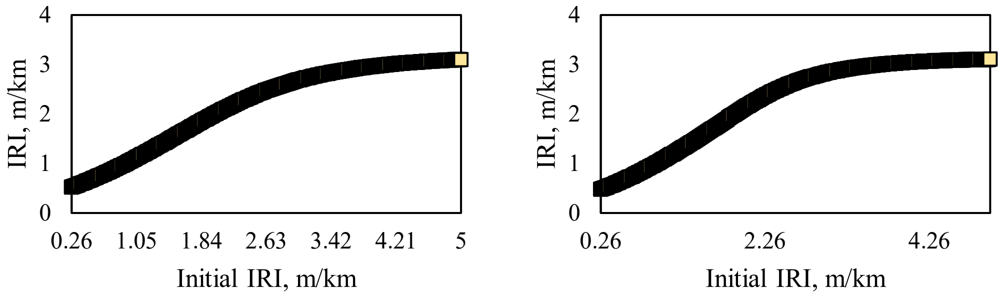
(a) (b)

Figure 11. Sensitivity Analysis Results Illustrating the Effect of Freeze Index on Predicted IRI using (a) All Features, and (b) The Selected Top Ten Features



(a) (b)

Figure 12. Sensitivity Analysis Results Illustrating the Effect of Annual Average Precipitation on Predicted IRI using (a) All Features, and (b) The Selected Top Ten Features



(a) (b)

Figure 13. Sensitivity Analysis Results Illustrating the Effect of Initial IRI on Predicted IRI using (a) All Features, and (b) The Selected Top Ten Features

CONCLUSIONS

Using data from the LTPP database, this study sought to create and assess sophisticated machine learning models for precisely forecasting the IRI in CRCP. A variety of advanced machine learning techniques were used in the study, such as ensemble trees, SVM, GPR, ANN, regression decision trees, and kernel approaches. Performance measures including RMSE, R^2, MSE, MAE, and training time were used to evaluate the models.

The main findings of this study are as follows:

1. The Matern 5/2 GPR and other sophisticated machine learning models showed superior predictive accuracy for IRI, according to the research. This model demonstrated its effectiveness in forecasting pavement roughness by achieving the lowest RMSE and greatest R^2 values. The robustness of these methods was demonstrated by the strong performance of the Fine Regression Tree and other GPR models.
2. The most important elements impacting IRI, according to a feature importance analysis, were temperature, initial IRI, L3 thickness, age, and annual precipitation. The evaluation of the Random Forest model's feature relevance yielded insightful information, highlighting the necessity of concentrating on these crucial factors in predictive modeling.
3. The substantial influence of age, temperature, precipitation, freeze index, and initial IRI on IRI forecasts was validated by sensitivity analysis. The findings demonstrated the strength of these crucial factors in affecting pavement roughness, since they were consistent between models that used all characteristics and those that used just the top ten significant features.
4. The study showed that predictive accuracy was comparable to utilizing all characteristics when the top ten most crucial features were used. According to this research, models may be made simpler without sacrificing performance by reducing the number of essential characteristics. This results in more effective data processing and model training.
5. The findings demonstrated how crucial structural elements like pavement layer thickness and beginning roughness, as well as environmental factors like temperature variations and precipitation, are in affecting pavement performance over the long run.
6. Using all variables, the Matern 5/2 GPR model achieved an R^2 of 0.97 and an RMSE of 0.0776, outperforming other models. With an R^2 of 0.97 and an RMSE of 0.0800 while utilizing the top 10 features, this model continued to perform at its best. This consistency emphasizes how reliable the model is and how crucial it is to concentrate on the most important variables.

Limitations and Future Directions

The study employs 33 CRCP sections filtered to exclude maintenance and rehabilitation operations, which improves data consistency but restricts generalizability. Future studies should include larger and more diversified datasets from other climates and structure types.

Model Generalization: While the models work well, their accuracy may be affected by unrecorded factors like material variations and construction quality. Expanding the input information to incorporate more physical and material attributes would improve prediction accuracy.

Application to Rehabilitated Pavements: Current models were trained on untreated sections. Future research should assess model performance for pavements undergoing maintenance or rehabilitation in order to better reflect real-world pavement management scenarios.

DECLARATION

Availability of Data and Materials: The dataset used in this study was extracted from the LTPP database, a publicly available resource maintained by the FHWA. The LTPP database can be accessed via the DataPave platform at https://infopave.fhwa.dot.gov/. Specific data processing and analysis steps are described in the manuscript to ensure reproducibility. Additional details or derived datasets used in this research are available from the corresponding author upon reasonable request.

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